Scaling AI Clinical Decision Support in Oncology: Infrastructure and Policy for Treatment Matching

Policy Issues for Integrating Artificial Intelligence in Cancer Research and Care
National Cancer Policy Forum

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The Problem

- Each year, >1.1 million patients in the US receive chemotherapy for cancer
- Connecting patients with the right treatment at the right time is fundamental to delivering high-quality cancer care
- Matching a patient to a treatment or clinical trial is challenging because clinical evidence and eligibility criteria are complex, fast-changing, and fragmented
- Many patients do not receive recommended treatments, and many clinical trials are under-enrolled
- Can AI-based clinical decision support overcome these barriers and help match patients to the 'best' chemotherapy regimen or clinical trial?
- If so, what is needed to make this solution work for everyone everywhere?

PMIDs: 18584358, 31366576, 36301585, 38423048,

AI to Support Clinical Decision Making

Original Reports | Artificial Intelligence

Large Language Models as Decision-Making Tools in Oncology: Comparing Artificial Intelligence Suggestions and Expert Recommendations

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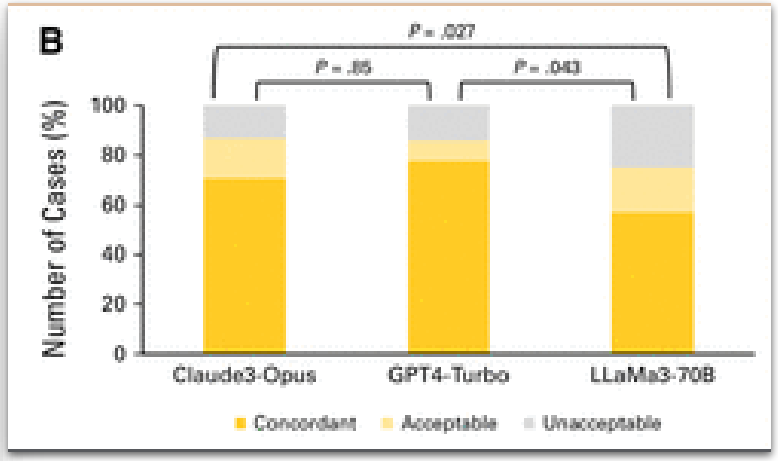
DOI https://doi.org/10.1200/CCI-24-00230



Sought to determine the accuracy of LLMs in generating appropriate treatment options for patients with early breast cancer

