
Large Language Models for Practice Optimization in Nuclear Medicine Theranostics

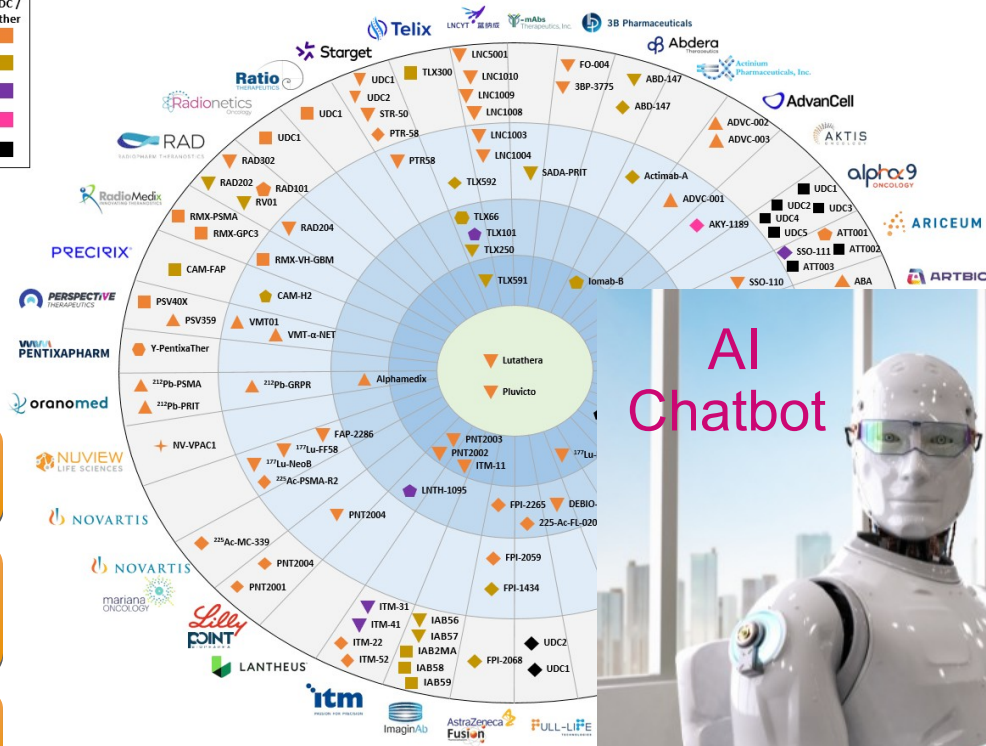
February 16th, 2026
EURADOS Annual Meeting
Helsinki, Finland

Kuangyu Shi, University of Bern

Potential of AI Chatbot for Nuclear Medicine Theranostics

	^{177}Lu	^{225}Ac	^{212}Pb	^{124}I , ^{125}I , ^{131}I	^{67}Cu	^{90}Y	UDC / Other
Peptide / Ligand	▼	◆	▲	◆	◆	◆	◆
Antibody	▼	◆	▲	◆	◆	◆	◆
Small Molecule	▼	◆	▲	◆	◆	◆	◆
Mini Proteins	▼	◆	▲	◆	◆	◆	◆
UDC / Other	▼	◆	▲	◆	◆	◆	◆

Preclinical	○
Phase 1/2	○
Phase 2	○
Phase 3 / Reg.	○
Approved	○



Blooming

Multi-disciplinary

Diverse

AI Chatbot

7×24 h
Individualized
service

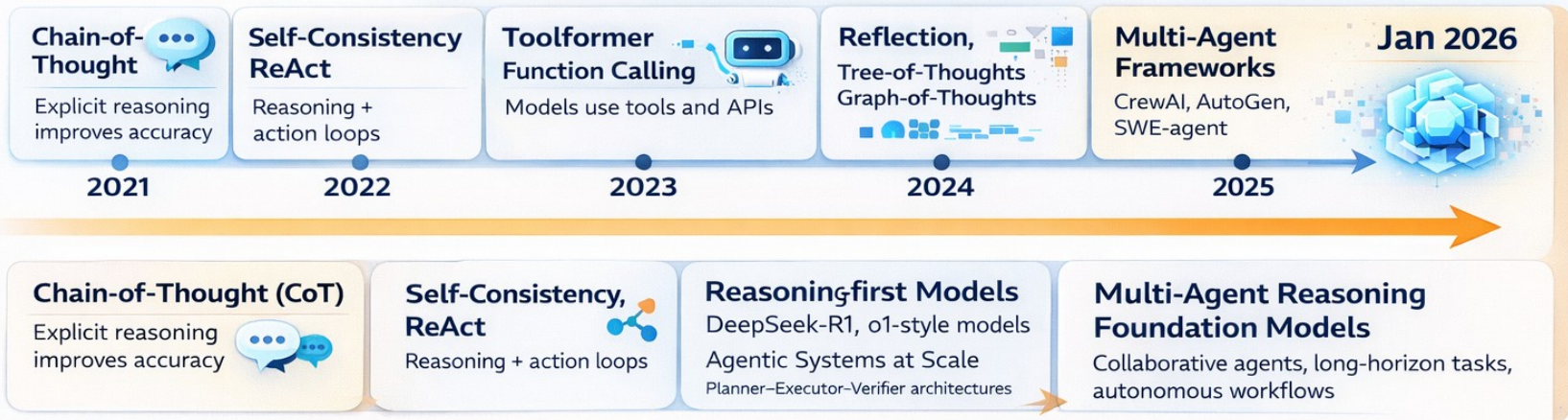
<https://medium.com/new-writers-welcome/is-ai-coming-for-your-job-in-2023-ef32f365e7c8>

Large Language Models (LLMs)

Foundation & Scaling Models



Reasoning, Agentic & Multi-Agent Systems



Large Language Models (LLMs)

- ❑ AI models trained on vast amounts of text
- ❑ Generate text like a human
- ❑ Billions or trillions of parameters
- ❑ Transformer architecture



Principles of LLMs

❑ Tokenization

“Bern is a picturesque city”



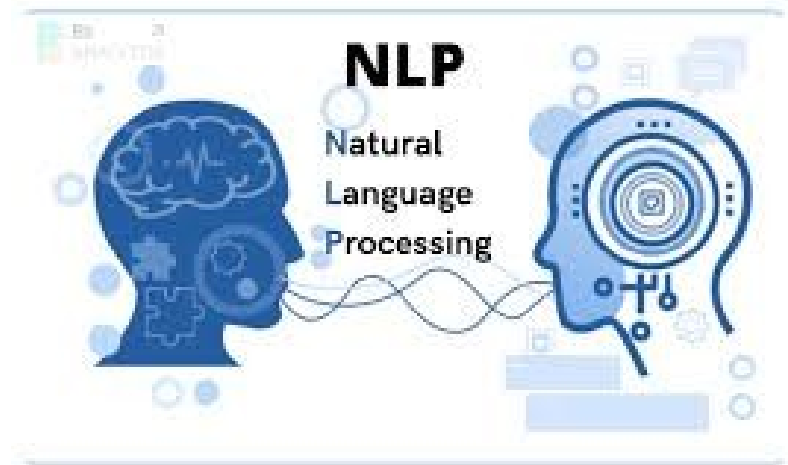
[“Bern ”, “ is”, “ a”, “ picture” , “sque”, “ city” , <EOF>]

- ❑ The tokenizer allows to convert words (computer will not understand) into pieces of information (tokens)
- ❑ Converted into numbers and vectors (embedding) → the computer can process.

Not a new concept! Used in the past for Natural Language Processing (NLP)

Before the LLMs → Natural Language Processing

- ❑ NLP allows computers to “understand” and manipulate human language
- ❑ Voice detection → transcribing
- ❑ Automatic translation
- ❑ Text processing
- ❑ Based on process of tokens
- ❑ Tokens were processed sequentially and independently to the others



From NLP to LLMs

Attention Is All You Need

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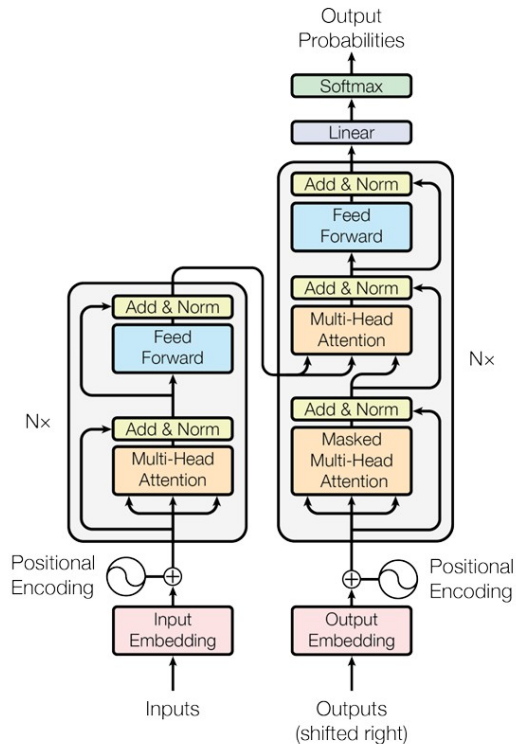
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LLMs - Transformers

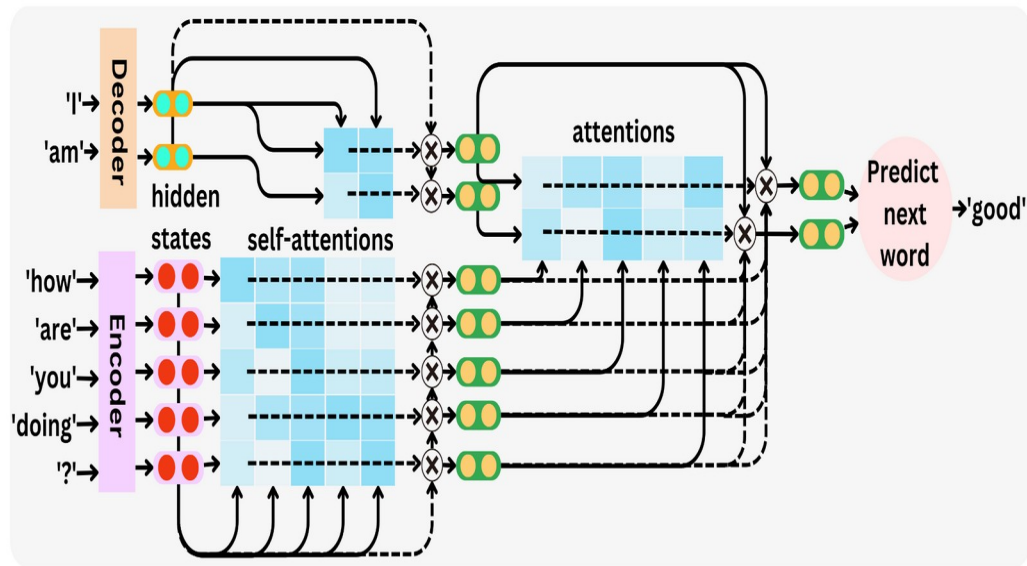
□ Attention Mechanism → Transformers NN

Words are not evaluated one by one, but all together in parallel, so many more evaluations in the same time.

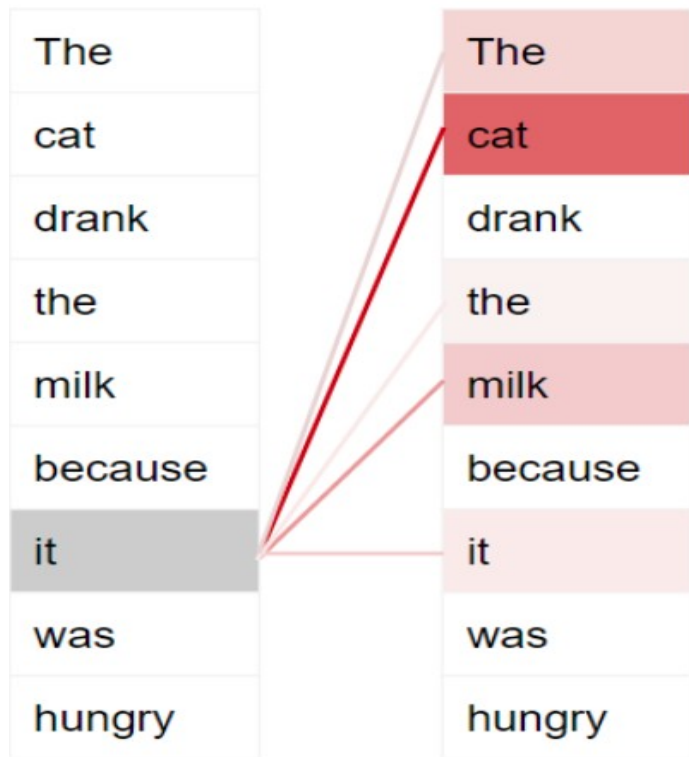
Self-attention mechanism

Attention Mechanism:

- The model focus on words related to the input word
- It focus both on word meaning and word positioning



Attention Examples



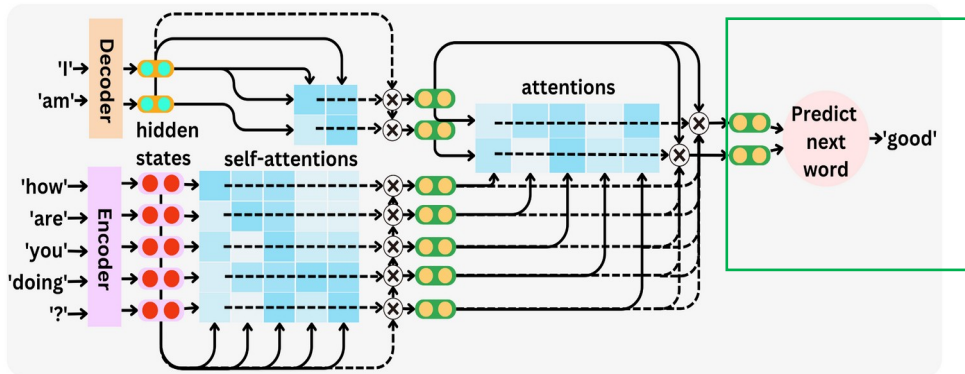
How do LLMs work?

- ❑ An LLM does not learn to think or talk in the way a human brain does
- ❑ It is just based on predicting which the next “token” will be
- ❑ That is done thanks to the attention mechanism
- ❑ Probabilistic approach
- ❑ New outputs are recursively considered to continue the conversation

Example:

- Input: “Helsinki is a city located in ____”
- Output (most likely statistically continuation of the sentence): “Finland”

Self-attention mechanism



Generalized LLMs

- ❑ Broad knowledge
- ❑ Pretrained on data from several domains
- ❑ Can address both medical and non-medical tasks
- ❑ May perform worse on medical knowledge

Medical LLMs

- Strong domain knowledge in medicine
- Pretrained on specific medical datasets (clinical notes, lab values, images)
- Likely to perform better on medical-related tasks

LLM in Nuclear Medicine Board Examination

European Journal of Nuclear Medicine and Molecular Imaging (2023) 50:1549–1552
<https://doi.org/10.1007/s00259-023-06172-w>

EDITORIAL



Large language models (LLM) and ChatGPT: what will the impact on nuclear medicine be?

