Clinical Artificial Intelligence

Past, Present and Future

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Disclosures

The speaker has the following relevant financial relationships to disclose:

No relevant financial relationships to disclose

Today's Talk

Big picture, three axes of impact, Some tensions to watch

The big picture — how clinical AI is evolving

From rule-based scores to predictive, generative, and agentic systems — and where uro-onc fits.

Three axes of impact in Clinical AI

AI in the patient journey, in clinical workflows, and in the patient–clinician interaction.

Some Practical Examples

The Modern AI Clinic: Agentic AI, AI based biomarkers(ADT Zero) and the ASCO living Guidelines

Open problems & where you come in

The open tensions in the field — and the research problems they create.

The Evolution of Clinical AI

From AI that calculates to AI that acts — with the clinician as attending

Rule-Based AI

“The Calculator”

Fixed formulas. Same inputs always give the same score.

D'Amico, NCCN risk groups, CAPRA, Briganti nomogram

Predictive AI

“The Pattern Spotter”

Learns from thousands of patients to predict what's coming next.

Artera, Decipher, PSMA-PET response models, ctDNA classifiers

Generative AI

“The Medical Student”

Ask a question, get a thoughtful answer — but only when asked.

ChatGPT for patient education, LLM literature synthesis, draft notes

Agentic AI

“The Senior Resident”

You give it a goal — it plans, uses tools, returns a draft for your sign-off.

Living guidelines, agentic trial matching, autonomous evidence synthesis

Each tier is already in practice today. The frontier is moving — quickly — toward the right.

From Clinic to Computation

The same clinical problems, named as the ML problems you already know

Treatment Selection

Policy learning / ITE

Pick the action that maximizes this patient's outcome.

COMPASS-CSPC, causal forests, T-/X-learners

Staging & Imaging

Detect / segment / quantify

Find it, outline it, measure it on MRI / PET / path.

PSMA-PET quantification, MRI lesion detection, Gleason grading

Evidence at Scale

Retrieval + NLP + meta-analysis

Keep a synthesis current as new trials report.

Living guidelines, LLM screening & extraction

Genomic Risk

Representation learning on omics

Turn high-dimensional omics into a usable signal.

Decipher, ctDNA classifiers, omic foundation models

Every clinical task in this talk maps to a problem class you can model, validate, and improve.

AI Voice Capabilities

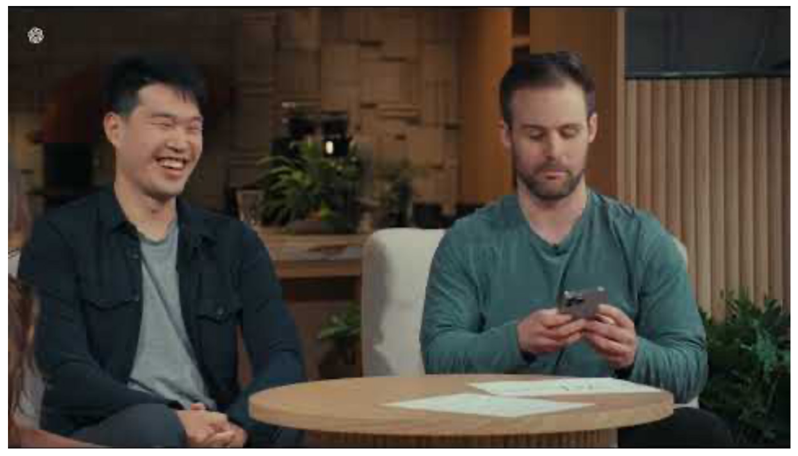
OpenAI — Natural Voice Interaction

Natural, real-time voice conversation with AI. The foundation for ambient documentation, patient communication, and hands-free clinical decision support.

Video: *https://www.youtube.com/watch?v=c2DFg53Zhvw*

AI Vision Capabilities

OpenAI — Multimodal Visual Understanding



AI interprets real-world scenes, reads medical images, and understands visual context in real time. Imagine this applied to radiology, pathology slides, or bedside assessment.