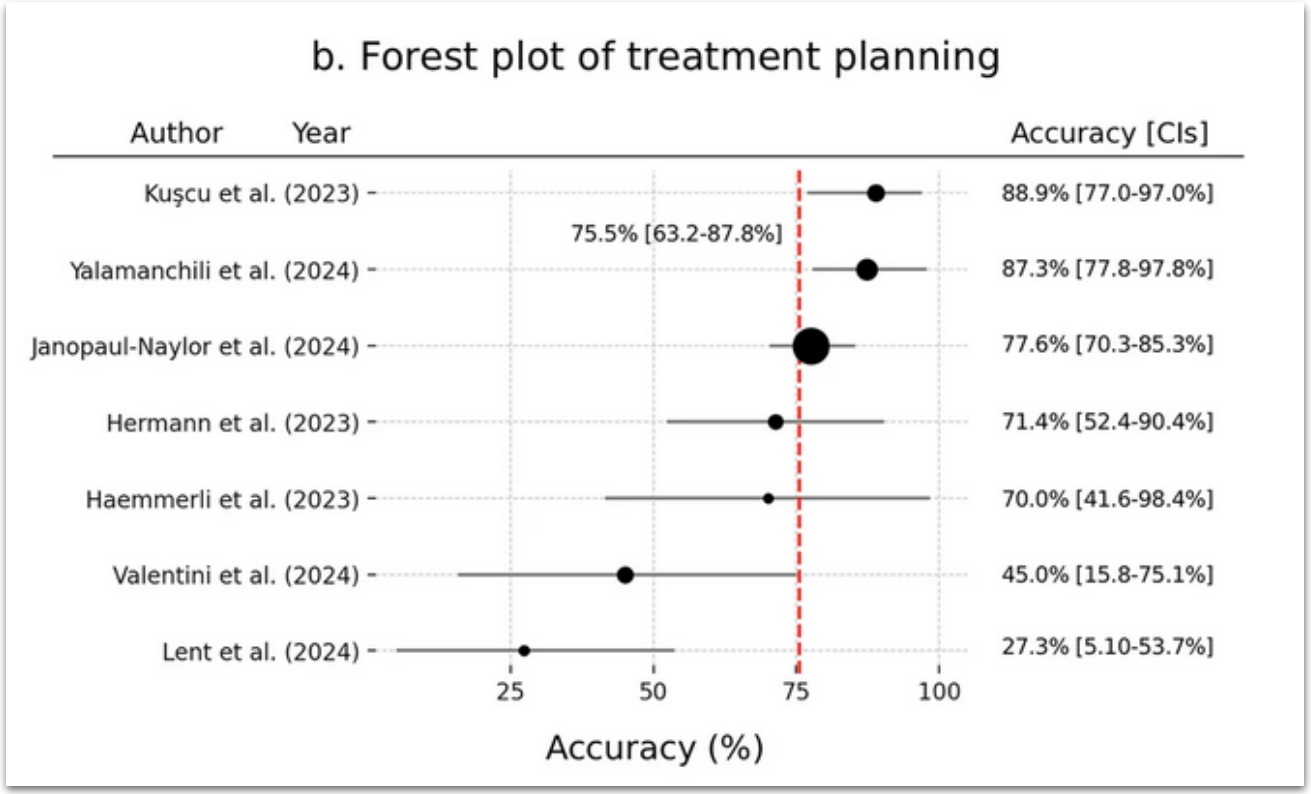
Compared suggestions from 3 generalist artificial intelligence models (Claude3-Opus, GPT4-Turbo, and LLaMa3-70B) with expert decisions

Found a 75-87% rate of appropriate suggestions (concordant + acceptable)

PMID: 40112233

A systematic review and meta-analysis of LLM integrations in cancer decision-making

- Regarding LLMs for treatment planning
  - 75.5% average quality and correctness rating (95% CI: 63.2–87.8%; standard error 6.30%)
  - Moderately high heterogeneity ($Q = 72.3$, $p < 0.01$, $I^2 = 92.7\%$) across treatment-oriented studies
- Systems had limited domain knowledge and dependend on human oversight



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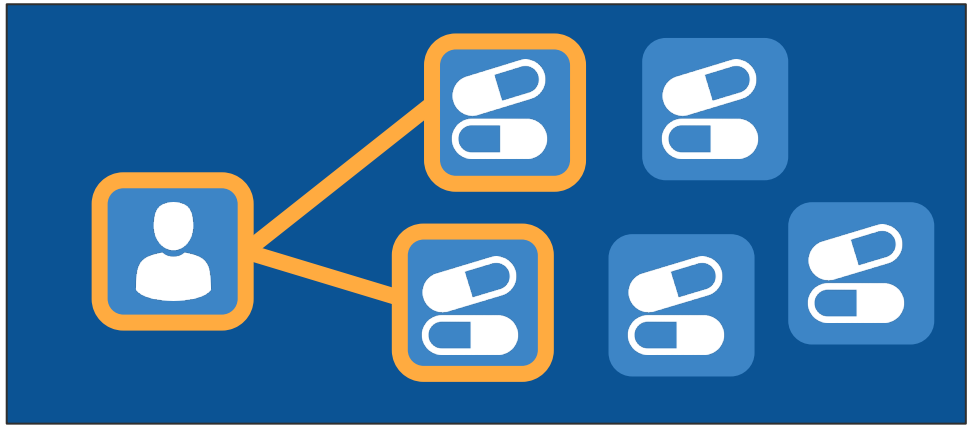
MatchMiner

An application developed at Dana-Farber to match patients with clinical trials based on genomic criteria. It has two modes…

