FACULTY OF ENGINEERING AND ARCHITECTURE
FACULTY OF MEDICINE AND HEALTH SCIENCES
IMIT Innovative Molecular Imaging and Therapy

POTENTIAL AND PITFALLS OF AI FOR DENOISING AND SYSTEM DESIGN IN NUCLEAR MEDICINE (PET-CT)

Prof. Stefaan Vandenberghe

Research professor, Innovative Molecular Imaging and Therapy
MEDISIP -Infinity lab, UGent Belgium
Stefaan.Vandenberghe@ugent.be
☏ 0032 93325854

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Penn University of Pennsylvania
University of Pisa

SPEAKER DISCLOSURE

- Editor-in-Chief EJNMMI Physics (Springer Nature)
- One of the founders of Nuclivision.com (Ghent, Belgium)
- Patents with Ugent used by Molecubes

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THE PRESENT	**STATE OF THE ART IN (TB)-PET-CT**
POTENTIAL	HOW TO USE AI TO IMPROVE PET-CT ?
THE FUTURE	HOW TO CHANGE PET-CT WITH AI ?

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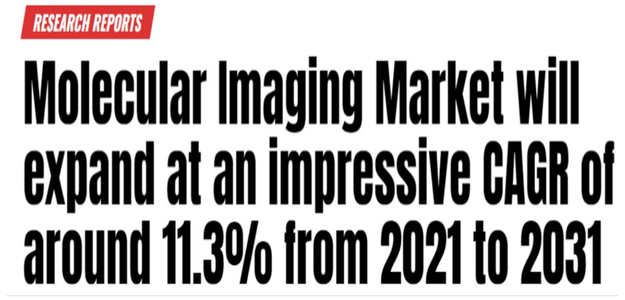
PET-CT

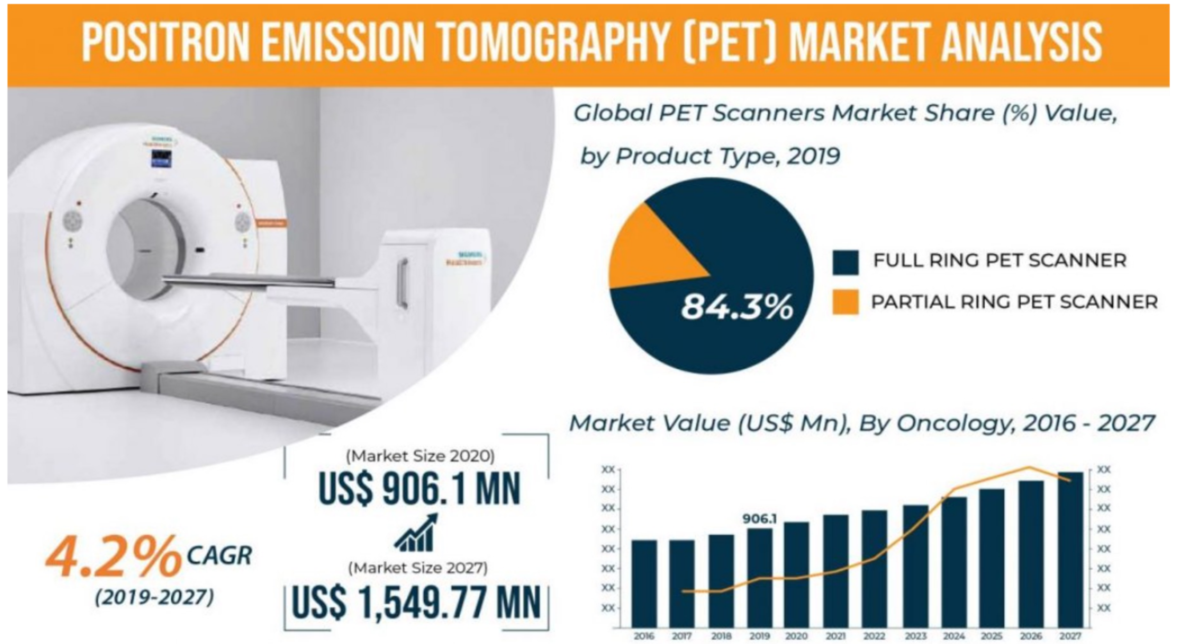
Important role in cancer diagnosis and treatment
FDG
Medium throughput