Video: *https://www.youtube.com/watch?v=RI-BxtCx32s*

Ambient Documentation in Practice

Microsoft DAX Copilot — AI Scribe Demo

DAX Copilot listens to the patient encounter, generates the clinical note in real time, and drafts orders — already deployed at Mayo Clinic and 600+ health systems.

Three Axes of AI in Clinic

Same underlying shift — three different surfaces where it shows up

AXIS 1

Patient Journey

AI in the disease.

From pre-cancer risk to end-of-life — touching diagnosis, staging, treatment selection, and monitoring.

Artera · COMPASS · PSMA-AI · ctDNA

AXIS 2

Clinical Workflows

AI in the system.

Removing friction from the work of cancer care — intake, documentation, decision support, and trial operations.

Ambient scribes · MAYA · Living guidelines

AXIS 3

Patient–Clinician Interaction

AI in the relationship.

Patients are already using AI to engage with their cancer — interpretation, education, trial-finding, communication.

Open Notes · Trial matching · Virtual counselors

We'll walk through each axis in turn — anchored on one prostate cancer patient: Mr. K.

AXIS 2 | WORKFLOWS

AI in Clinical Workflows

Where AI quietly removes friction from the work of cancer care

1 Intake & Triage Automation

AI intake assessments, automated routing of new referrals to the right specialist.

2 AI-Assisted Chart Search

Tools like MAYA surface relevant prior notes, imaging, labs in seconds — not hours of scrolling.

3 Ambient Documentation

DAX, Abridge, Carellon — listen, draft note, propose orders. Returning time to the encounter.

4 Decision Support

Guideline-concordant recommendations surfaced at point of care — and (next slide) updated continuously.

5 Trial Operations

Activation, patient identification, eligibility screening, reporting — automation across the trial lifecycle.

6 Registry & Database Automation

Cancer registries, real-world data extraction, structured reporting — without armies of abstractors.

Most workflow AI is invisible to patients. The deep dive: living evidence — the only one they will eventually feel.

AI Across the Prostate Cancer Journey

From pre-cancer to end-of-life — AI is already at every stop

Pre-cancer	Diagnosis	Staging	Treatment	Follow-up	End-of-Life
Population PSA risk modeling	MRI lesion detection	PSMA PET interpretation	Treatment selection (Artera)	PSA trajectory modeling	Symptom prediction
Genetic risk (HOXB13, BRCA)	Pathology foundation models	Automated quantification	Individualized policy (COMPASS)	ctDNA monitoring	Care preference prediction
AI-guided MRI screening	Augmented Gleason grading	Multi-modal prognostication	Dose personalization in RT	Recurrence prediction	Advance care planning
Lifestyle / EHR risk	Multi-modal diagnostics	LN prediction (vs ePLND)	Toxicity prediction	Survivorship support	Caregiver support

Two deep dives ahead — Artera at the moment of treatment selection, COMPASS for individualized treatment policy.