Trial-centric mode

First released 2016

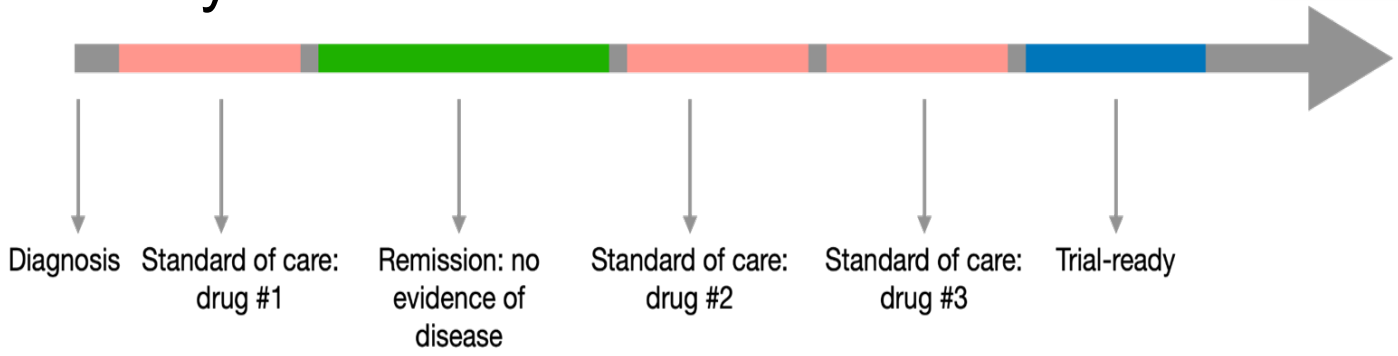
Patient-centric mode



To date, responsible for hundreds of clinical trial enrollments

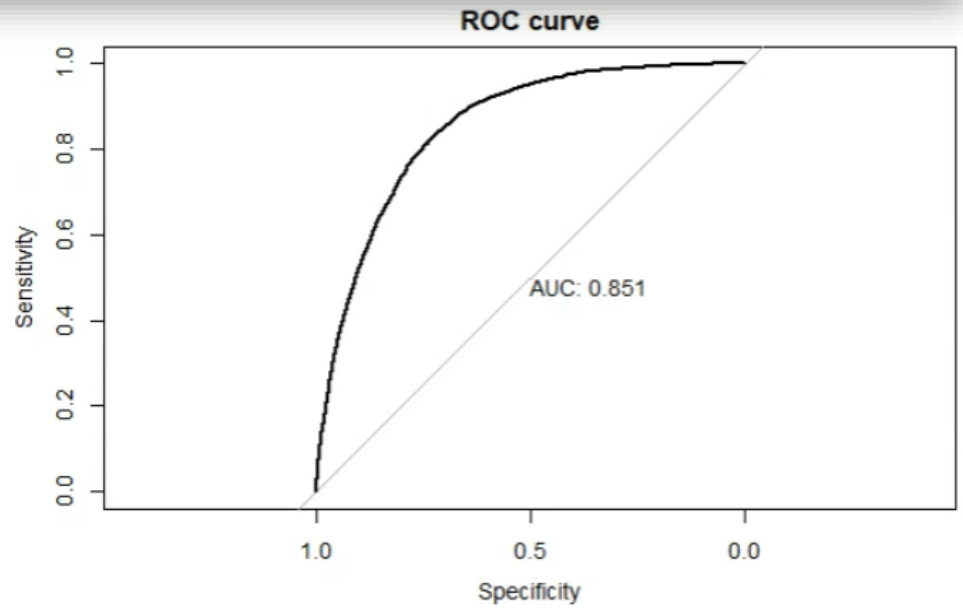
Incorporate AI-based treatment change prediction

- MatchMiner connects patients to trials based on genomics
- However, patients are often not “trial-ready”



Clinical Inflection Point Detection on the Basis of EHR Data to Identify Clinical Trial–Ready Patients With Cancer

Kenneth L. Kehl, MD, MPH[1]; Stefan Groha, PhD[1]; Eva M. Lepisto, MA, MSc[1]; Haitham Elmarakeby, PhD[1]; James Lindsay, PhD[1]; Alexander Gusev, PhD[1]; Eliezer M. Van Allen, MD[1]; Michael J. Hassett, MD, MPH[1]; and Deborah Schrag, MD, MPH[1]