Cyclotron
Expensive
Radioactivity


RESEARCH REPORTS
Molecular Imaging Market will expand at an impressive CAGR of around 11.3% from 2021 to 2031

New evolutions on tracers: Theranostics, PSMA and Fapi

New evolutions in detectors and AI



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LARGE CHANGES IN PET PERFORMANCE

PET detector and system improvements

1995	2000	2005	2010	2020
BGO/NaI → L(Y)SO	Septa → Fully 3D	PET → PET-CT	Coincidence → Time-of-Flight	Total Body PET **Deep learning** **Detectors Denoising** **Data analysis**

Gradual changes

Longer Axial FOV

Improvements in iterative recon and scatter correction

Increase in computing power, memory and storage

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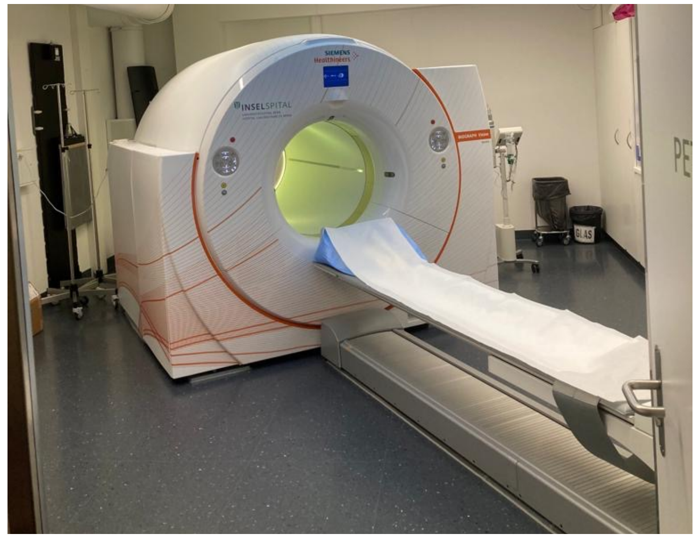
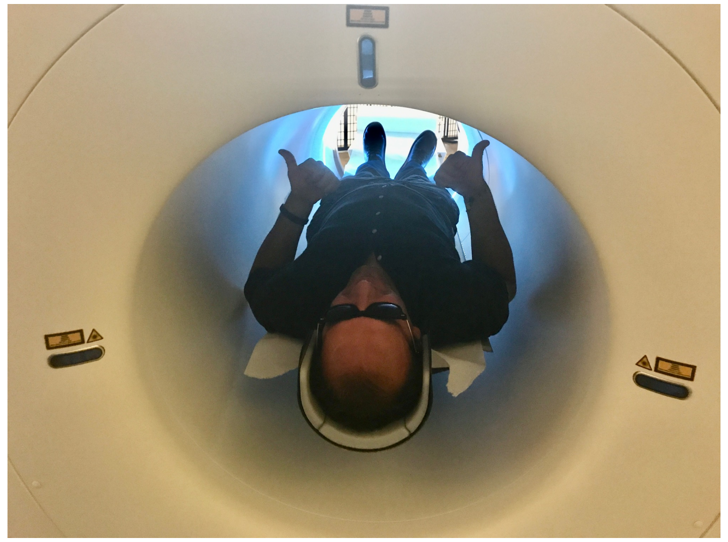
TOTAL BODY PET-CT





Low dose imaging
Faster
Total Body at once

Very high acquisition cost
8-12 MEuro
Expensive service contract

Research tool
Why would I need it ?
Too expensive
Hospital will never pay this

Private

Academic

Interesting/innovative
I want the best
Other academics have it
Grant will pay for it