CASE VIGNETTE

Meet Mr. K

62-year-old man — newly diagnosed prostate cancer

PSA 12 ng/mL | Gleason 4+3 = 7 (Grade Group 3) | cT2c

MRI: PI-RADS 5 lesion, no extracapsular extension

Conventional staging: no metastatic disease

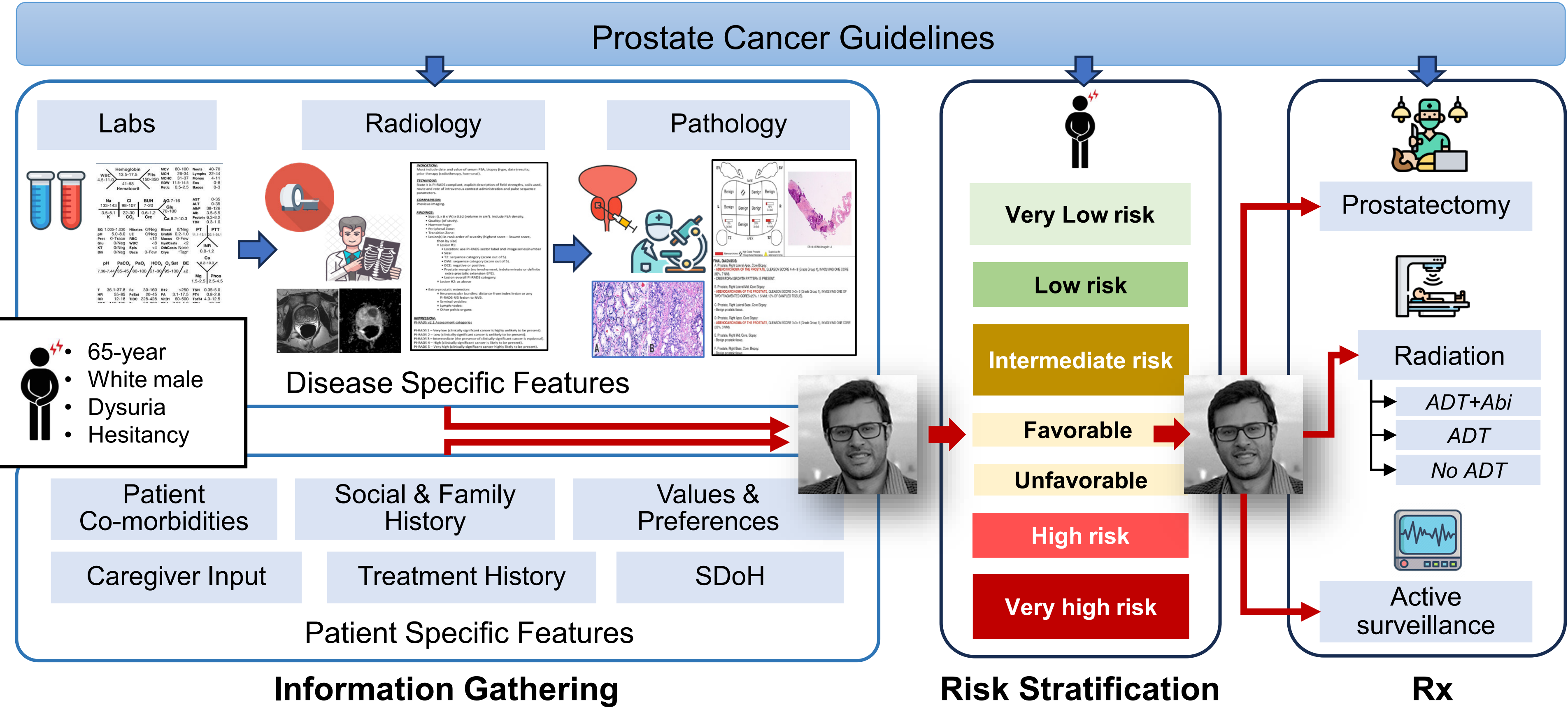
Unfavorable intermediate risk. The decision in front of us:

Definitive radiation alone — or radiation plus short-course ADT?