Ian L. Alberts¹ · Lorenzo Mercolli¹ · Thomas Pyka¹ · George Prenosil¹ · Kuangyu Shi¹ · Axel Rominger¹ · Ali Afshar-Oromieh¹

Original Research Article

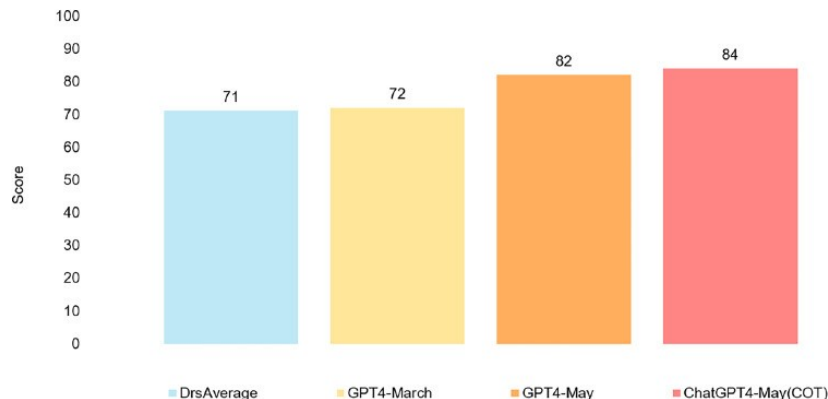
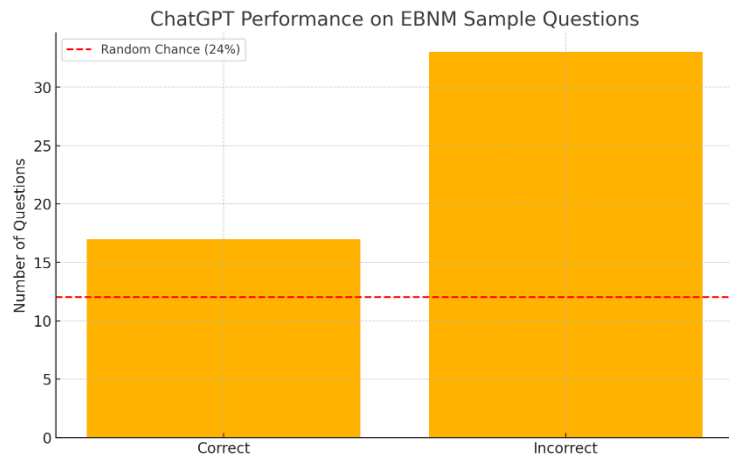
Performance of ChatGPT incorporated chain-of-thought method in bilingual nuclear medicine physician board examinations

Yu-Ting Ting^{1,*}, Te-Chun Hsieh^{1,2,*}, Yuh-Feng Wang^{3,4,5}, Yu-Chieh Kuo⁶, Yi-jin Chen⁶, Pak-Ki Chan⁶ and Chia-Hung Kao^{1,6,7,8}

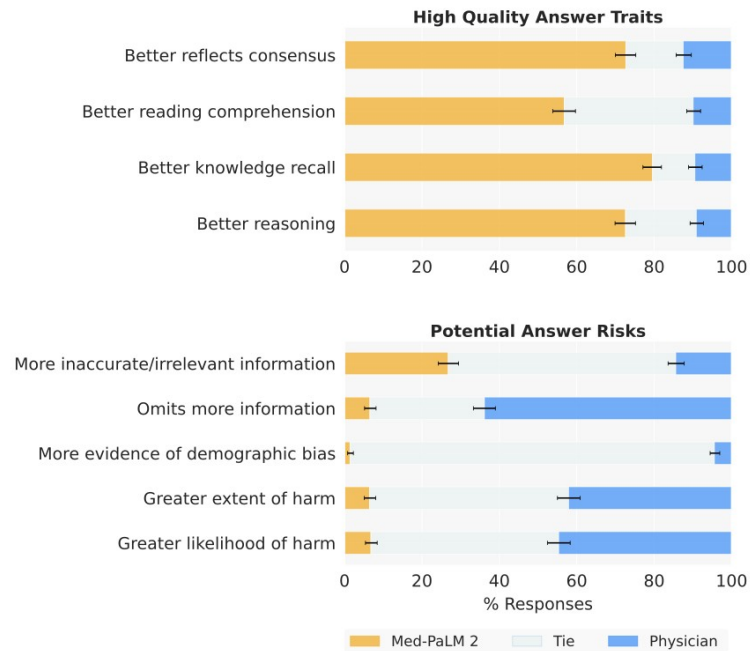
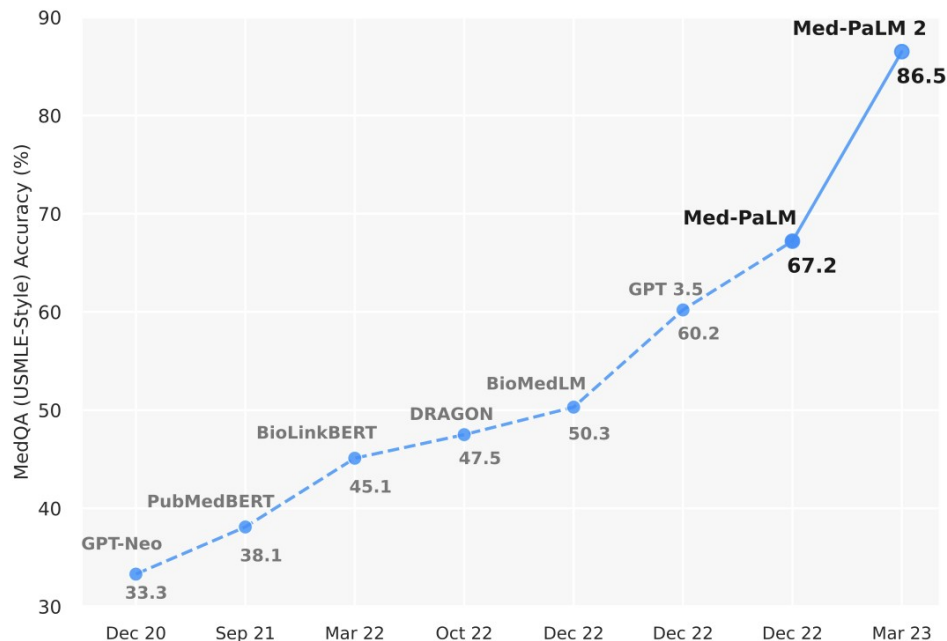
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Volume 10: 1–10
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DOI: 10.1177/20552076231224074
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Medical Question Answering



Singhal et al., 2023

LLMs - Limitations

❑ Lack of True Understanding

- LLMs generate text based on patterns in data, not genuine comprehension
- They can simulate reasoning, but don't truly "understand" concepts

❑ Hallucinations

- LLMs may produce plausible-sounding but factually incorrect or completely fabricated information

❑ Dependence on Training Data

- Their knowledge is limited to what they were trained on and may be outdated
- They inherit biases, errors, and gaps from their training data

❑ Bias and Fairness Issues

- LLMs can reinforce or amplify societal, racial, gender, and cultural biases present in the data
- Bias mitigation is still an active area of research and far from solved
- Overindulging with the user → reinforcing of ideas that may be wrong or harmful

❑ Poor at Real-World Reasoning

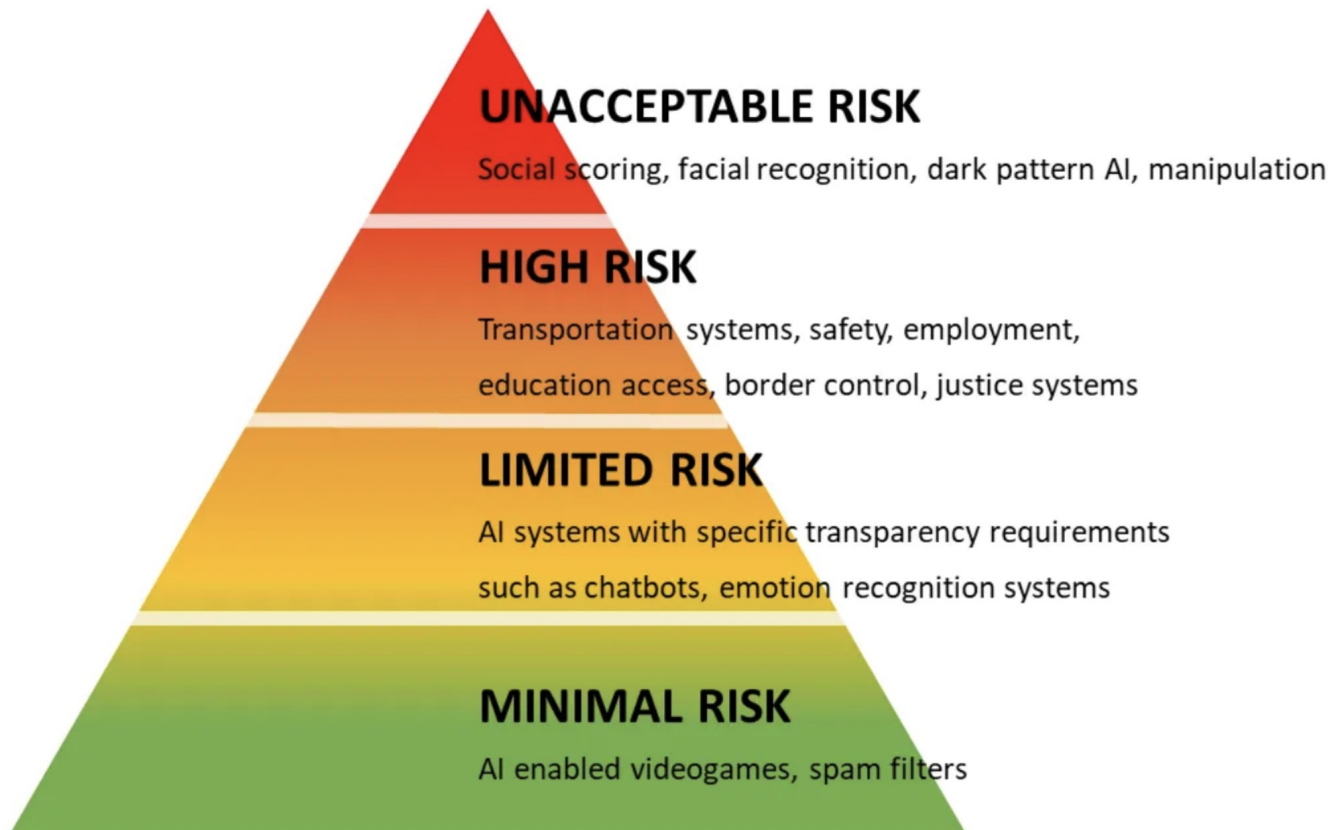
- Temporal reasoning (e.g., understanding dates or schedules)
- Spatial/logical reasoning (e.g., complex puzzles)
- Common-sense reasoning in unfamiliar context

European Union AI Act

Medium

Write

Subscribe



Images generated by AI that only exist virtually in the network and space

Hallucination in Theranostic Radiation Protection Counselling



Generated using ChatGPT 5.0



I peed in the bed... What should I do?



You should change your bed sheets.



Uh... how do I do that?



If you don't know, maybe ask your mom or wife!

Missing relevant professional knowledge

Retrieval-Augmented Generation (RAG)

- ❑ Feeding AI models with more sources or information from specific and relevant data sources.
 - Link generative AI services to external resources, especially ones rich in the latest technical details
 - Gives models sources they can cite, like footnotes in a research paper, so users can check any claims.
 - Example: a generative AI model supplemented with a medical index could be a great assistant for a doctor or nurse.

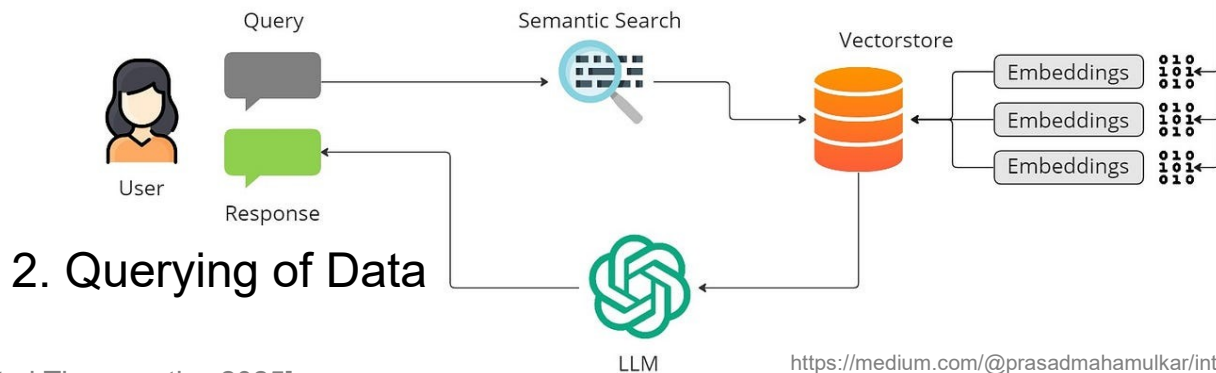
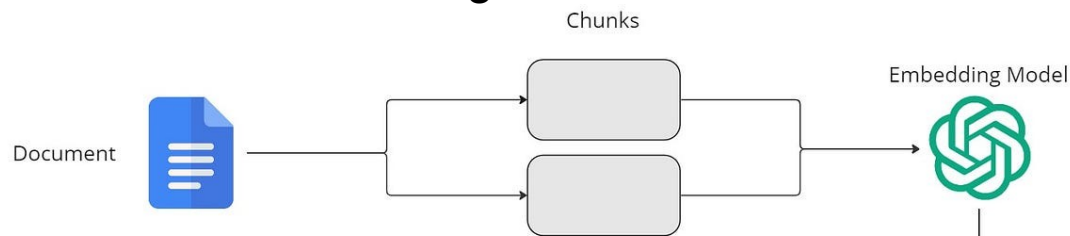
Lewis, Patrick, et al. "Retrieval-augmented generation for knowledge-intensive nlp tasks." *Advances in neural information processing systems* 33 (2020): 9459-9474. <https://arxiv.org/pdf/2005.11401>

<https://blogs.nvidia.com/blog/what-is-retrieval-augmented-generation/>

LLM Model with Professional Knowledge

- ❑ Method: Retrieval Augmented Generation (RAG)
- ❑ ChatGPT Over Professional Data
 - LLMs are trained on enormous bodies of data but not on professional data
 - RAG adds its professional data to the data LLMs have access to

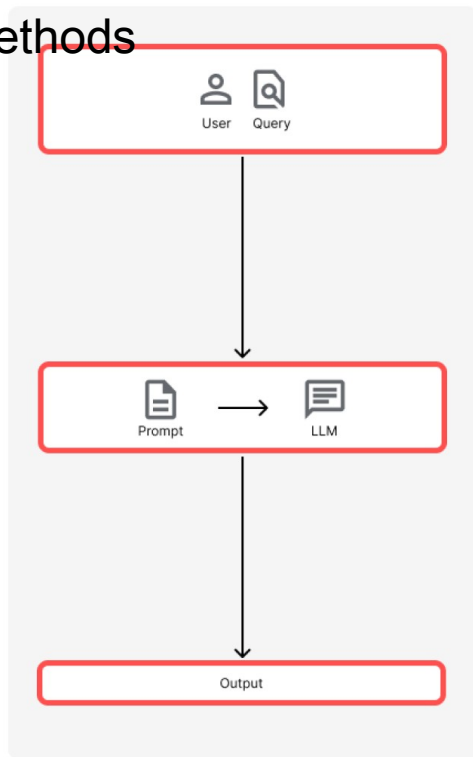
1. Ingestion of Data



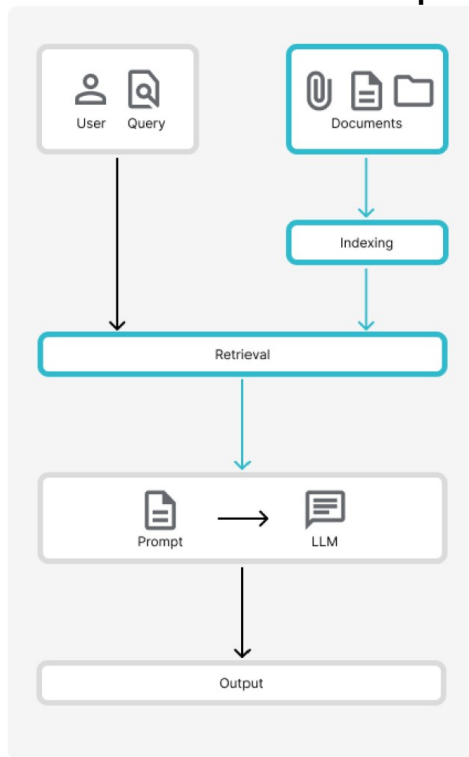
In collaboration with Dr. Albert van Eijk, Prof. Jingjing Zhang, Prof. Mike M. Sathekge, Prof. Ken Hermann, Prof. Richard Baum & Prof. Wolfgang Weber

Contextual Augmentation for LLM

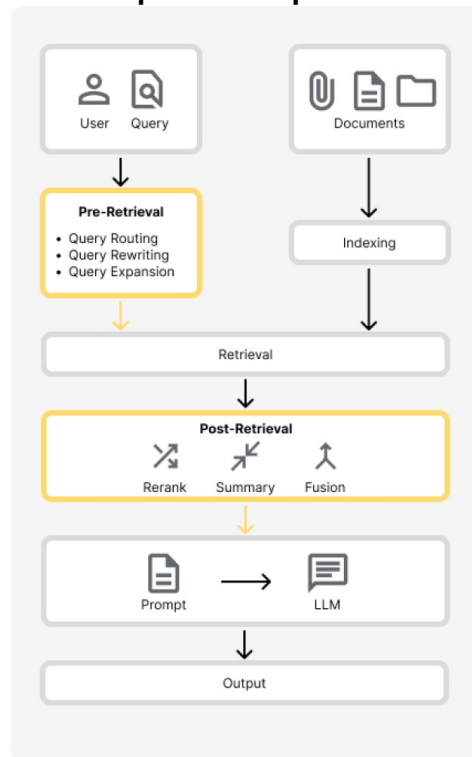
- ❑ Naive RAG: only use the set of 198 research papers
- ❑ Advanced RAG: use the set of 198 research papers & pre- or post-retrieval methods



No Context



Naive RAG



Advanced RAG

Evaluation

Go Back

Question 6 / 10

****Please note:**** Answers are generated by AI models and may not be entirely accurate.
It is also possible that answers are similar or the same.