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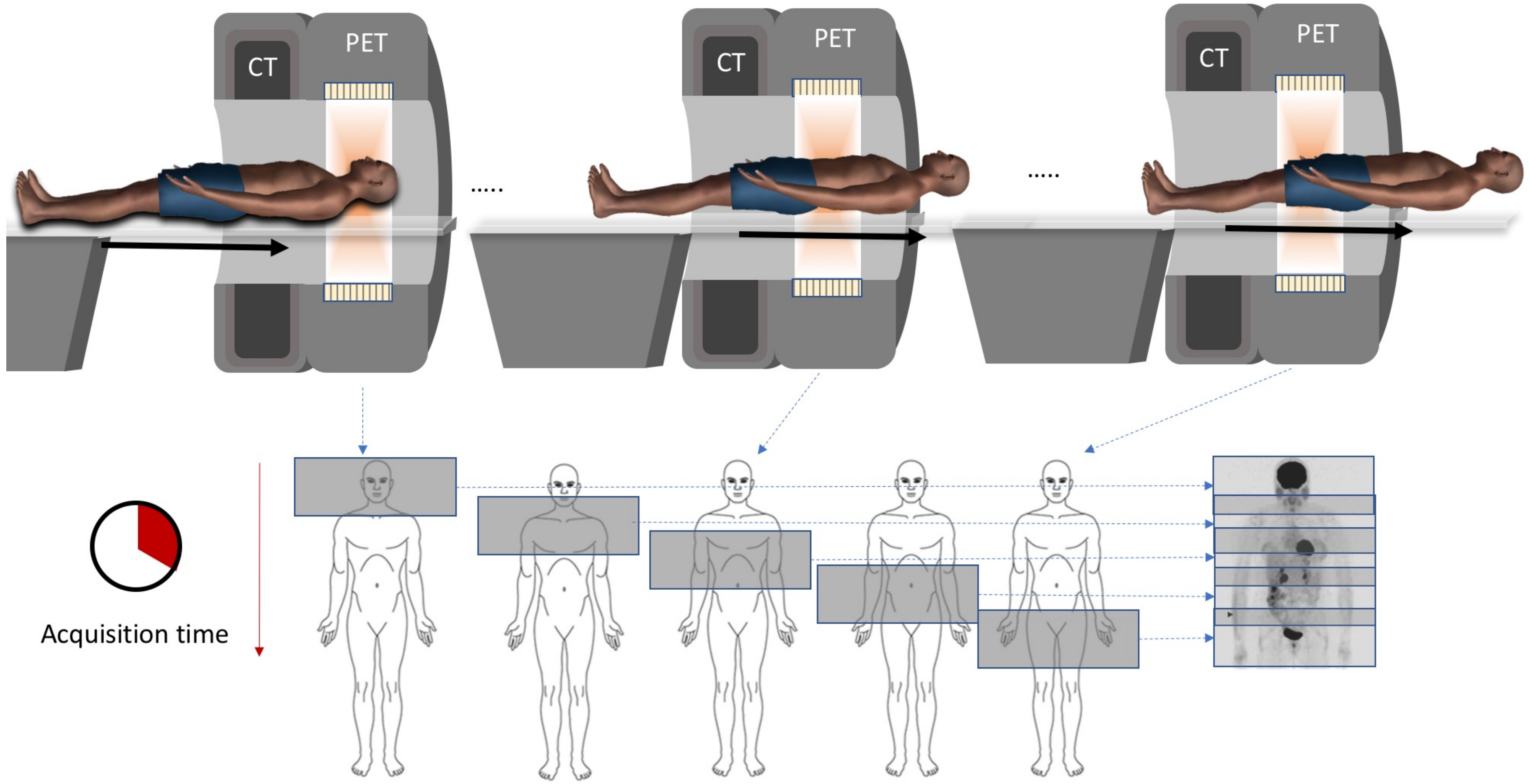
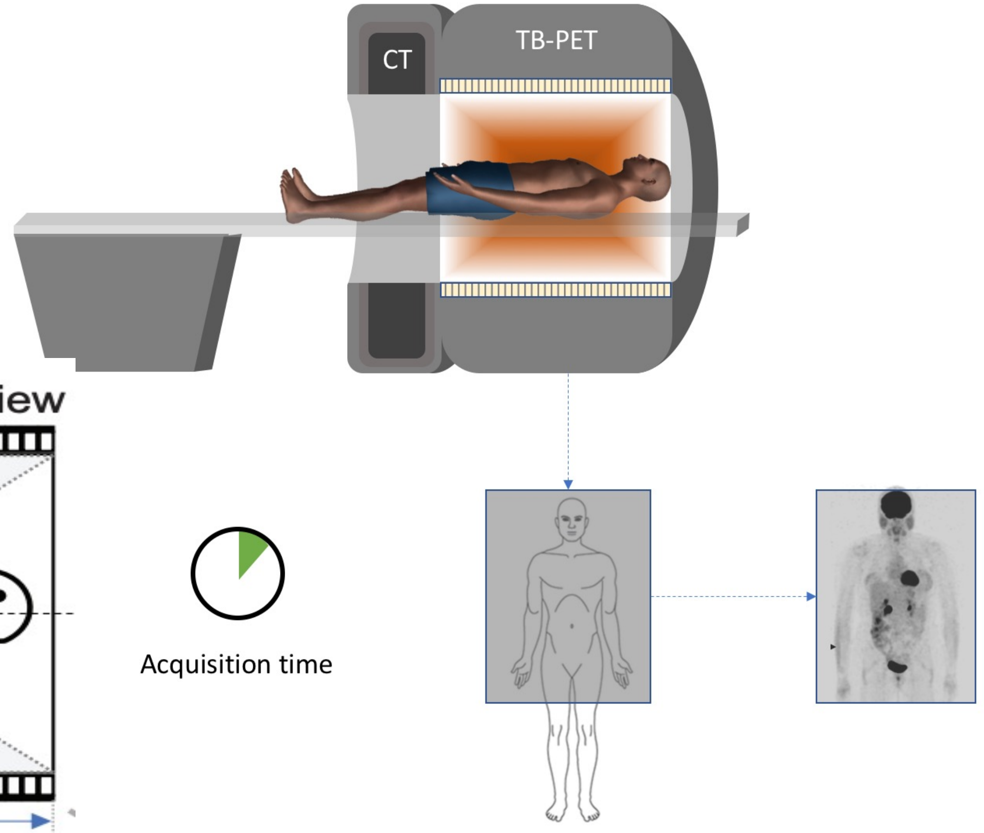
PET-CT VERSUS TOTAL BODY PET-CT