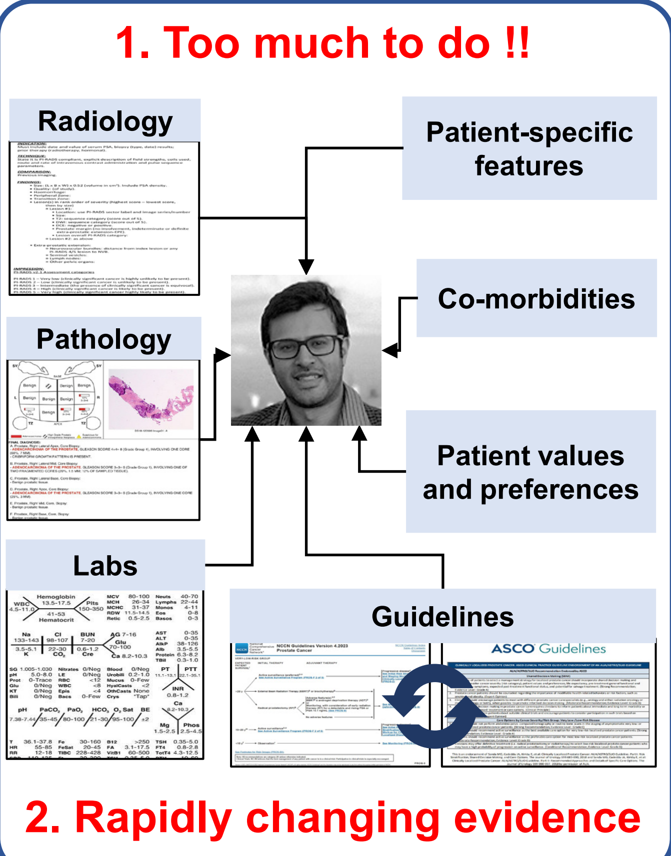
Trial-average benefit of ADT in this group: small.
Individual benefit: highly variable. How do we choose?

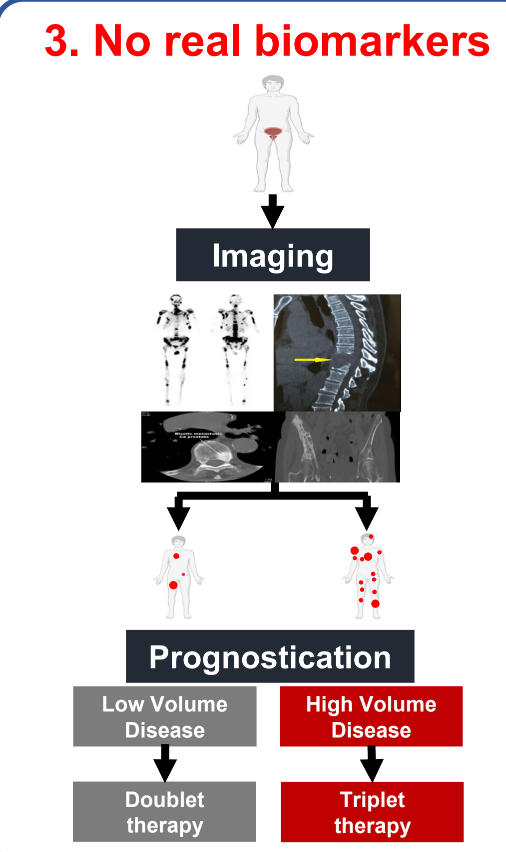
AI already touches Mr. K's care today — and within 3 years will touch every step. Let's walk through it.

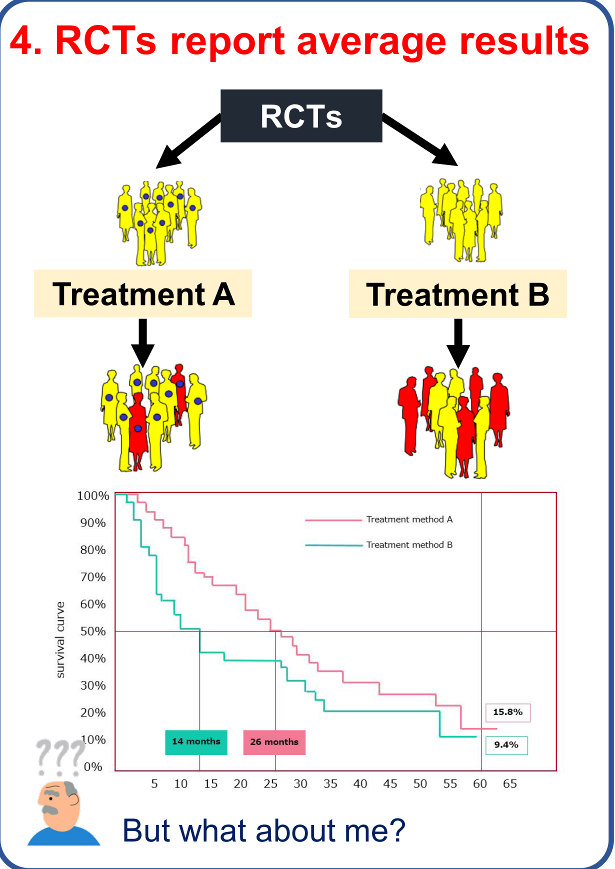
Process of treatment selection: localized prostate cancer