What is Peptide Receptor Radionuclide Therapy (PRRT)?

Choose the better fitting answer.
If you can't decide or both answers are incorrect choose "Neither"

Neither

Peptide receptor radionuclide therapy (PRRT) is a targeted radiation treatment for non-operable or metastatic neuroendocrine tumors that overexpress somatostatin receptors. It involves the systemic administration of radiolabeled peptides, such as somatostatin analogs, that bind specifically to peptide receptors on tumor cells, delivering destructive radiation to cancer cells. (Nicolas et al., 2019; Zaknun et al., 2013)

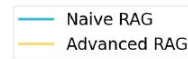
Peptide Receptor Radionuclide Therapy (PRRT) is a targeted radionuclide therapy that delivers cytotoxic radiation to cancer cells through the specific binding of radiolabeled peptides to peptide receptors, which are expressed in higher density on the tumor cell membrane compared to non-tumor tissues (Nicolas et al., 2019). This therapy is particularly used for treating nonoperable or metastatic neuroendocrine neoplasms that frequently express somatostatin receptors, utilizing radiolabeled somatostatin analogues (Hirmas et al., 2018).

Do you have any comments or feedback about the user study, the questions or the answers?
Your input helps us improve the user study. Please feel free to add them here:

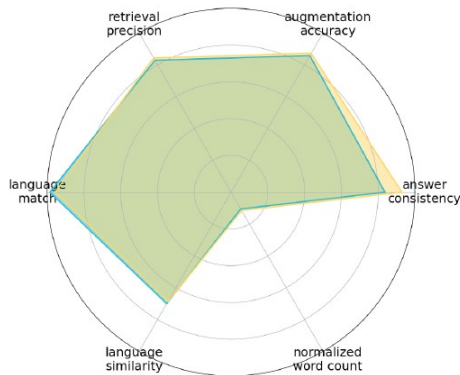
Enter your Comments or Feedback

Submit

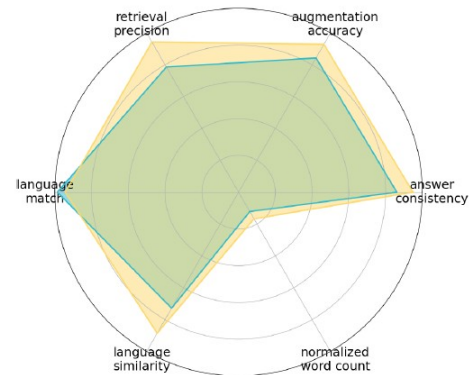
Evaluation Results



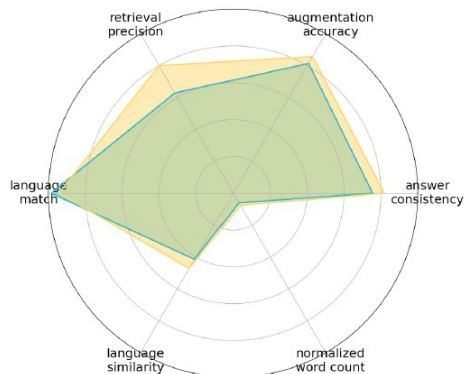
GPT-4



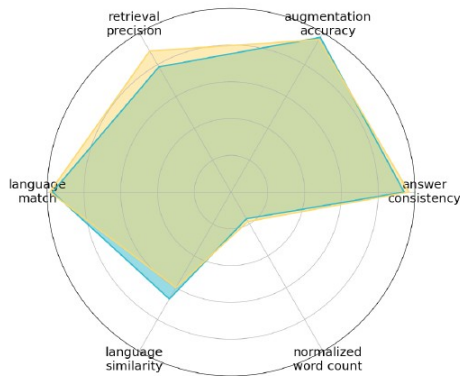
GPT-4o



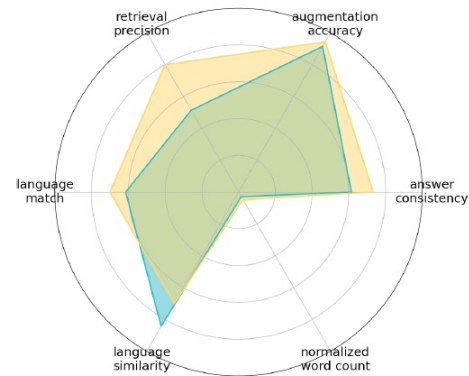
Command R+



Claude 3 Opus



Gemini 1.5



Theranostic Chatbot

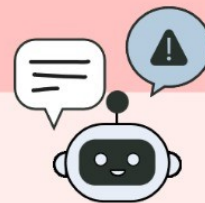
! Theranostic Consultancy Challenges

For ...

- Medical Professionals
- Patients
- The Public



- **Rapid evolution** → knowledge gaps
- **Multi-disciplinary** → fragmented view
- **Complex knowledge integration**



Chatbots are appealing
! Limited expert knowledge

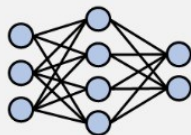
Solution: Advanced Theranostic Chatbot System

Interchangeable
Large Language Models
(LLMs)

Theranostic
Literature



Advanced
Retrieval Augmented
Generation (RAG)



Evaluation



Example
Performance Evaluation



Hallucination in Theranostic Consultation



Generated using ChatGPT 5.0

Where should I throw my tissue after sneezing?

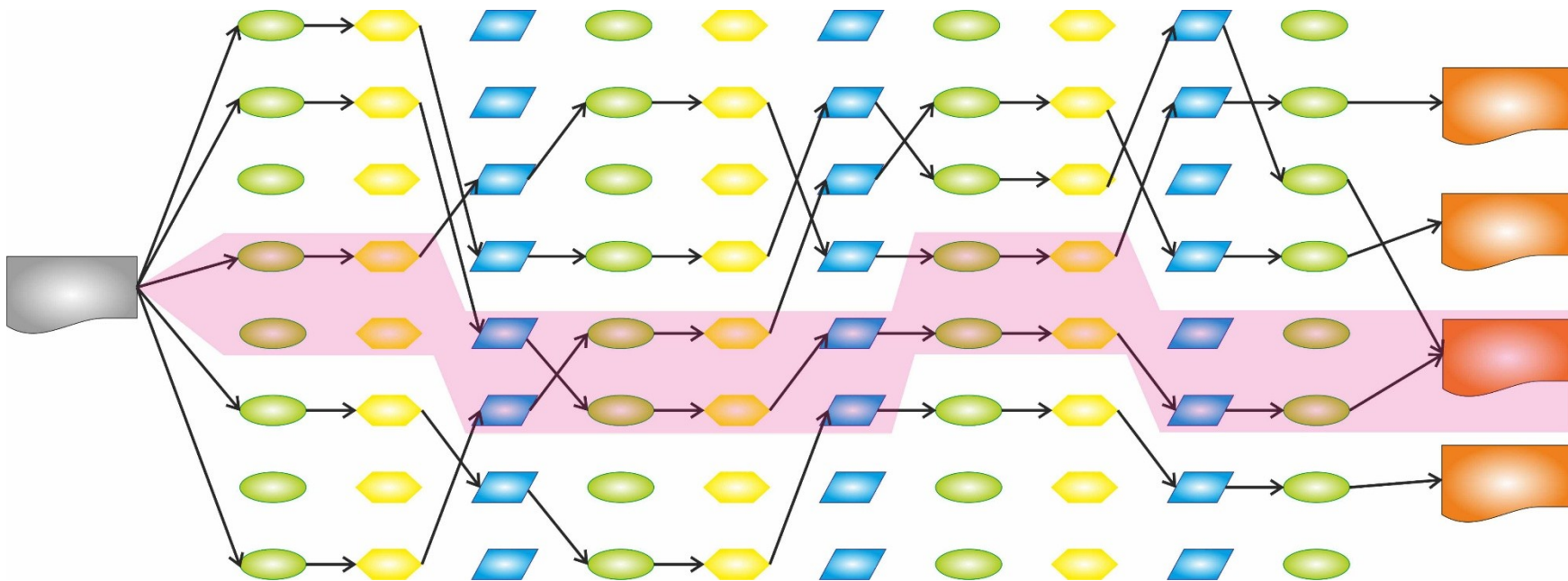
Well, I'm an experienced medical physicist, and since you're in nuclear medicine, we should check the radioactivity first before deciding what to do.

Okay... but how do I do that?

Easy! Just use the CoMo-170 portable contamination monitor. If the activity is over 100 mSv/h, that's a radiation accident!

Missing proper logic

Risks of LLM



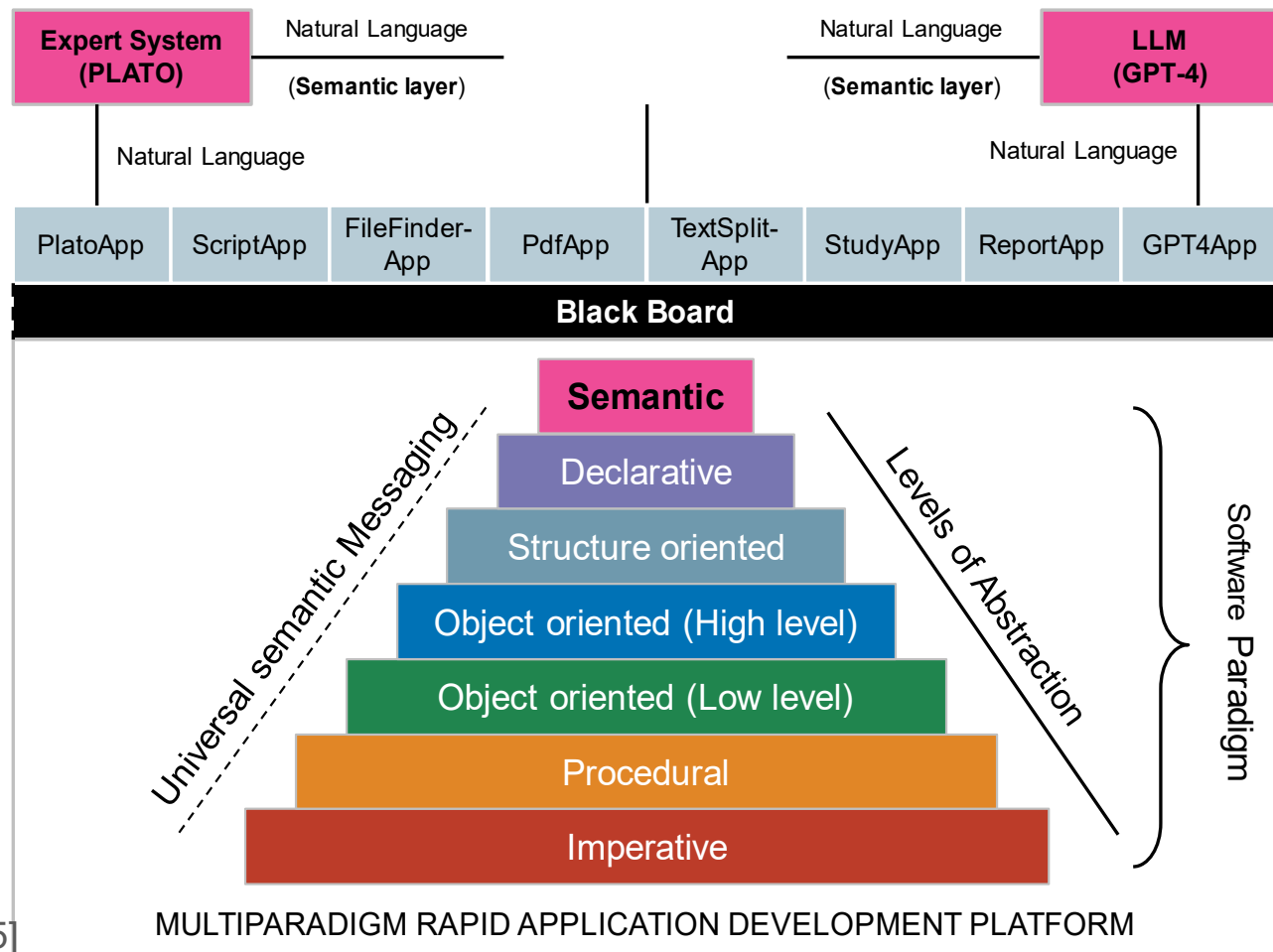
LLM does not have logic to follow

Solution: Restrict LLM to follow defined logic

AI with Expert Reasoning: Neuro-Symbolic AI

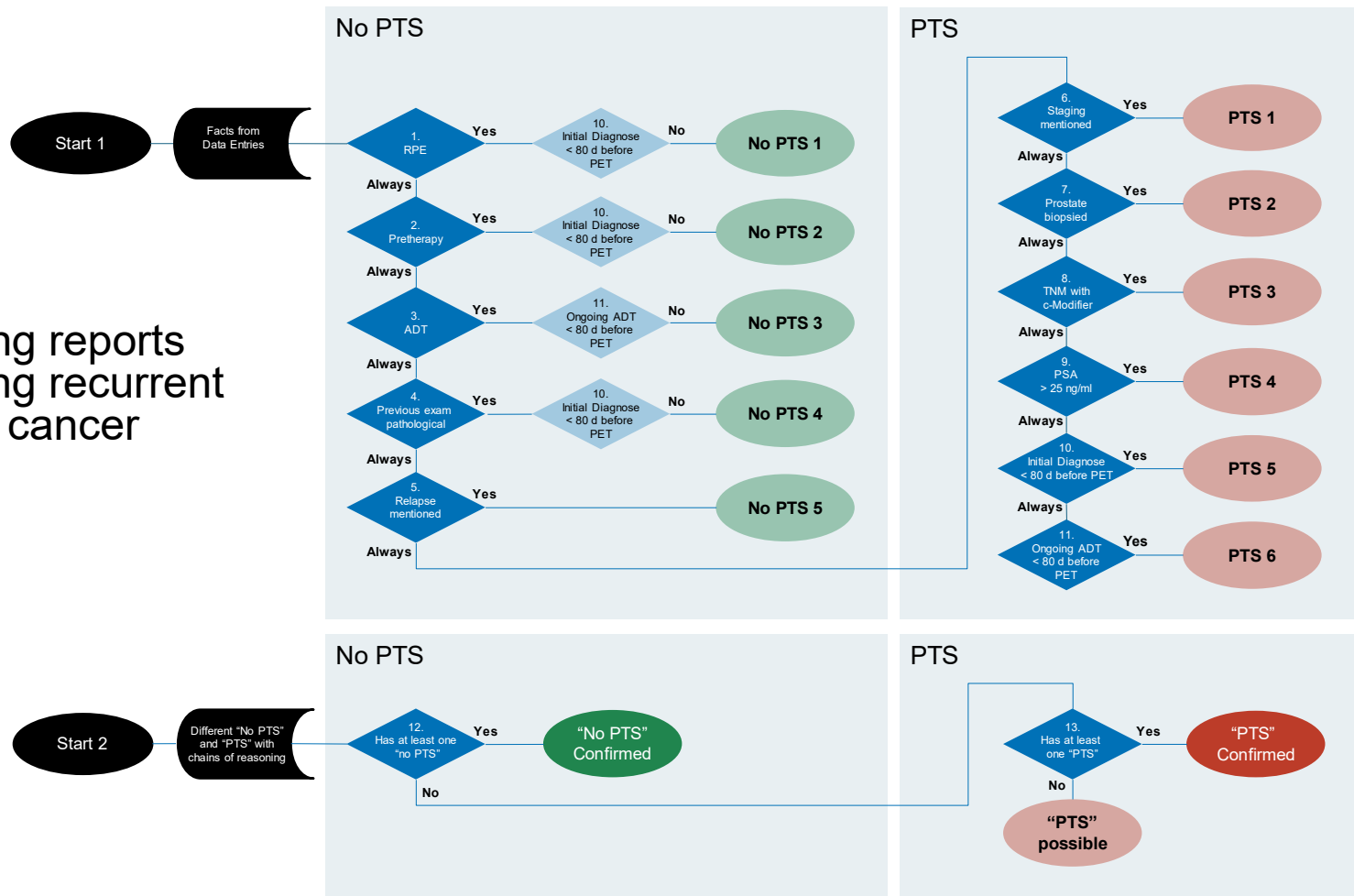
□ LLM + Rule-based expert system for traceable reasoning and fact-checking:

- test in a 206 PSMA PET/CT diagnostic reports
- identifying reports describing recurrent prostate cancer (rPC) from 27 study metrics



Neuro-Symbolic AI in Detection of Primary Tumor Staging

Identifying reports
describing recurrent
prostate cancer
(rPC)



Neuro-Symbolic AI in Detection of Primary Tumor Staging

A) Plato-3 PTS decision

"**fact** : **current finding is PTS.**

because : current finding meets PTS criterion.

because : PTS is possible.

because : current examination is staging.

because : staging information verified by LLM.