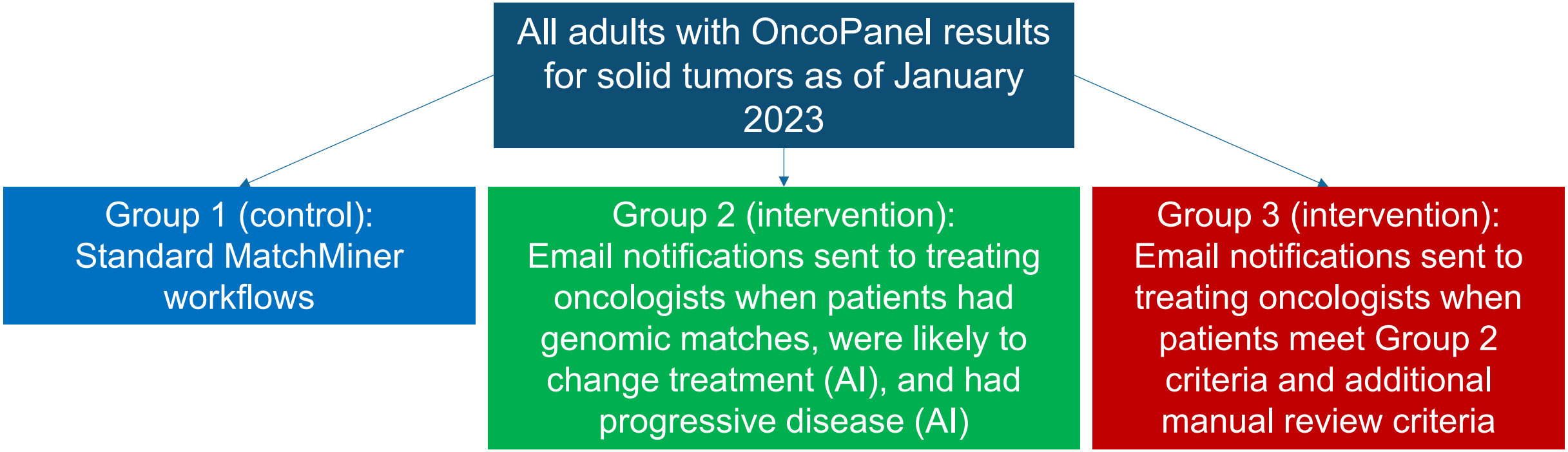


PMID: 34097438

		Control enrollment rate	Intervention enrollment rate	
Ever “trial-ready”	2,127	18.0%	18.5%	0.80

OPTIONS: Jan. 2023 – July 2024

(Optimizing Precision Trials with an artificial Intelligence driven Oncologist Notification System)



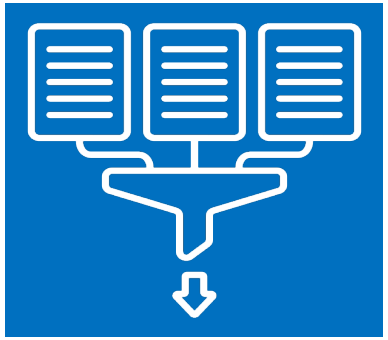
	N	Control enrollment rate	Intervention enrollment rate	P
Ever “trial-ready”	2,127	18.0%	18.5%	0.80

MatchMiner-AI:
Open-source Clinical Trial Matching for All

- Match patients to **all trials** (not just genomic trials) based on clinical text and eligibility criteria documents