Challenges in Treatment Selection and Predicting Outcomes







The Modern AI Clinic

- AI agents acting as assistants to optimize treatment decisions
- Artificial intelligence-enabled **living clinical practice guidelines**
- **Patient-specific (individualized) treatment effects**
- **Digital biomarkers** utilizing multi-modal data

#1 AI agents as assistants to healthcare providers

Labs

Radiology

Pathology

mCRPC patient. Next line of Rx?

Agents

Clinical notes

Patient Co-morbidities

Caregiver Input

Social & Family History

Treatment History

SDoH

Values & Preferences

Patient Specific Features

ASCO Guidelines

Guidelines

Information Gathering

Summary

Disease status mCRPC

Previous treatment

1. Abiraterone, disease progression
2. Docetaxel, disease progression

Performance status

ECOG 1, peripheral neuropathy from docetaxel

Genomics No HRR mutation

Imaging Bone mets

PSMA PET scan: SUVmax 15

Labs Hgb: 10, creatinine 1.5

Recommendations

Plan

1. Lutetium-177 for six cycles, no dose adjustment required.
2. Monitor Hb and Cr closely (likely to worsen with lutetium)
3. F/u up in 6 weeks with PSA, CBC, and CMP.

Counsel for common side effects

Dry mouth, decreased appetite, abdominal pain, constipation, anemia, fatigue

Planning

Orders

Reject

Accept

Orders placed in EHR

Action

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#2 AI-enabled Living clinical practice guidelines

“Optimization of the standard guideline process, such that it allows updating of individual recommendations as soon as new relevant evidence becomes available”

Living evidence synthesis workflow

Ovid
MEDLINE

The Watcher

NLP Push and
Pull Retrieval
System

Screenin
g

Collaborative
LLMs

Data
Extraction

Human-LLM
Interaction

Central Data Repository

Living Systematic Review
&
Meta-Analysis

Automated rule
based analytic
algorithms

Interactive
Decision Aids

Interactive
Decision Algorithms

Interactive
Evidence Profiles

Living Clinical
Guidelines

Integration to
EHR

GETUG
NCT00104715

CHAARTED
NCT00309985

STAMPEDE
NCT00268476

LATITUDE
NCT01715285

Ovid MEDLINE

Screenin
g

Data Extraction

Systematic Review & Meta-Analysis

Evidence Presentation to Guideline-Panel

ASCO®

Clinical practice guidelines

Decision Aids

Decision Algorithms

Integration to EHR

TITAN
NCT02489318
ENZAMET
NCT02446405
ARCHES
NCT0267896

GETUG
NCT00104715
CHAARTED
NCT00309985
STAMPEDE
NCT00268476
LATITUDE
NCT01715285

Ovid
MEDLINE

Screenin
g

Data
Extraction

Living Systematic Review
&
Meta-Analysis

Evidence Presentation to
Guideline-Panel

ASCO®
Living clinical practice guidelines

Interactive
Decision Aids

Interactive
Decision Algorithms

Integration to
EHR

Living interactive evidence synthesis framework has **transformed** the evidence ecosystem for prostate cancer

Real-time evidence synthesis

Methods innovation

Living guidelines

10+ abstracts & full-text publication

JAMA Oncology | Original Investigation

First-line Systemic Treatment Options for Metastatic Castration-Sensitive Prostate Cancer
A Living Systematic Review and Network Meta-analysis

Irbaz Bin Riaz, MD, PhD; Syed Arsalan Ahmed Naqvi, MBBS; Huan He, PhD; Noureen Asghar, MBBS;

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journal homepage: www.europeanurology.com