[*clinInfo_staging*]

because : The description of the intensely PSMA avid lesions in the prostate, lymph nodes, and bones indicates staging, as the spread of the carcinoma is being assessed.
(txt)

[*clinInfo_stagingReason*]

[Tag *clinInfo_staging*]

[rule_pts_prep_1_staging]

[rule_pts_2]

and **not** : current finding is not PTS.

[*notInDB*]

[rule_pts_5]

B) Plato-3 identified controversy

"**fact** : **status PTS is not confirmed**

because : **current finding is PTS.**

because : current finding meets PTS criterion.

because : PTS is possible.

because : current examination is staging.

because : staging information verified by LLM.

[*clinInfo_staging*]

because : The description of the intensely PSMA avid lesions in the prostate, lymph nodes, and bones indicates staging, as the spread of the carcinoma is being assessed.
(txt)

[*clinInfo_stagingReason*]

[Tag *clinInfo_staging*]

[rule_pts_prep_1_staging]

[rule_pts_2]

and **not** : LLM is not PTS.

[*notInDB*]

[rule_pts_5]

and **because** : **LLM is not PTS.**

because : PTS information verified by LLM.

[*clinInfo_pts*]

and **because** : The indication for the PET/CT examination seems to be more related to recurrence search, therapy, or follow-up monitoring due to the rapid PSA increase and already identified metastases, not primary tumor staging. (txt)

[*clinInfo_pts*]

[*clinInfo_pts*]

[rule_pts7]

Neuro-Symbolic AI in Detection of Primary Tumor Staging

C) Plato-3 re-prompting GPT-4 about PTS

Below, you will again receive a previous prompt. Your answer to this prompt may not have been entirely correct. Therefore, please try again. To assist you, along with the original prompt, you will receive an explanation written by an expert system explaining why your first answer might have been incorrect.

Below are the previous prompt, along with your first answer and the expert system's explanation. Previous Prompt:

Derive from the previous information whether the indication for the PET/CT examination was a primary tumor staging (PTS). You can also use your previous findings for this. Answer in two lines. On the first line with the following three options:

PTS: Yes

if you can infer PTS from the text.

PTS: No

if you cannot infer PTS from the text, or if the patient came for recurrence search, therapy, or follow-up monitoring.

PTS: n/a

if you are unsure about the PTS status.

Respond without any commentary or options, but with a justification on the second line according to:

Justification: Your justification

Your original response was: **PTS: No**

Your justification was: **Justification: The indication for the PET/CT examination seems to be more related to recurrence search, therapy, or follow-up monitoring due to the rapid PSA increase and already identified metastases, not primary tumor staging.**

The expert system's response was:

Primary tumor staging Yes,

because the current finding is PTS,

because the current finding meets PTS criterion and not current finding is not PTS.

The current finding meets PTS criterion because PTS is possible. PTS is possible because the current examination is staging. The current examination is staging because staging information was verified by LLM. The description of the intensely PSMA avid lesions in the prostate, lymph nodes, and bones suggests staging, as the spread of the carcinoma is being assessed.

Please respond again with the same keys and two new lines exactly as requested in the prompt above.

Answer from GPT-4

(String): **PTS: Yes**

(String): **Justification: The examination serves the purpose of staging prostate carcinoma by determining the spread of the carcinoma in the prostate, lymph nodes, and bones, which represents primary tumor staging.**

Neuro-Symbolic AI in Detection of Primary Tumor Staging

TABLE I
PTS CONFUSION MATRIX

	GPT-4-only				Combined AI				Reference Standard				
Reviewed Standard	206 T	5 PP	201 PN	Reviewed Standard	206 T	11 PP	195 PN	Reviewed Standard	206 T	10 PP	196 PN		
	11 P	5 TP	6 FN			11 P	11 TP		0 FN		11 P	10 TP	1 FN
	195 N	0 FP	195 TN			195 N	0 FP		195 TN		195 N	0 FP	195 TN

A) PATHOLOGICAL REPORT CONFUSION MATRIX

	GPT-4-only*				Combined AI				Reference Standard		
Reviewed Standard	206 T	192PP	14 PN	Reviewed Standard	206 T	177 PP	29 PN	Reviewed Standard	206 T	11 PP	195 PN
	177 P	176 TP	1 FN		177 P	177 TP	0 FN		11 P	10 TP	1
	29 N	16 FP	13 TN		29 N	0 FP	29 TN		195 N	1	194

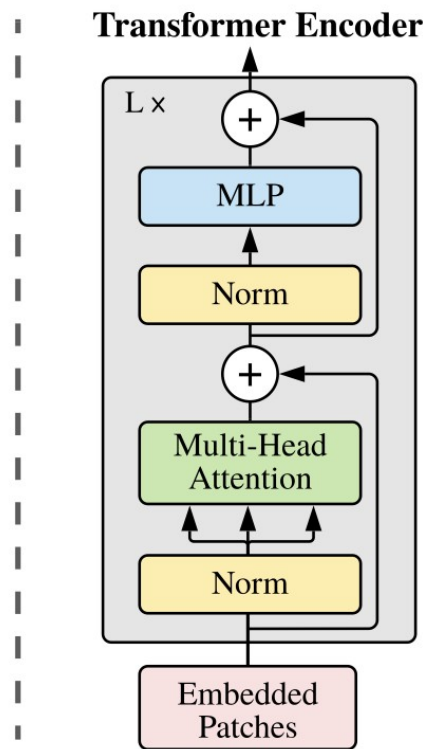
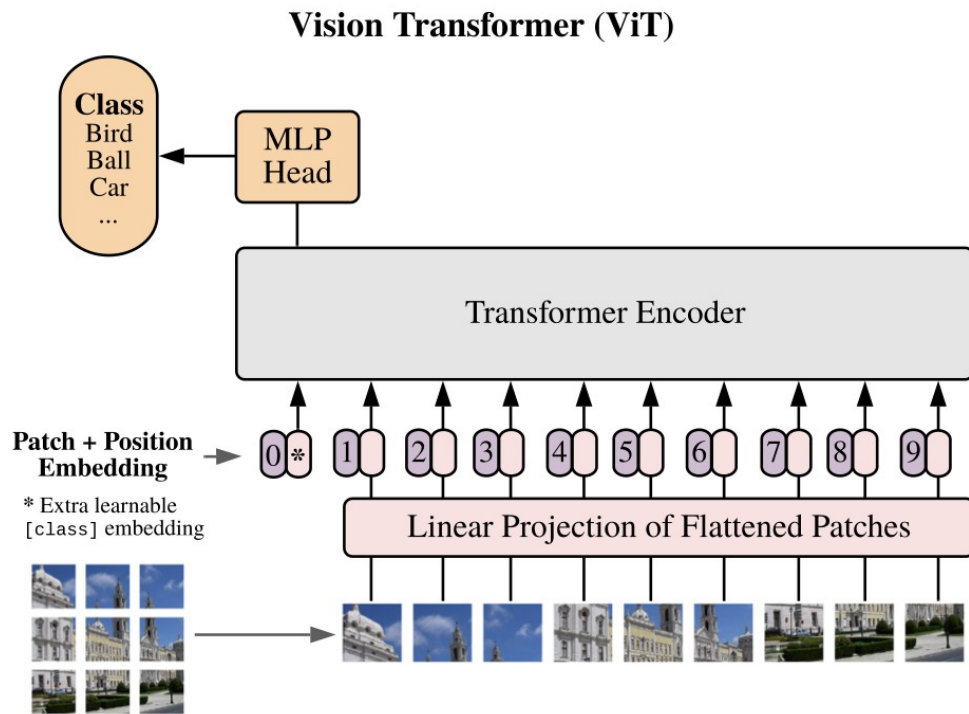
FN = False Negative; FP = False Positive; N = Negative; P = Positive; PN = Predicted Negative; PP = Predicted Positive; PTS = Primary Tumor Staging; T = Total; TN = True Negative; TP = True Positive; * marks output sets that differ significantly ($p < 0.05$) from the reviewed standard.

Vision Transformer

AN IMAGE IS WORTH 16X16 WORDS:
TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

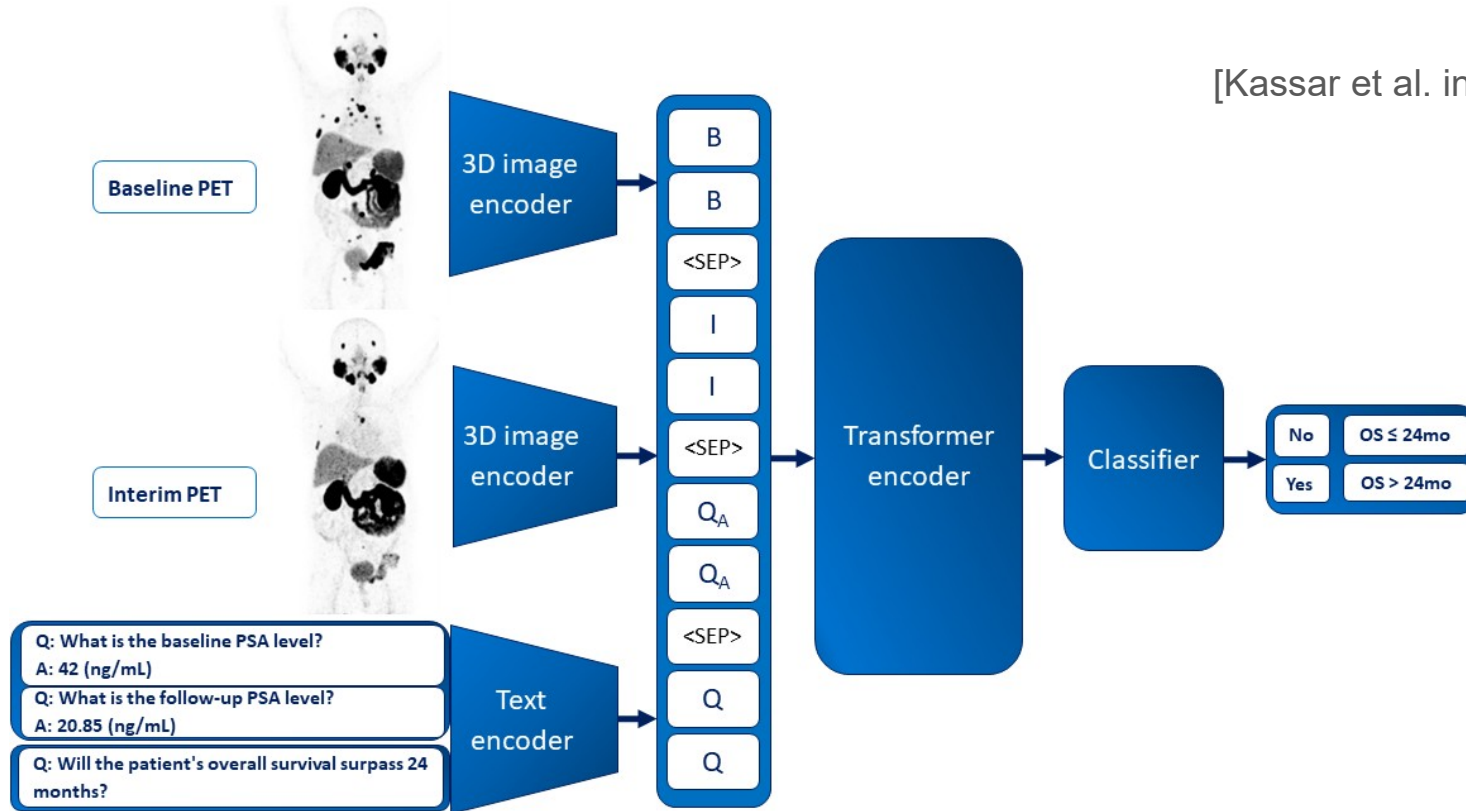
Alexey Dosovitskiy^{*,†}, Lucas Beyer^{*}, Alexander Kolesnikov^{*}, Dirk Weissenborn^{*},
Xiaohua Zhai^{*}, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer,
Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby^{*,†}

^{*}equal technical contribution, [†]equal advising
Google Research, Brain Team



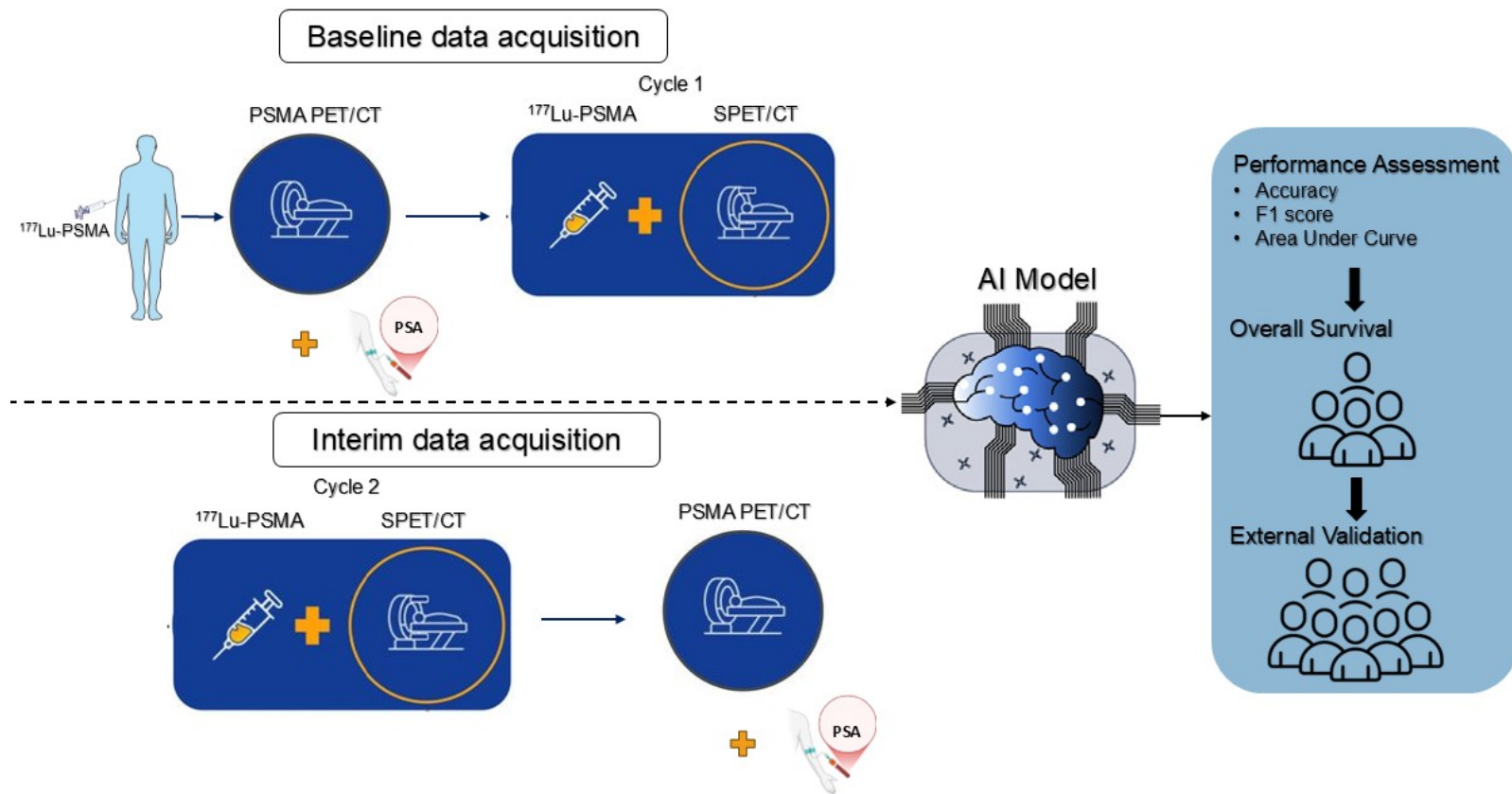
AI Agent: Deep Multimodal Visual Question Answering (VQA) for Prognostication of PSMA-RPT Outcomes