10-20 x
Faster torso imaging
And/or lower dose
+
Simultaneous imaging of organs



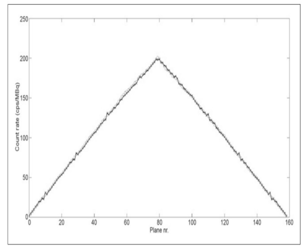
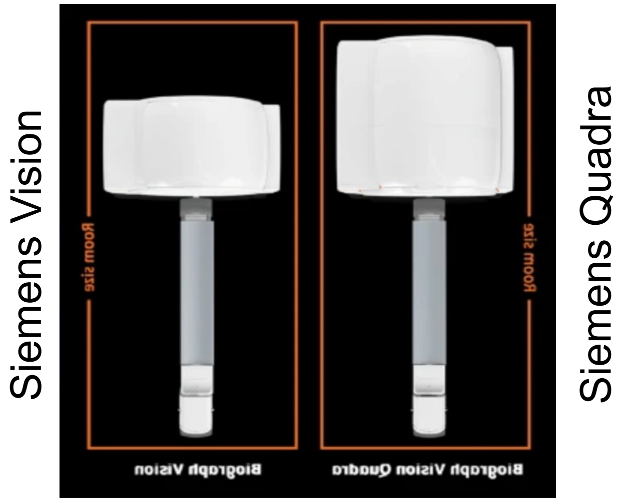
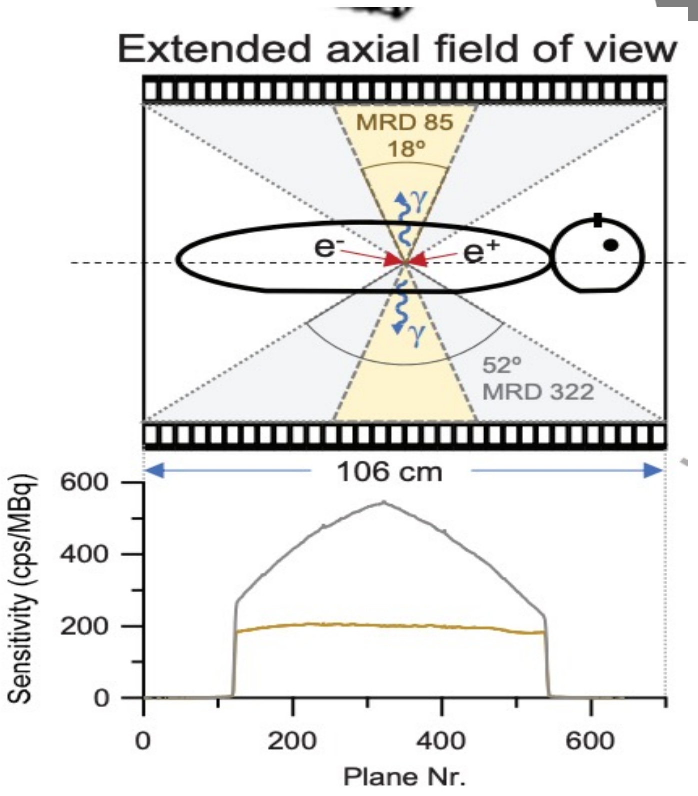