European Association of Urology

Review – Prostate Cancer
Elena Castro, David Lorente, David Olmos on pp. 641–642 of this issue

Heterogeneity of the Treatment Effect with PARP Inhibitors in Metastatic Castration-resistant Prostate Cancer: A Living Interactive Systematic Review and Meta-analysis

Syed Arsalan Ahmed Naqvi [a,†], Irbaz Bin Riaz [a,†,*], Arifa Bibi [b], Muhammad Ali Khan [a],

Systemic treatment options for metastatic castration resistant prostate cancer: A living systematic review

Syed Arsalan Ahmed Naqvi [a,**], Muhammad Umair Anjum [a,**], Arifa Bibi [b], Muhammad Ali Khan [a], Kaneez Zahra Rubab Khakwani [c], Huan He [d], Manal Imran [e], Syeda Zainab Kazmi [e], Ammad Raina [f], Ewan K Cobran [g], R Bryan Rumble [h], Thomas K Oliver [h], Neeraj Agarwal [i], Yousef Zakharia [a], Mary-Ellen Taplin [j], Oliver Sartor [k], Parminder Singh [a], Jacob J Orme [k], Daniel S Childs [k], Rahul A Parikh [l], Rohan Garje [m], Mohammad Hassan Murad [n], Alan H Bryce [o], Irbaz Bin Riaz [a]

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https://doi.org/10.1093/jamia/ocae325
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Research and Applications

Research and Applications

Collaborative large language models for automated data extraction in living systematic reviews

Muhammad Ali Khan, MBBS[1], Umair Ayub, PhD[1], Syed Arsalan Ahmed Naqvi, MD[1], Kaneez Zahra Rubab Khakwani, MD[2], Zaryab bin Riaz Sipra, MD[3], Ammad Raina, DO[4], Sihan Zhou, BS[1], Huan He, PhD[5], Amir Saeidi, MS[1,6], Bashar Hasan, MD[7], Robert Bryan Rumble, MSc[8], Danielle S. Bitterman, MD[9], Jeremy L. Warner, MD, MS[10,11,12,13], Jia Zou, PhD[6], Amye J. Tevaarwerk, MD[14], Konstantinos Leventakos, MD, PhD[7], Kenneth L. Kehl, MD, MPH[15], Jeanne M. Palmer, MD[1], Mohammad Hassan Murad, MD[7], Chitta Baral, PhD[6], Irbaz bin Riaz, MD, PhD[*,1,16]

Journal of Biomedical Informatics
Available online 28 May 2025, 104860
In Press, Journal Pre-proof What's this?

Do it faster with PICOS: Generative AI-Assisted systematic review screening

Sai Krishna Vallamchetla [a], Omar Abdelkader [a], Ali Elnaggar [b], Doaa Ramadan [a], Md Manjurul Islam Shourav [a], Irbaz B. Riaz [c], Michelle P. Lin [a]

MAYO CLINIC PROCEEDINGS:
DIGITAL HEALTH

Future of Evidence Synthesis: Automated, Living, and Interactive Systematic Reviews and Meta-analyses

Irbaz Bin Riaz, MD, MS, MBI, PhD; Syed Arsalan Ahmed Naqvi, MD; Bashar Hasan, MD; and Mohammad Hassan Murad, MD, MPH

ASCO Special Articles

Systemic Therapy in Patients With Metastatic Castration-Resistant Prostate Cancer: ASCO Guideline Update