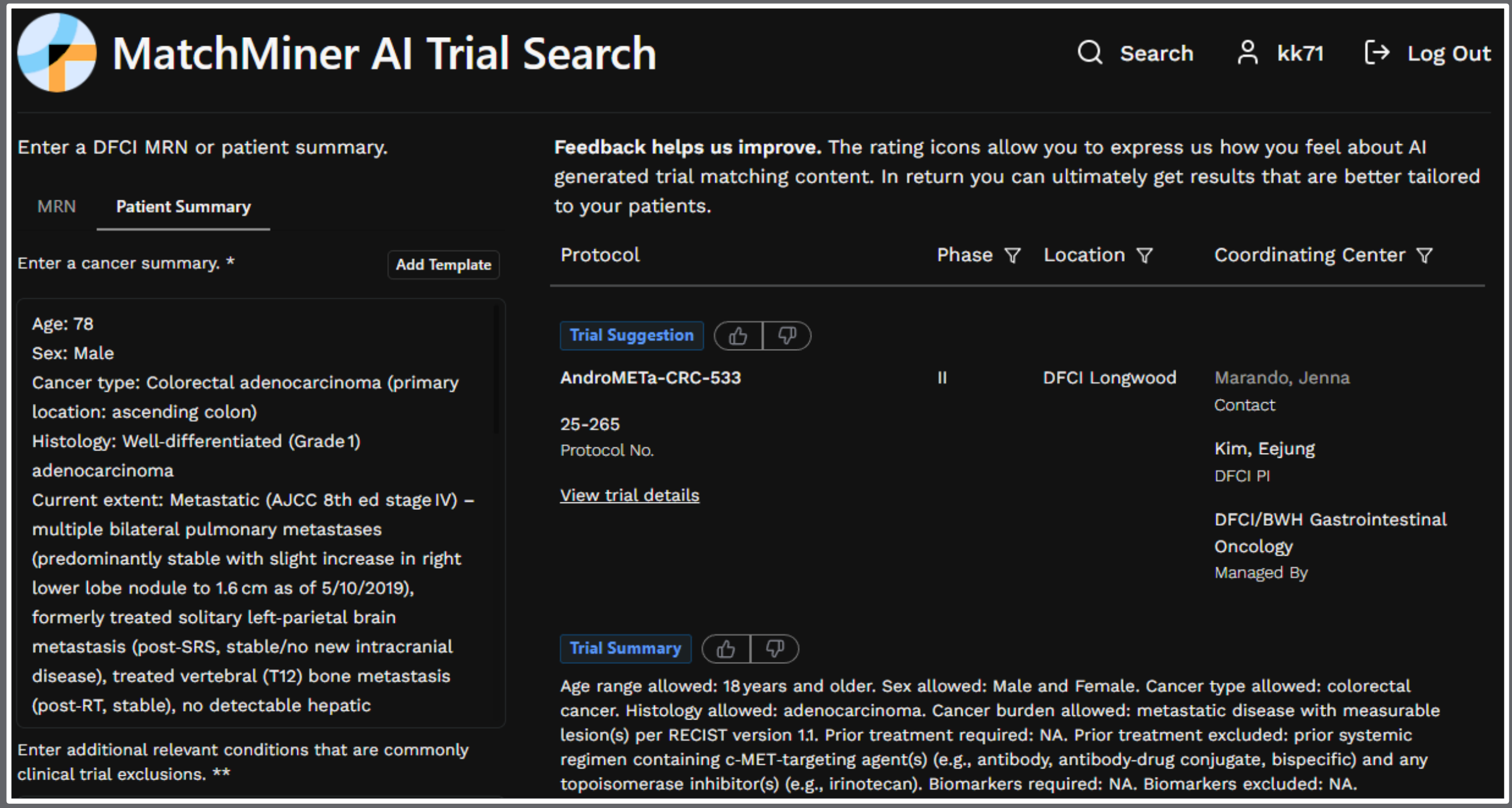
- Train on **synthetic clinical data** for shareability without patient privacy risks

MatchMiner AI: Model Development



1. Focus on core clinical criteria: age, sex, cancer type/histology, disease burden, prior treatment, biomarkers
2. Use LLM to generate patient summaries and trial target populations
3. Use synthetic patient data to train models
4. Use retrospective patient data to evaluate models
5. Create a three-step screening tool
    1. Trial space embedding model: derive a similarity metric between patient and target population summaries
    2. Trial checker: is patient a reasonable match for a trial?
    3. ‘Boilerplate’ checker: does patient match any broad exclusion criteria?
6. Create a front-end app

Patient-centric Frontend



Cohort estimation for feasibility analysis

🔍 Find Matching Patients

📊 Results

📊 Summary: Patients Meeting Your Criteria

Metric	Count
Total patients in database	63865
Top patients checked with classifiers	500
Meeting eligibility criteria (≥0.5)	485
Without boilerplate exclusions (<0.5)	488
Meeting BOTH criteria	473