FIGURE 2. Axial sensitivity profiles for both 0-cm off-center position (circles) and 10-cm off-center position (crosses).

24 cm





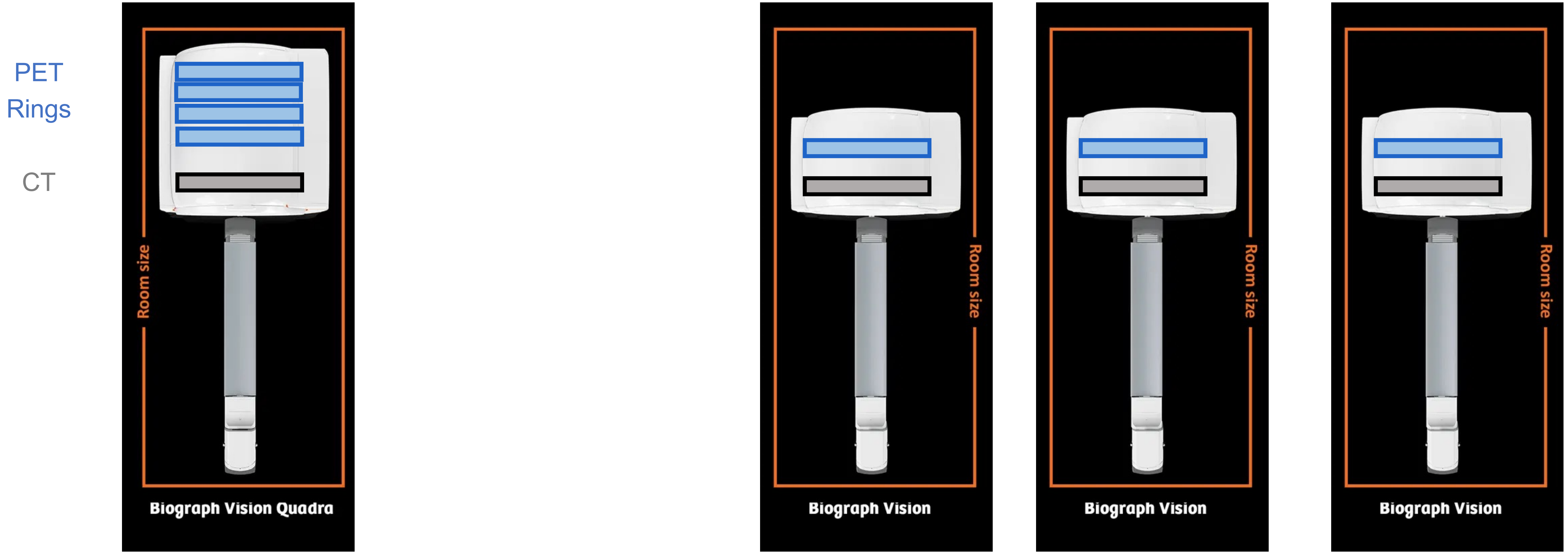
106 cm

World most sold sedan: 30 kEuro

Lamborghini Huracan: 300 kEuro

PET VS TOTAL BODY PET (ACQ COST)