[Kassar et al. in preparation]



In collaboration with Prof. Dr. Isabel Rauscher, Prof. Matthias Eiber & Prof. Wolfgang Weber

VQA for Prognostication of PSMA-RPT Outcomes



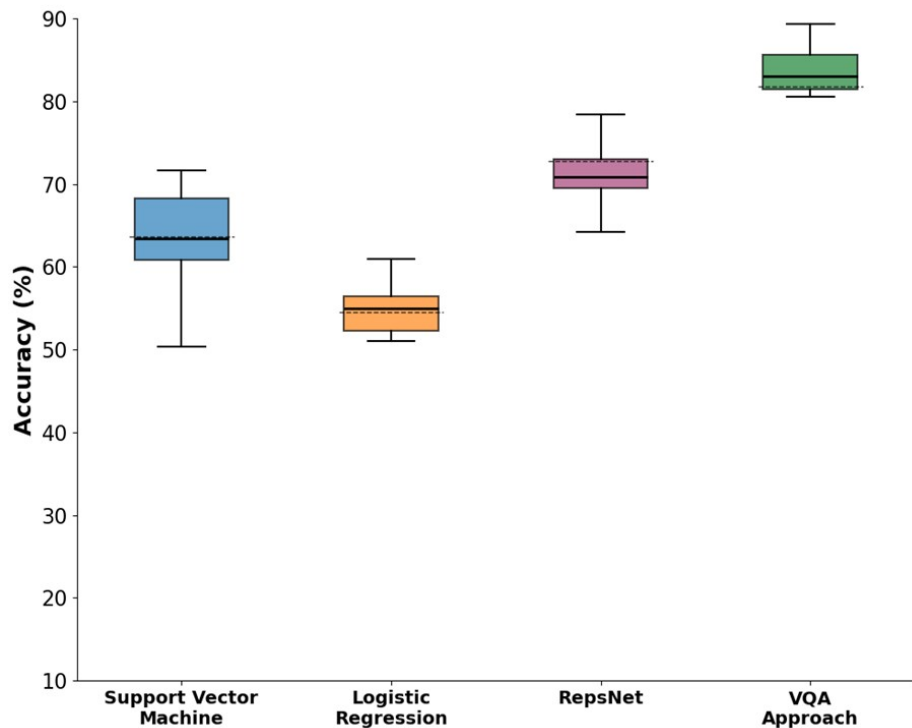
VQA for Prognostication of PSMA-RPT Outcomes: Data

Characteristics	Development cohort	Validation cohort
Number of patients	64	46
Source	TUM Klinikum Rechts der Isar	University Hospital Bern, Inselspital
PET-imaging tracers	[⁶⁸ Ga] PSMA-11 PET	[¹⁸ F] PSMA-1007 PET
PSMA therapy ligands	[¹⁷⁷ Lu] PSMA-I&T	[¹⁷⁷ Lu] PSMA-617
Purpose of the cohort	Training and internal testing	External validation
Overall survival (OS) range (months)	2 - 107	6 - 60
Median OS (months)	17	15.3
Percentage of patients passing 24mo survival	40.0%	44.7%
Baseline PSA (ng/mL) median (mean ± SD)	71.9 (384.0 ± 688.2)	198 (672.8 ± 1273.6)
Interim PSA (ng/mL) median (mean ± SD)	36.4 (287.3 ± 636.7)	131 (458.9 ± 968.4)

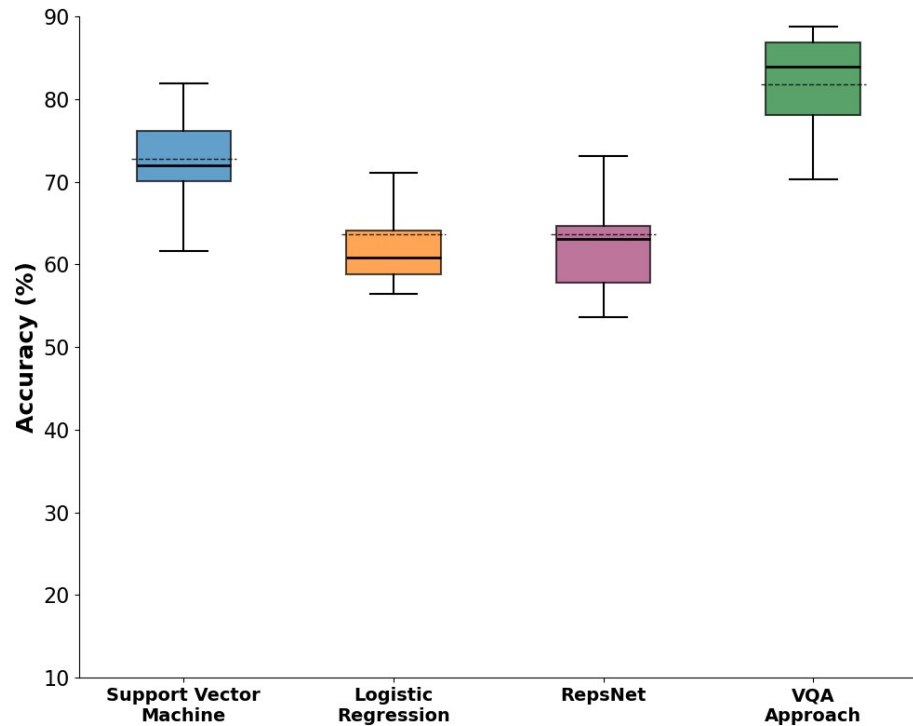
In collaboration with Prof. Dr. Isabel Rauscher, Prof. Matthias Eiber & Prof. Wolfgang Weber

Results of VQA for Prognostication of PSMA-RPT Outcomes

SPECT



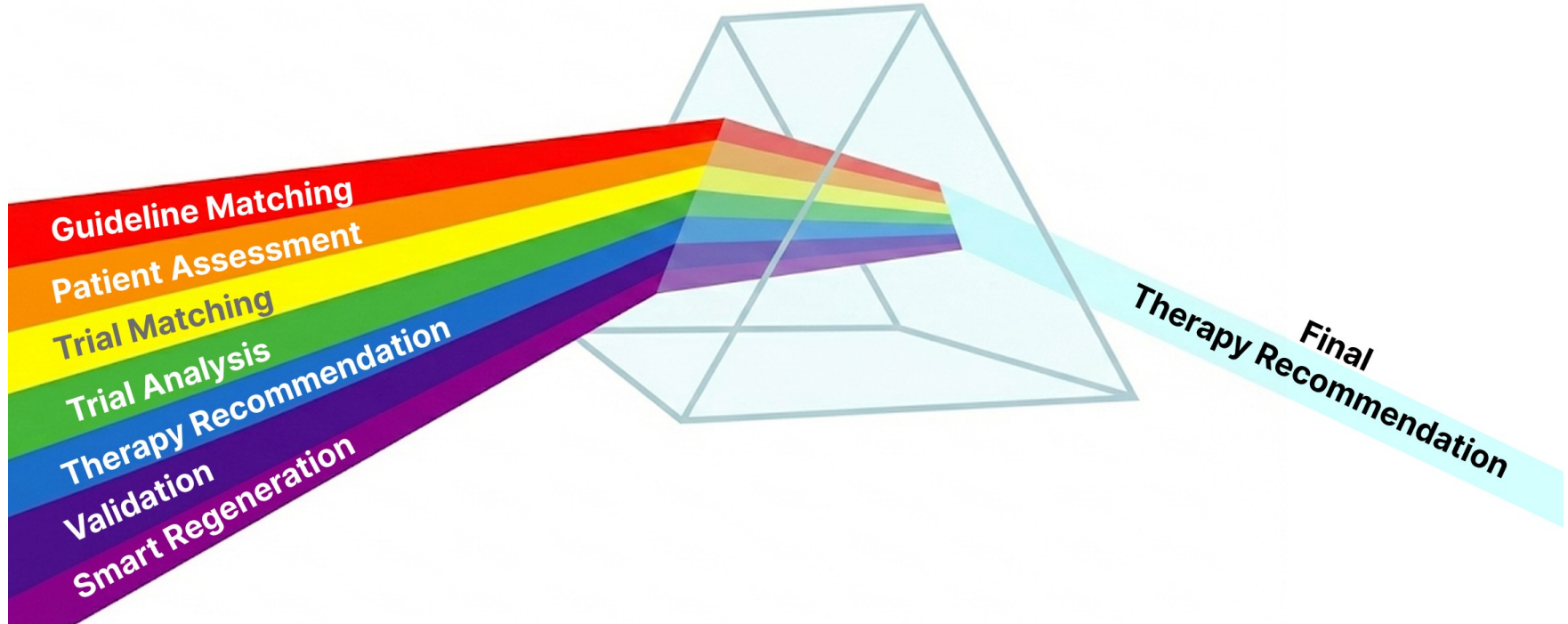
PET

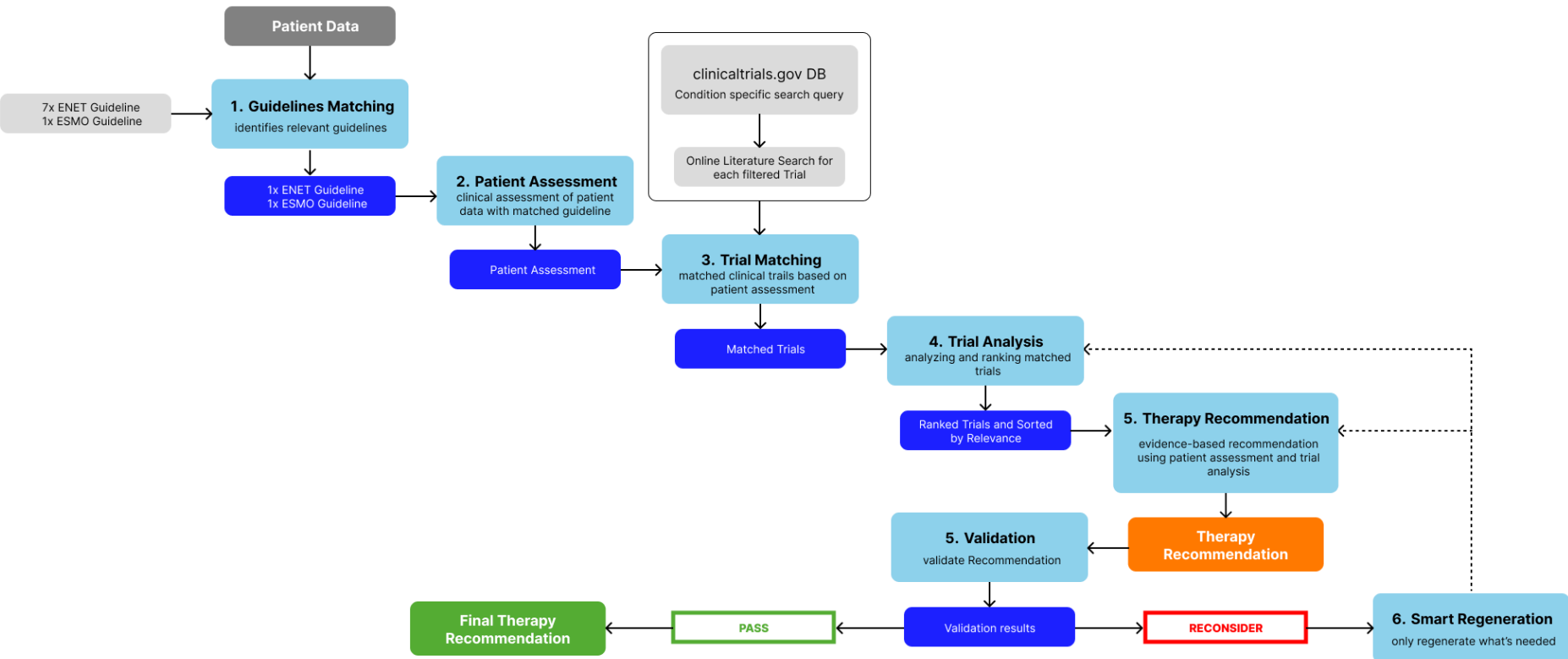


LLM in Tumor Board Recommendation:PRISM



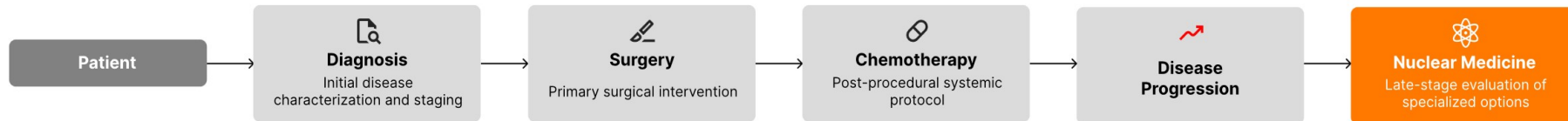
Personalized **R**ecommendations via **I**ntegrated **S**ynthesis & **M**odeling



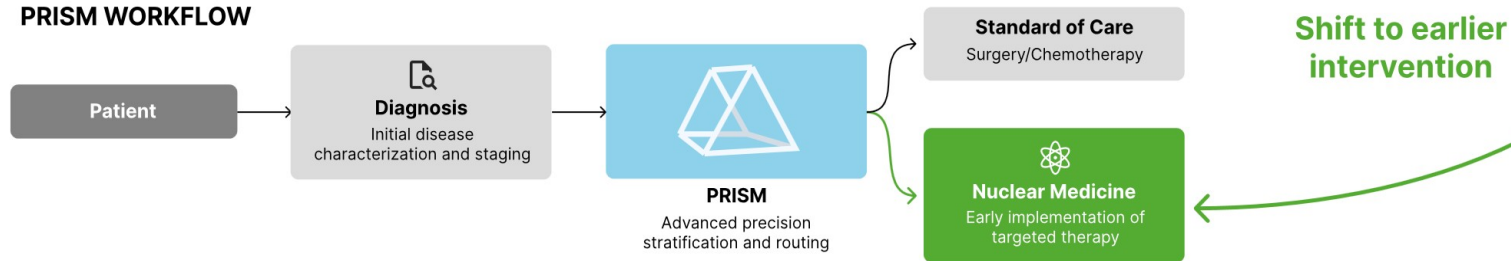


Timeline Shift

CURRENT WORKFLOW

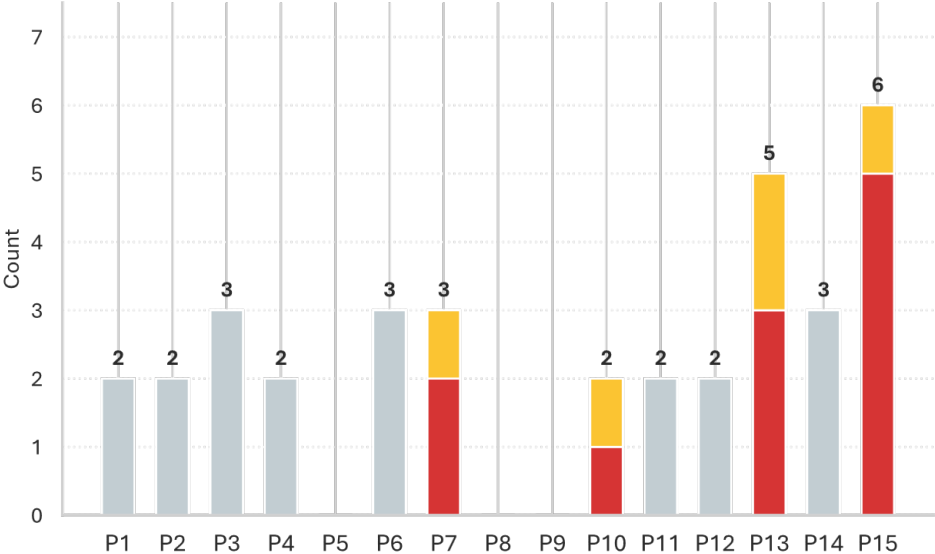


PRISM WORKFLOW



Preliminary Results

Remaining Issues per Patient



Status Detail

ID	Status	Iter	Crit	Warn
P1	PASS	3	0	2
P2	PASS	1	0	2
P3	PASS	2	0	3
P4	PASS	3	0	2
P5	PASS	3	0	0
P6	PASS	2	0	3
P7	FAIL	3	2	1
P8	PASS	3	0	0
P9	PASS	3	0	0
P10	FAIL	4	1	1
P11	PASS	2	0	2
P12	PASS	2	0	2
P13	FAIL	3	3	2
P14	PASS	2	0	3
P15	FAIL	3	5	1