Matched Patients

Patient ID	Eligibili…	Exclusion	Simila…	Summary Preview
13137	1.00	0.00	0.812	Age: 78 Sex: Male Cancer type: Colorectal adenocarcinoma (primary location: ascending colon) Histology: Well-differentiated (Grade 1) adenocarcinoma Current extent: Metastatic (AJCC 8th ed stage IV) – multiple bilateral pulmonary metastases (predominantly stable with slight increase in right...
28227	1.00	0.00	0.815	Age: 84 Sex: Female Cancer type: Colorectal adenocarcinoma – primary site rectum (C20.9) Histology: Moderately differentiated (grade 2) adenocarcinoma Current extent: Metastatic disease – peritoneal carcinomatosis, hepatic metastasis (segment II/V lesions ~1.6 cm), solitary right upper-loba...
11771	1.00	0.00	0.827	Age: 39 Sex: Male Cancer type: Colorectal adenocarcinoma (ascending colon) Histology: Poorly differentiated adenocarcinoma, intestinal phenotype Current extent: Stage IV/metastatic disease with peritoneal carcinomatosis, hepatic metastases (multiple lesions ≤1.5 cm), and bilateral pulmonar...

https://huggingface.co/ksg-dfci

Integration & Scaling Challenges (local)

Governance regarding data access and AI use-cases
Computational expertise and infrastructure (e.g., cloud services)
Timely and reliable pipelines to access current, accurate, standardized, longitudinal data
Ability to access and customize proprietary clinical systems
Hook into existing workflows – right provider at the right time (ensuring human in the loop)
Report the explainability and confidence of model outputs
Demonstrate clinical impact and return on investment
Versioning, monitoring/auditing, and updating models
Facilitating change management, training, and support

Integration & Scaling Challenges (system)

- Financial reimbursement model to cover the costs of AI tools and infrastructure while ensuring equitable access to these resources
- Overcome interoperability barriers to accessing data
  - Incentives to use data standards and make data available
  - Develop data resources (e.g., simulated, public deidentified)
- Ensure that models are developed using data from a diverse set of patients and clinical practices
- Ensure that data privacy and security incorporate AI-relevant provisions: minimum necessary, encryption, access controls, logging, secondary use boundaries
- Clarify regulation across agencies and levels of government: rules for regulated medical device, customization, post-deployment updates and monitoring, etc.
- Liability/accountability: who is responsible for missed matches or inappropriate suggestions?

Using AI for Clinical Decision Support

- Requirements
  - Inputs: cancer type, cancer status, genomics, pathology, staging, prior therapy, labs, performance status, comorbidities, preferences, regimen characteristics (e.g., eligibility criteria) etc.
  - Functions: normalize data (e.g., notes, lab, radiology) → interpret eligibility (pathway, clinical trail, etc.) → rank options
  - Outputs: actionable “best options” for clinician + trial team
- Dependencies
  - Governance + data + technical expertise/capacity + workflow integration + support systems
  - Trust, collaboration, and a socio-technical approach

Major considerations regarding the effective development & clinical translation of AI in cancer care

Data curation and sharing	Bias and fairness	Regulation and evaluation	Integration into clinical workflows
Diverse multimodal data sets	Clinical deployment	Transparency and reproducibility	Clinician–AI interface and explainability

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Artificial Intelligence in Oncology: Current Landscape, Challenges, and Future Directions

William Lotter; Michael J. Hassett; Nikolaus Schultz; Kenneth L. Kehl; Eliezer M. Van Allen; Ethan Cerami

Check for updates

+ Author & Article Information

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Many AI Platforms for Oncology Trial Matching

A growing ecosystem of AI-driven platforms—mostly in the commercial space--has developed to match patients to trials.

Deep 6 AI (Tempus)

Massive Bio

Proscia Aperture

TrialX

Lifebit

Flatiron OncoTrials

TriNetX

TrialGPT

MatchMiner-AI

Trial Library

Navify Clinical Trial Match (Roche)

Mendel.ai

Trialjectory/Leal Health

Clinerion

My Cancer Genome

Antidote Match

When it comes to scaling AI, the list of stakeholders is growing and changing. Who should do what?

- Health systems
- Electronic health record vendors
- Clinical vendors (e.g., radiology, lab)
- Informatic/analytic vendors
- Payers
- Regulators

Stakeholders have different priorities, expertise, data access, and resources.

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