Rohan Garje, MD[1]; Irbaz Bin Riaz, MD, PhD[2]; Syed Arsalan Ahmed Naqvi, MD[2]; R. Bryan Rumble, MSc[3]; Mary-Ellen Taplin, MD, FASCO[4]; Terry M. Kungel, MBA[5]; Daniel Herchenhorn, MD, PhD[6]; Tian Zhang, MD, MHS[7]; Kathryn E. Beckermann, MD, PhD[8]; Neha Vapiwala, MD[9]; Michael A. Carducci, MD, FASCO[10]; Paul Celano, MD, FASCO[11]; Sebastien J. Hotte, MD, MSc[12]; Arnab Basu, MBBS, MPH[13]; Hala Borno, MD[14]; Alan H. Bryce, MD[15]; Peng Wang, MD, PhD[16]; Elizabeth Wulff-Burchfield, MD[17]; Lisa Bodei, PhD, MD[18]; Andrew Loblaw, MD, FASCO[19]; Robert J. Hamilton, MD, MPH[20]; Hamid Emamekhoo, MD[21]; Thomas A. Hope, MD[14]; Huan He, PhD[22]; M. Hassan Murad, MD, MPH[23]; Hongfang Liu, PhD[2]; James Elbert Williams Jr, MS[24]; and Rahul A. Parikh, MBBS, PhD[17]

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ASCO Genitourinary Cancers Symposium

The Modern AI Clinic

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Treatment: A Decision Made on Average

AXIS 1 | JOURNEY

The mHSPC question:

ADT alone, doublet (ADT + ARPI), or triplet (ADT + ARPI + docetaxel)?

Trial-Average Effects

PEACE-1, ARASENS, ENZAMET, TITAN, STAMPEDE — all show benefit on average. None tells us which individual patient benefits.

Underpowered Subgroups

High-volume vs. low-volume, de novo vs. metachronous — subgroup forests are noisy. We act on them anyway.

Where Experts Disagree

The live controversies are exactly the patients the trial average can't resolve — where an individualized estimate would change the call.

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COMPASS-CSPC

ML for individualized treatment policy in mHSPC

THE APPROACH

1. **Longitudinal EHR cohort**

   Multi-site mCSPC patients with full treatment + outcome trajectories

2. **ML treatment policy learning**

   Estimate individualized treatment effects across doublet / triplet / ARPI options

3. **Clinician-facing dashboard**

   Decision support — not replacement. Surface the model's reasoning; clinician decides.

THE BIGGER FRAME

“The next mHSPC debate won't be settled by trial subgroups.It will be settled by individualized policy models.”

Mr. K in 18 months: if his disease progresses, the question stops being 'what's the trial-average best.' It becomes 'what's best for him.'

COMPASS-CSPC Under the Hood

Estimating individualized treatment effects from observational EHR data

1

Potential Outcomes

We want each patient's outcome under every option — doublet, triplet, ARPI alone. Only one is ever observed; the rest are counterfactual. The estimand is the contrast between them — the individualized treatment effect.

2

Why EHR Is Not an RCT

Treatment was never randomized. Sicker patients get intensified therapy (confounding by indication); some patient types never receive a given option (positivity). A naive outcome comparison recovers bias, not effect — adjustment is the whole game.

3

Validating the Counterfactual

You can't directly score a prediction you never observe. We lean on held-out sites, calibration against known trial subgroup effects, and sensitivity analysis for unmeasured confounding — not accuracy alone. Decision support stays human-interrogable.

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#3 Individualized treatment effects

Causal inference artificial intelligence

ADT

No ADT

ADT Zero

AI

$$ITE_{i,j} = \mathbb{E}[y_{t_j} - y_{t_i} \mid X]$$

Prostate cancer patient

62 years
Gleason = 4+3
cT2c
PI-RADS 5
No metastases

Probability of 5-year survival

100

0

Causal treatment effect

No ADT

ADT

Multimodal individualized treatment effects

Probabilistic modeling

- To develop a multi-modal artificial intelligence model that integrates longitudinal data:
  - Clinical
  - Pathological
  - Imaging
  - Genomic data

- Provides patient-specific treatment effects using a probabilistic deep-learning causal inference framework for prostate cancer patients

Patients	Age	Wt
Patient-1	54	76
Patient-2	25	89
Patient-3	87	78
Patient-n	15	34

Patient Data (Tabular)