PASS RATE

73.3%

PASS: 11 FAIL: 4

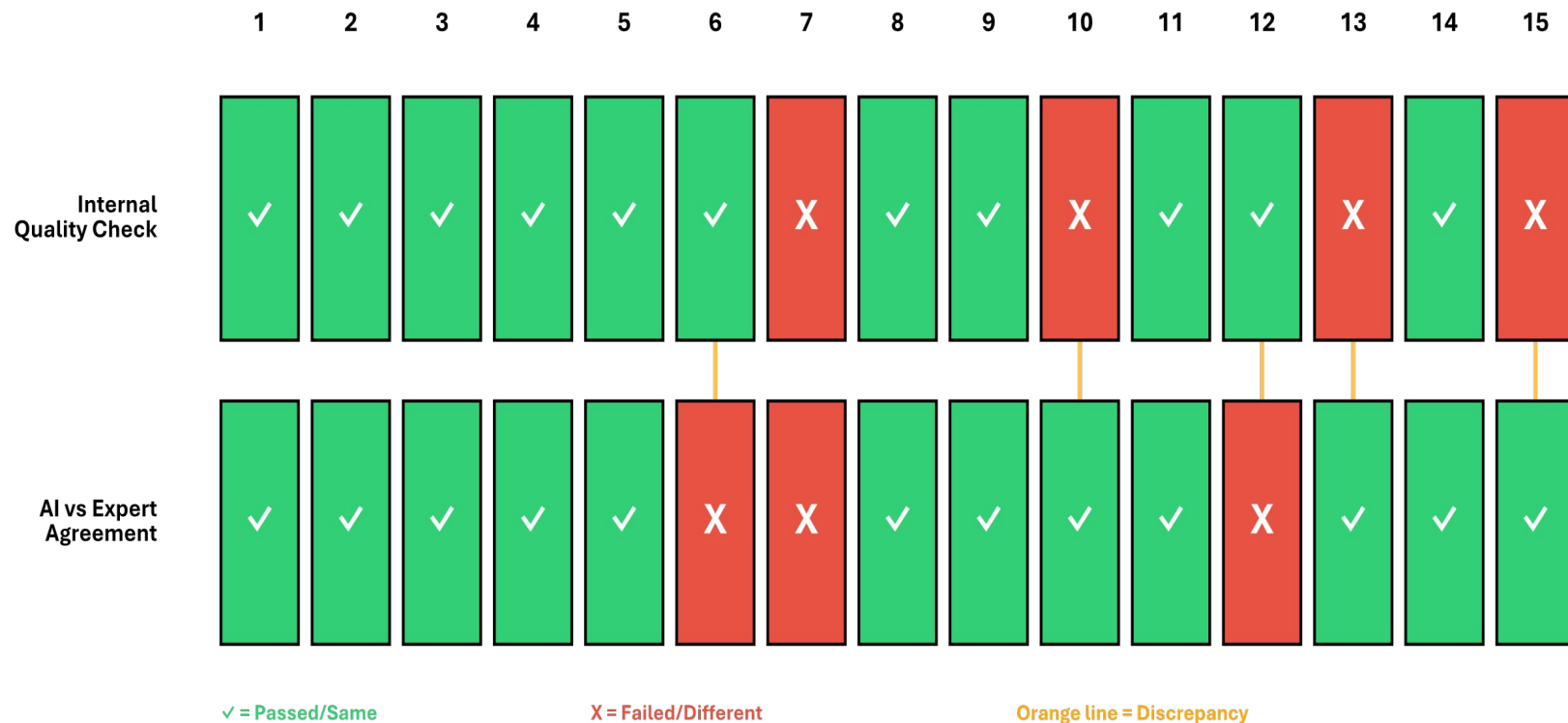
- Critical
- Warning (Fail)
- Warning (Pass)

Validation Issues – Failed Cases

Patient ID	Critical Issues	Primary Cause of Failure
Patient 7	2	Assessment Contradiction: The clinical assessment explicitly stated "TKI re-challenge is NOT supported" due to prior intolerance. The model ignored this and persisted in recommending a TKI (Cabozantinib) as the primary option.
Patient 10	1	Safety Check Omission: The model failed to include mandatory safety checks for bone marrow and renal function before recommending PRRT, which is critical for a heavily pre-treated patient.
Patient 13	3	Anatomical/Surgical Error: Persistently recommended "Curative-Intent Surgery" (Whipple) for a patient with paraaortic lymph node metastases, which constitutes incorrect surgical staging and intent.
Patient 15	5	Persistent Hallucination: The model refused to stop citing three non-existent trials (LUNA, Telotristat real-world, Ribociclib) and unverified CABINET statistics despite explicit feedback.

Preliminary Results

Quality Check vs Clinical Agreement: Patient-by-Patient Comparison



Next Step: User Study with Experts

Recommendation

AI-Generated Recommendation

Here is the therapy recommendation for the tumor board based on the provided clinical data and trial evidence.

Primary Recommendation: Surgical Resection (Salvage Surgery) Given the life-threatening hemorrhagic complications, lack of distant metastasis, and failure of prior embolization, the primary recommendation is **surgical exploration for en bloc distal pancreatectomy, splenectomy, and partial gastrectomy**.

- **Justification:** The patient has locally advanced, non-metastatic disease with a mechanical complication (gastric invasion/bleeding) that systemic therapy cannot resolve acutely.
- **Reference:** ENETS and NCCN guidelines recommend resection for locoregional disease to manage refractory symptoms (bleeding/obstruction), even in locally advanced settings.

Diagnostic Prerequisite: 68Ga-DOTATATE PET/CT Before final therapeutic decision, perform Somatostatin Receptor (SSTR) imaging.

- **Purpose:** To confirm SSTR expression (essential for PRRT eligibility) and rule out occult distant metastases not seen on FDG-PET.
- **Note:** The high FDG uptake (SUV 16) suggests an aggressive phenotype; confirmation of SSTR retention is critical to validate NET-specific therapies.

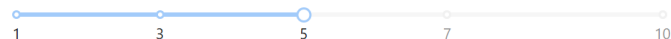
Systemic Therapy Recommendation (If Surgery is Contraindicated/Unresectable) If the tumor is deemed technically unresectable, the recommended first-line systemic therapy for this Grade 2 NET (Ki67 19%) is **Peptide Receptor Radionuclide Therapy (PRRT) with 177Lu-Dotatate (Lutathera)**.

- **Evidence Level:** High (Phase III Randomized Controlled Trial).
- **Study: NETTER-2 Trial (NCT03972488)**
 - **Population:** Well-differentiated G2 and G3 GEP-NETs (Ki67 10–55%).
 - **Results:** 177Lu-Dotatate (plus octreotide) demonstrated a significant improvement in Progression-Free Survival (PFS) compared to high-dose octreotide (median PFS **22.8 months** vs. 8.5 months; HR 0.37).

Evaluation

Overall Recommendation Quality

Rate the overall quality of this therapy recommendation (1 = very poor, 10 = excellent)



* Would you implement this recommendation in clinical practice?

☒ Yes, I would implement this

☐ Maybe, with modifications

☐ No, I would not implement this

Detailed Evaluation Questions

Category 1: Evidence Retrieval

Evaluates how well the recommendation is grounded in established medical knowledge

Has the chatbot found and included at least one relevant guideline (regardless if the recommendation is aligned with the guideline)?

☒ Yes ☐ No

Does the answer cite at least one peer-reviewed primary study (trial or high-quality observational study) relevant to the recommendation?

☒ Yes ☐ No

If newer, potentially practice-changing data exist (e.g., conference abstracts, preprints, press releases), does the answer acknowledge them?

Can we make dosimetry more patient friendly?

Shorten scan duration

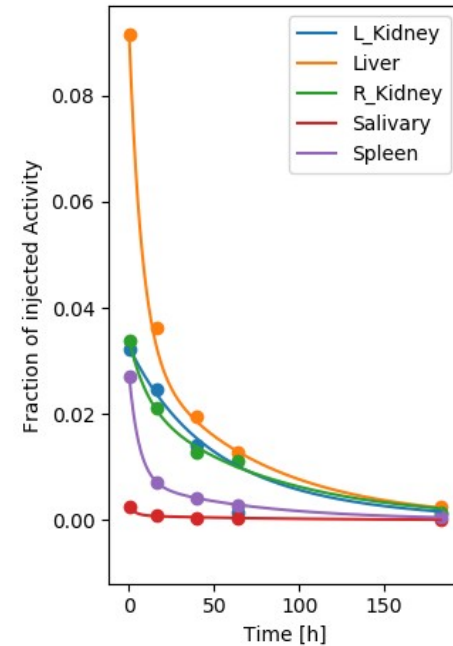
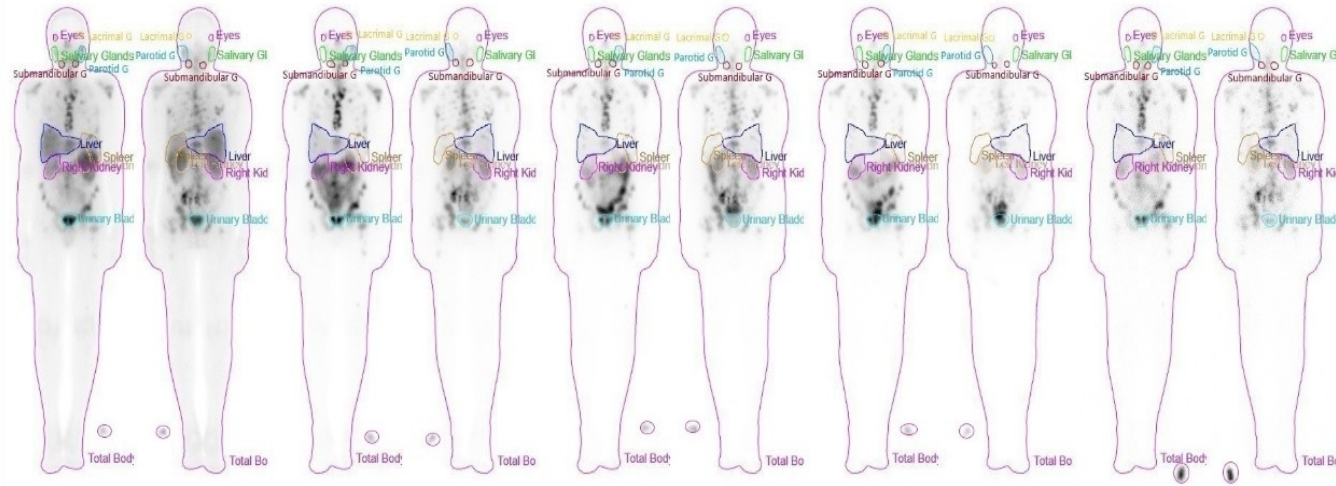
Reduce number of hospital visits

Rational: AI may minimize
redundant measurements



Generated using ChatGPT 5.0

Fast Dosimetry Scan



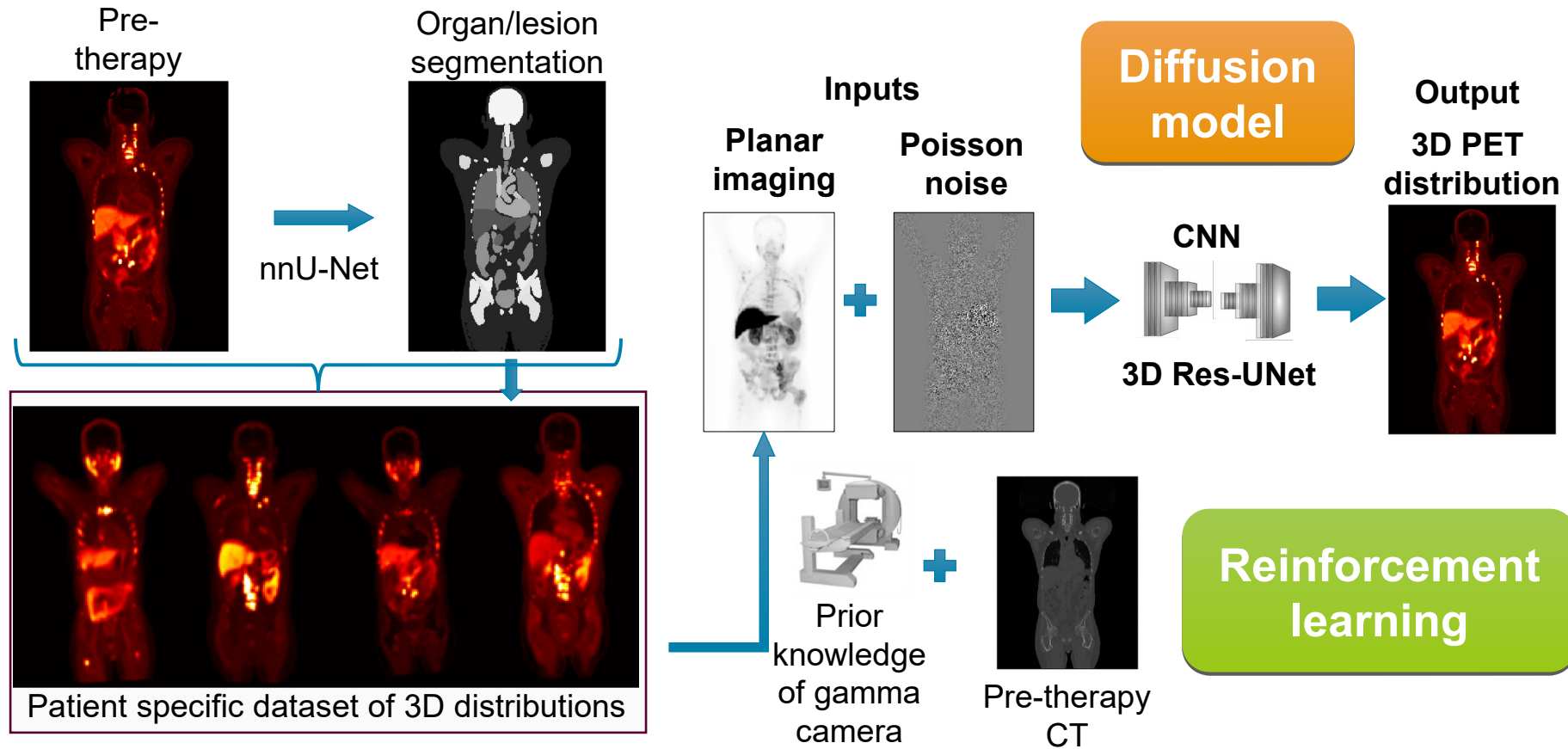
Planar dosimetry scan is convenient & routinely performed

Limited accuracy, challenge in tumor dose estimation

Can we reconstruct 3D imaging from planar imaging?

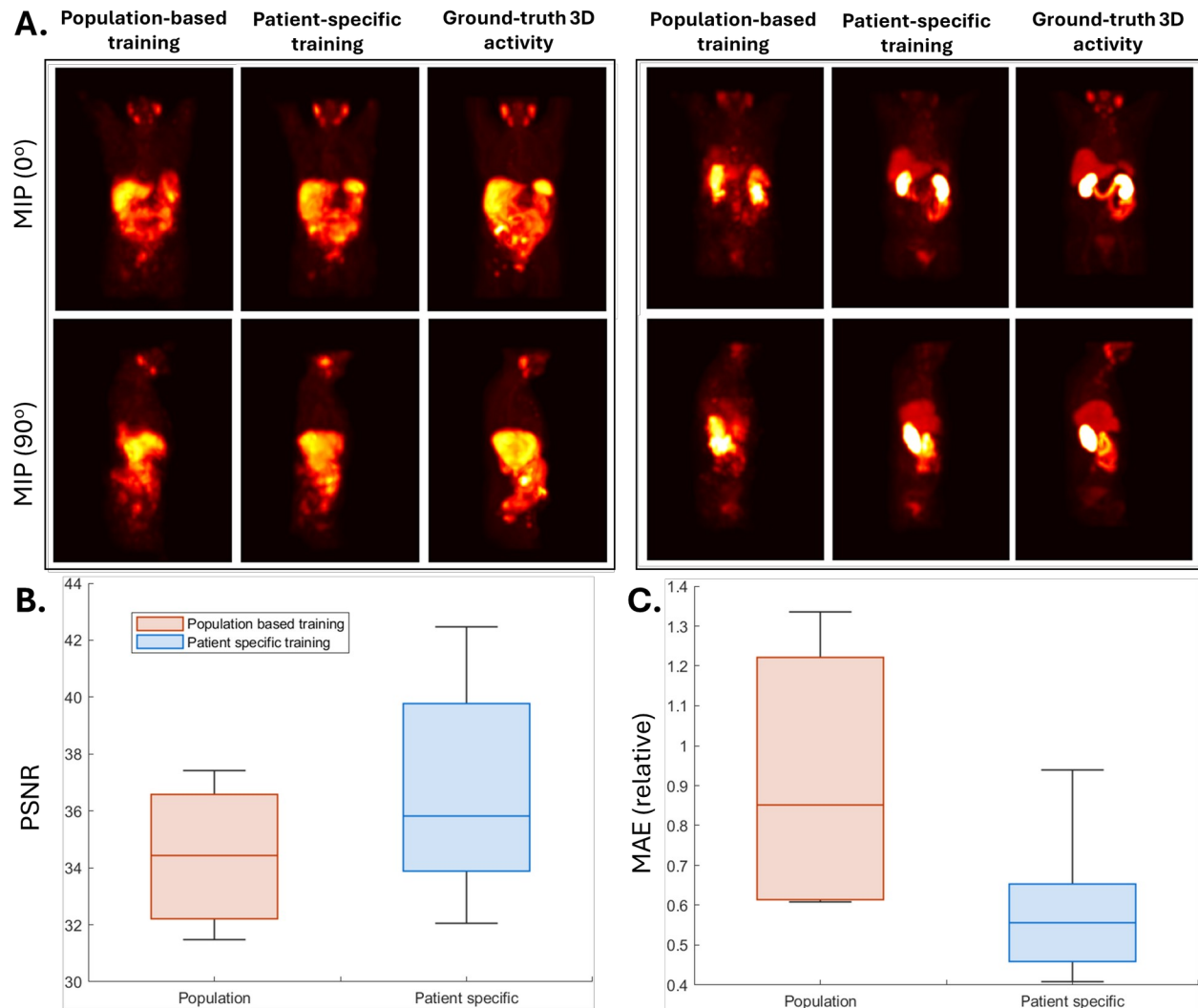
Proposed Method: Patient-Specific Reinforcement Learning

[Lopez-Montes et al. IEEE MIC 2025]

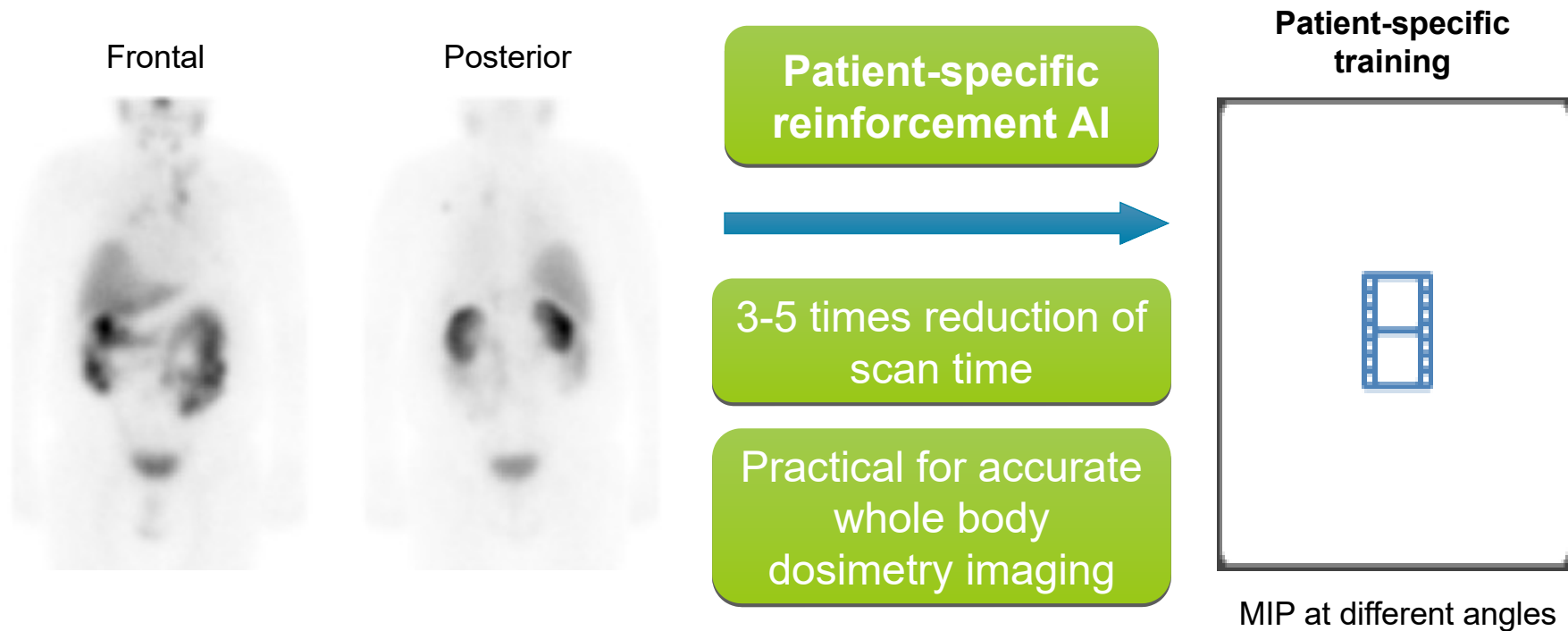


Preliminary Results on Realistic Simulations

In collaboration with Dr. Astrid Delker, Prof. Guido Böning, Prof. Mike Sathekge, Dr. Kamo Ramonaheng & Prof. Jingjing Zhang



Patient-friendly Dosimetry: Planar-based Synthetic 3D Imaging



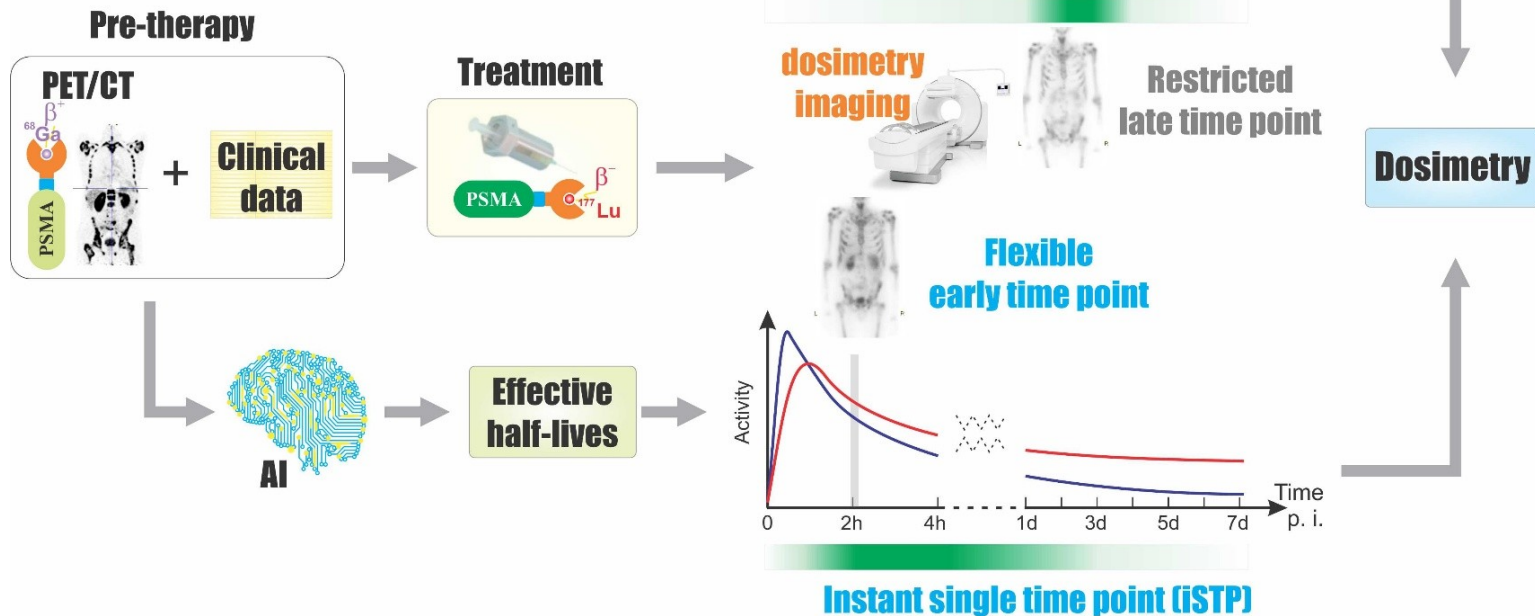
In collaboration with Dr. Astrid Delker, Prof. Guido Böning, Prof. Mike Sathekge, Dr. Kamo Ramonaheng & Prof. Jingjing Zhang

Patient-friendly Dosimetry: Instant Single Time Point Dosimetry

Journal of Nuclear Medicine, published on March 20, 2025 as doi:10.2967/jnumed.124.268175

Characterization of Effective Half-Life for Instant Single-Time-Point Dosimetry Using Machine Learning

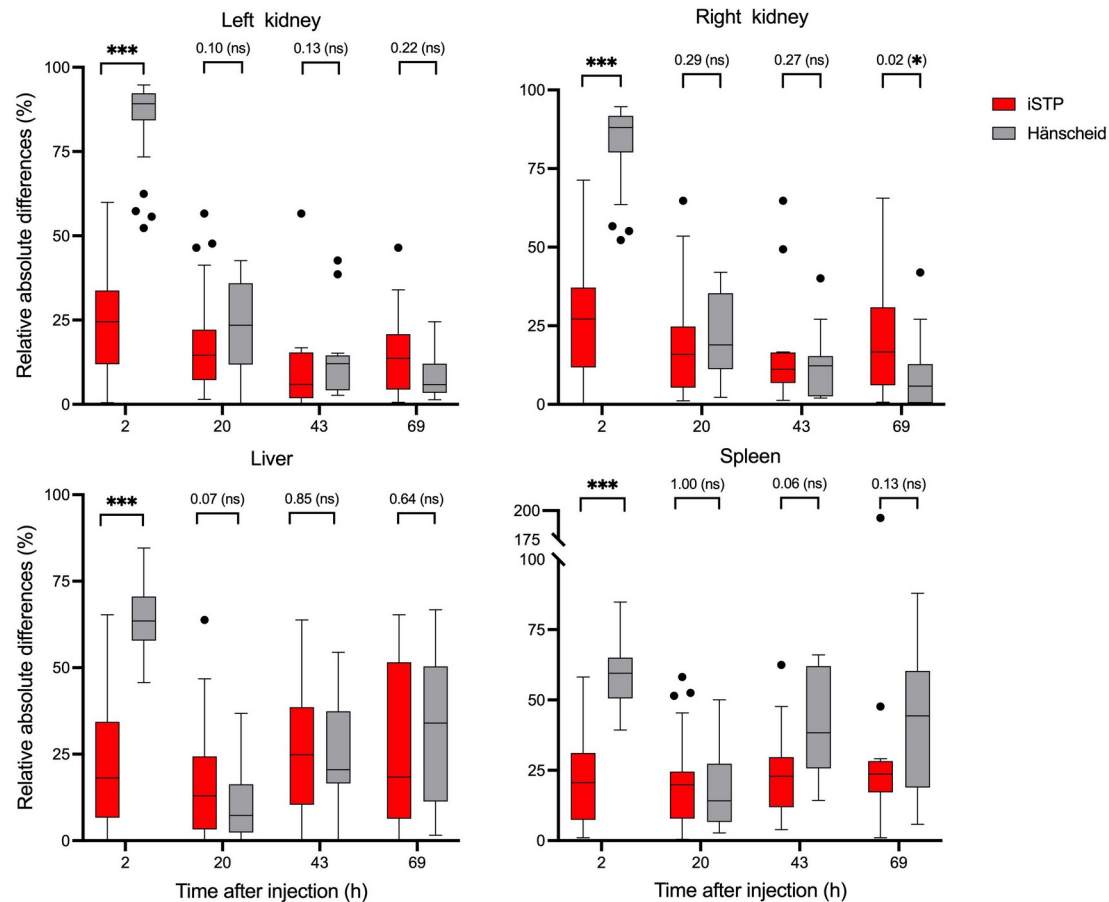
Carlos Vinicius Gomes¹⁻³, Yizhou Chen¹, Isabel Rauscher⁴, Song Xue^{1,5}, Andrei Gafita^{4,6}, Jiaxi Hu¹, Robert Seifert¹, Lorenzo Mercolli¹, Julia Brosch-Lenz^{4,7}, Jimin Hong¹, Marc Ryhiner¹, Sibylle Ziegler^{8,9}, Ali Afshar-Oromieh¹, Axel Rominger¹, Matthias Eiber⁴, Thiago Viana Miranda Lima^{2,10}, and Kuangyu Shi¹



Instant Single Time Point Dosimetry

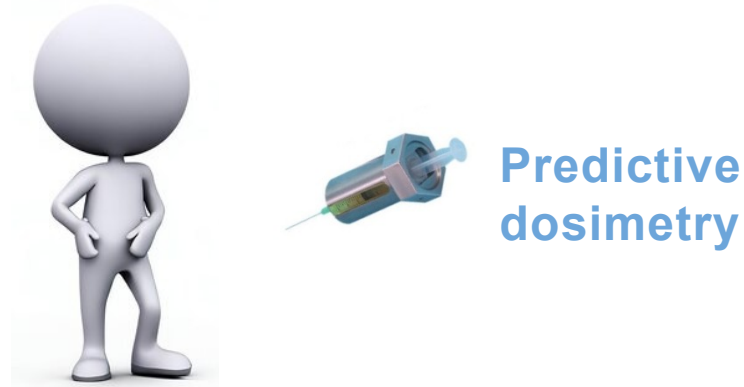
AI performance constrained by data limitations

	Characteristics per cycle			
Cycle #	1	2	3	4
Number of patients	22	11	6	5
Age (years)	69.9			
Weight (kg)	84.7 11.2			
Administered ^{68}Ga -PSMA-11 PET activity (MBq)*	122.4 25.8	118.7 29.7	113.0 11.1	108.6 12.2
Administered ^{177}Lu -PSMA I&T therapy activity (GBq) [†]	7.3 0.3	7.4 0.2	7.3 0.6	7.3 0.2
PSA (ng/mL) [‡]	655.3	644.7	611.7	379.0
LDH [§]	324.8	274.6	270.8	240.6
Creatinine	1.0	0.9	0.9	0.9



In collaboration with Prof. Dr. Isabel Rauscher,
Prof. Matthias Eiber & Prof. Wolfgang Weber

Patient-friendly Dosimetry: PET-based Predictive Dosimetry



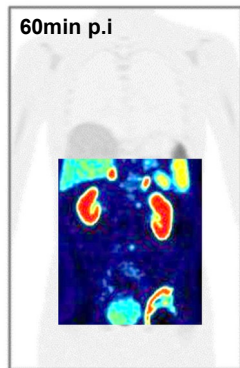
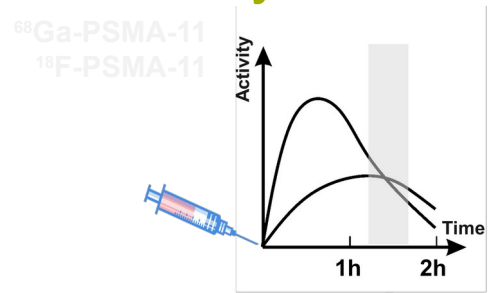
Before the treatment: know the dose

No additional burden on patients

Favorable for treatment planning

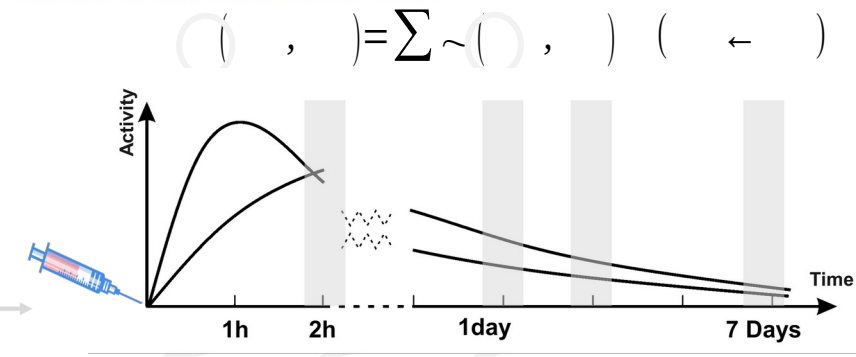
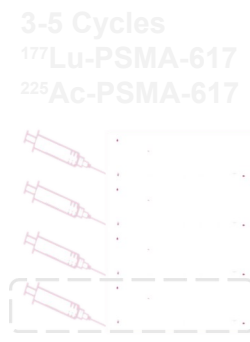
PET-based Predictive dosimetry

Diagnostic PET/CT



Static, PET/CT

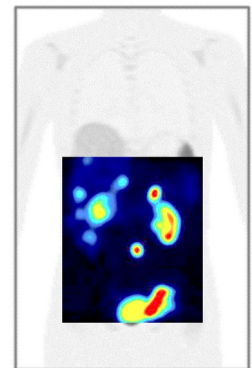
Therapy SPET/CT



2h p.i. 1d p.i. 2d p.i. ... 7d p.i.