Model 1: Deep Neural Network for Patient Data

Radiology, Pathology Reports and Provider Notes

Embedding Model Clinical-Bert / Med-Bert

Model 2: Deep Neural Network for Textual Data

Scan and Pathology Images

Input

Convolution

Pooling

Fully Connected

Output

Model 3: Deep Neural Network for Image Data

Genomic Data

Model 3: Deep Neural Network for Genomic Data

x1 x2 ... xn

y1 y2 ... yn

u1 u2 ... un

v1 v2 ... vn

Attention Unit

z1 z2 ... ... zn

Fusion of Multi Models

Probabilistic Deep Neural Network

70 years

Gleason=4+3

T4N1M1

Synchronous

High volume

Prostate cancer patient

Probability of 5-year survival

100

0

CTE

Docetaxel doublet

Triplet therapy

AI in the Patient–Clinician Interaction

AXIS 3 | INTERACTION

Patients are already using AI to engage with their cancer care — clinicians need a point of view

1 Know the Doctor

Patient-facing physician matching — finding the right oncologist for the right patient.

2 Consult Prep

Pre-visit preparation — particularly relevant for high-stakes prostate cancer treatment decisions.

3 Virtual Treatment Companion

Patient-facing education on complex regimens — ARSI, chemo, radioligand therapy.

4 Virtual Genetic Counselor

BRCA, HRR, Lynch — bridging the gap between testing demand and counselor capacity.

5 AI-Assisted Inbox & Open Notes

Patients reading their PSA, MRI, and pathology reports — with LLMs interpreting in plain language.

6 Patient-Facing Trial Matching

Community outreach for trial access — from health-system bottleneck to patient-initiated discovery.

The deep dive ahead: trial matching is the bridge — clinician-facing in clinic, patient-facing at home.

Clinical Trial Matching (CTM)

AXIS 3 | INTERACTION

Bridging the access gap — from 'what trials exist' to 'which trial fits this patient'

THE GAP

of adult cancer patients enroll in a clinical trial

The bottleneck isn't trial availability — it's the work of matching the right patient to the right trial.

BEACON CTM

Patient facing trial matching

Tiered Matching

Ranks trials by clinical fit, not just keyword overlap

Eligibility Explainability

Surfaces why a patient is or isn't eligible — at the criterion level

Patient Profile Panel

Clinician sees the structured profile the model is reasoning over

Dual-Mode Chatbot

Quick lookup or guided clinician/patient conversation

If Mr. K progresses to mCRPC, CTM is the difference between 'no trial available' and 'three trials, ranked, with eligibility flagged.'

What to Watch Out For

Three tensions the field has not yet resolved

The Evidence-Generation Gap

AI tools are being deployed faster than they're being validated. The field has no agreed standard for what counts as sufficient evidence — RCT? Prospective registry? External validation across N sites? Until this is resolved, every AI tool lives in a credibility limbo.

2

Distribution Shift & External Validation

Almost every model here was trained on US/European data. “Does this work on my patients?” is empirical, not rhetorical — demographics, biology, treatment patterns, and label definitions all shift across sites. Most papers report internal performance; few test external validation under distribution shift.

Division of Labor — What Should Be Automated?

The useful question isn't replacement — it's which tasks to automate and which to keep human. Pattern recognition, documentation, surveillance, and evidence retrieval are increasingly learnable. Judgment under uncertainty, accountability, and the goals-of-care conversation are not — and may not be the right targets. If you build these systems, you draw that line: design the human-AI handoff deliberately, not by default.

Back to Mr. K

What AI touches in his care today, in 2 years, and what it shouldn't touch at all

TODAY

What AI already touches

- Pathology foundation models confirm Gleason grade
- Artera predicts his benefit from adding ADT
- AI-quantified MRI informs RT planning

IN 24 MONTHS

What AI will likely touch

- COMPASS-style policy models guide intensification at progression
- PSMA PET interpretation fully AI-augmented
- Living guidelines surface relevant trials in real time

NEVER

What AI shouldn't touch

- The conversation about goals of care
- What this diagnosis means for him and his family
- The decision itself — it remains his and ours

AI in uro-oncology is neither as far along as the hype, nor as distant as the skeptics claim. The interesting work is in the middle.

Thank You

Questions & Discussion

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