Multiple Time points, SPET/CT



Dose

Theranostics

Spatiotemporal conjugation

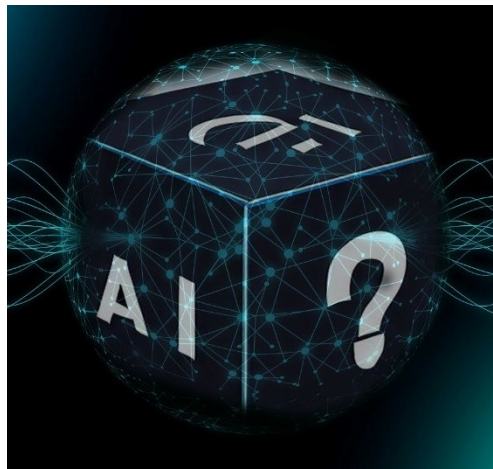
Application of machine learning to pretherapeutically estimate dosimetry in men with advanced prostate cancer treated with ^{177}Lu -PSMA I&T therapy

Song Xue¹ · Andrei Gafita^{2,3} · Chao Dong⁴ · Yu Zhao⁵ · Giles Tetteh² · Bjørn H. Menze⁵ · Sibylle Ziegler⁶ · Wolfgang Weber² · Ali Afshar-Oromieh¹ · Axel Rominger¹ · Matthias Eiber² · Kuangyu Shi^{1,2,4}

Pre-therapy PET-based voxel-wise dosimetry prediction by characterizing intra-organ heterogeneity in PSMA-directed radiopharmaceutical theranostics

Song Xue^{1,4} · Andrei Gafita² · Yu Zhao⁵ · Lorenzo Mercolli¹ · Fangxiao Cheng¹ · Isabel Rauscher² · Calogero D'Alessandria² · Robert Seifert¹ · Ali Afshar-Oromieh¹ · Axel Rominger¹ · Matthias Eiber^{2,5} · Kuangyu Shi^{1,3}





<https://www.makeuseof.com/what-are-ai-black-boxes/>

IEEE TRANSACTIONS ON RADIATION AND PLASMA MEDICAL SCIENCES, VOL. 8, NO. 6, JULY

PBPK-Adapted Deep Learning for Pretherapy Prediction of Voxelwise Dosimetry: In-Silico Proof of Concept

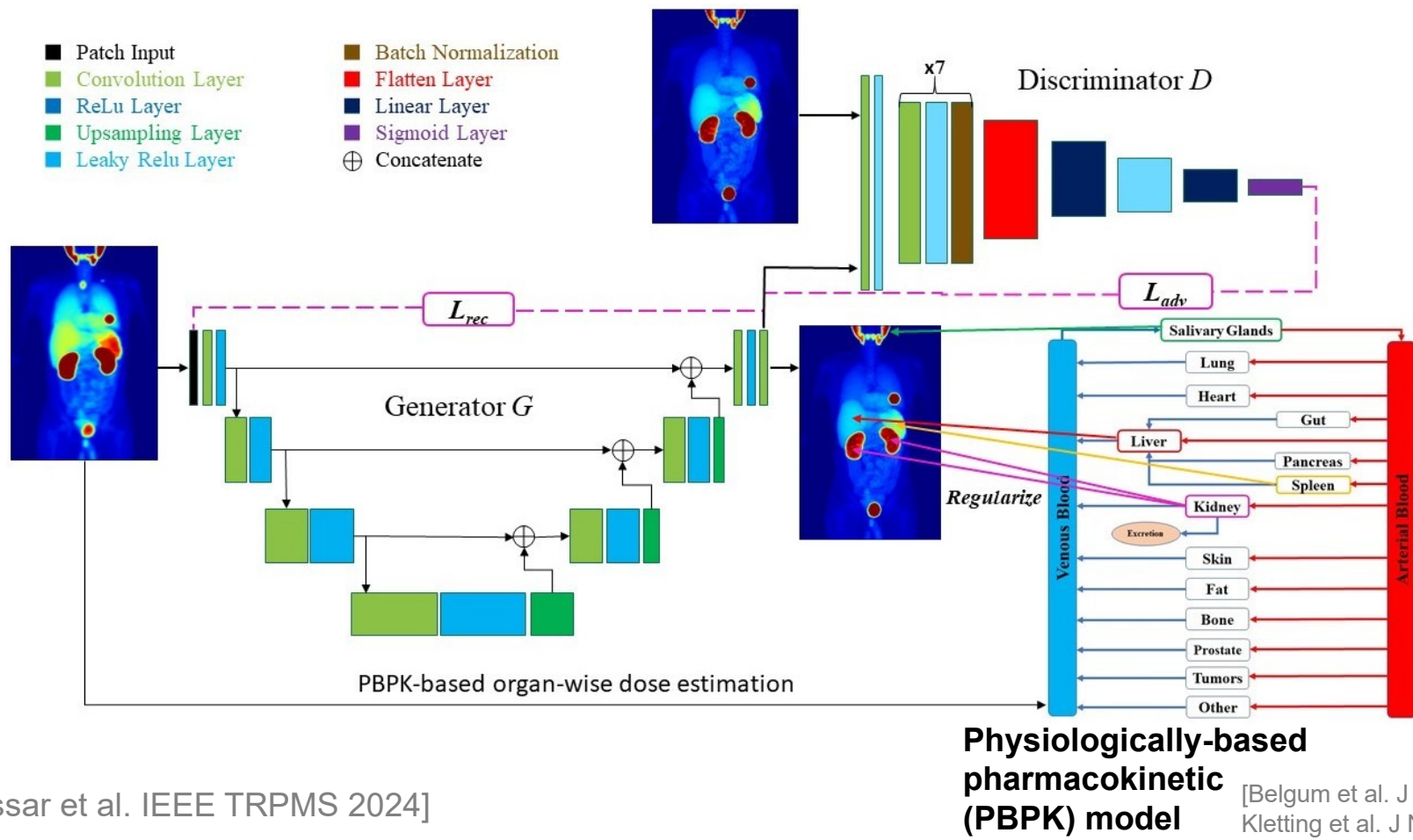
Mohamed Kassab[✉], Milos Drobnjakovic, Gabriele Birindelli, Song Xue[✉], Andrei Gafita,
Thomas Wendler[✉], *Member, IEEE*, Ali Afshar-Oromieh, Nassir Navab[✉], *Fellow, IEEE*,
Wolfgang A. Weber, Matthias Eiber, Sibylle Ziegler[✉], *Senior Member, IEEE*,
Axel Rominger[✉], and Kuangyu Shi[✉], *Member, IEEE*

Pure AI-base voxel-wise prediction is challenging

**Can we make the AI-base voxel-wise prediction more
robust & interpretable?**

Consider domain knowledge, i.e. pharmacokinetics

PBPK-adapted Deep Learning for Predictive Dosimetry

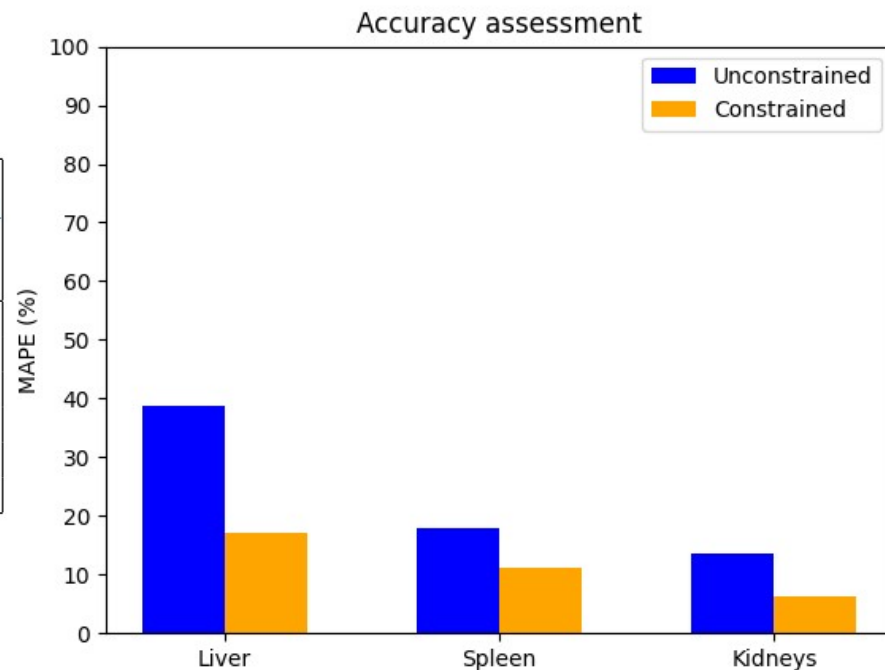


Proof of Concept on Digital Twin Phantoms

D50 and EUD

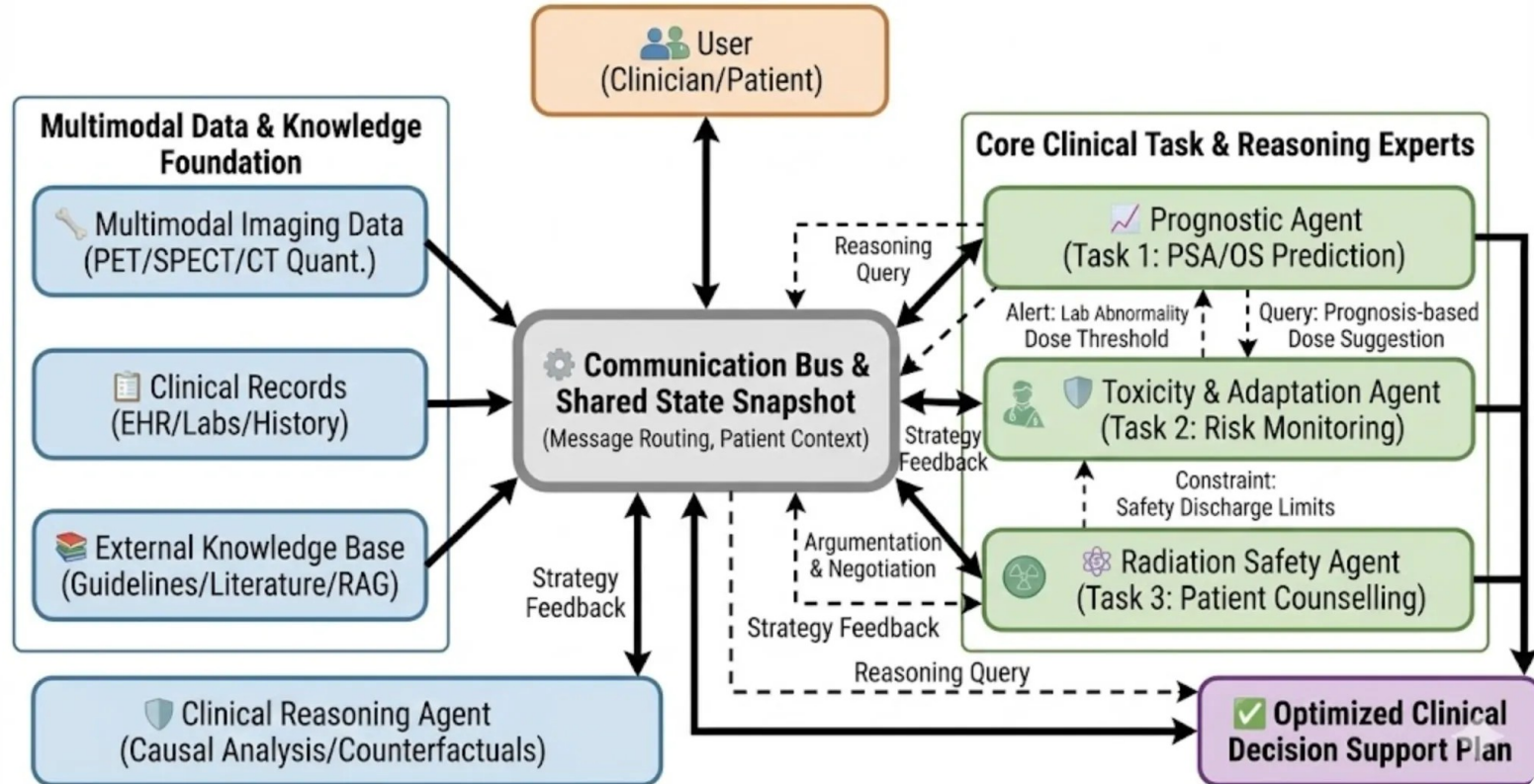
Organ	D50-Unconstrained (Gy)	D50-Constrained (Gy)	EUD-Unconstrained (Gy)	EUD-Constrained (Gy)
Liver truth	0.28	0.28	0.27	0.27
Liver predicted	0.17	0.24	0.16	0.23
Spleen truth	0.95	0.95	0.97	0.97
Spleen predicted	0.74	0.84	0.82	0.94
Kidneys truth	9.02	9.02	9.05	9.05
Kidneys predicted	7.80	8.51	7.83	8.54

Prediction error



Theranostic Multi-Agent System

Develop **an multi-agents system** to support ^{177}Lu -PSMA theranostic patient consultation and management by predicting treatment outcome, side effect management, and providing radiation safety consultation



Conclusion

- ❑ LLM and AI agent provide potential to integrate diverse and multi-disciplinary knowledge in theranostic consultation
- ❑ Integrate professional knowledge/logic/principles improves the robustness & trustworthiness
- ❑ AI may simplify dosimetry procedure
- ❑ Further clinical evaluation is needed

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Mohamed Kassab
Yale, USA
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Pretoria, South Africa

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Dr. Kamo Ramonaheng

NUS, Singapore

Prof. Jingjing Zhang

Wiesbaden, Germany

Prof. Richard Baum

Essen, Germany

Prof. Ken Herrmann

SNU, Korea

Prof. Hongyoon Choi

Brest, France

Prof. Dimitris Visvikis

Ulm, Germany

Prof. Gerhard Glatting



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R01





Thank you very much
for your attention!