1 TB PET-CT **or** 3 standard PET-CT



Long Axial FOV= LAFOV

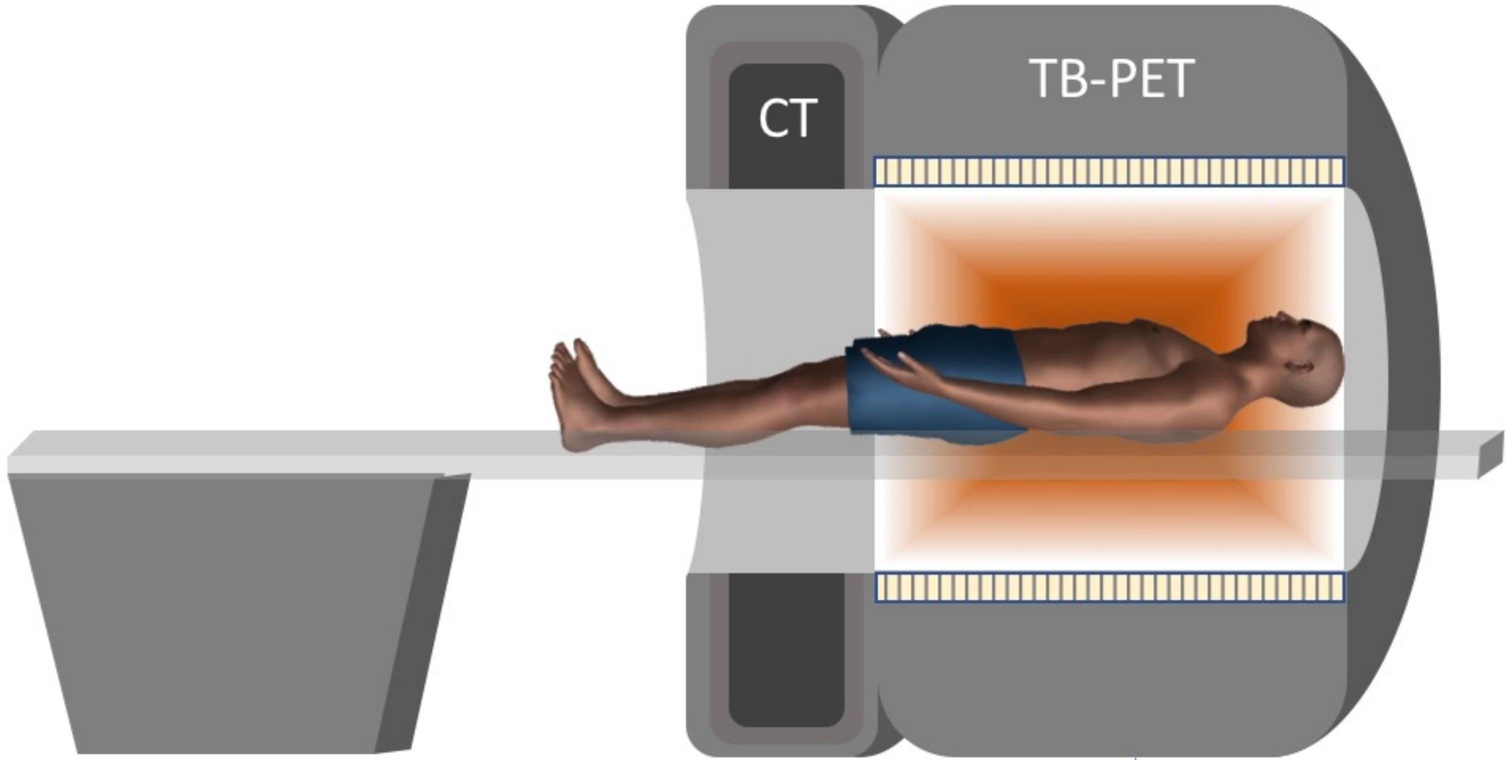
Short Axial FOV= SAFOV

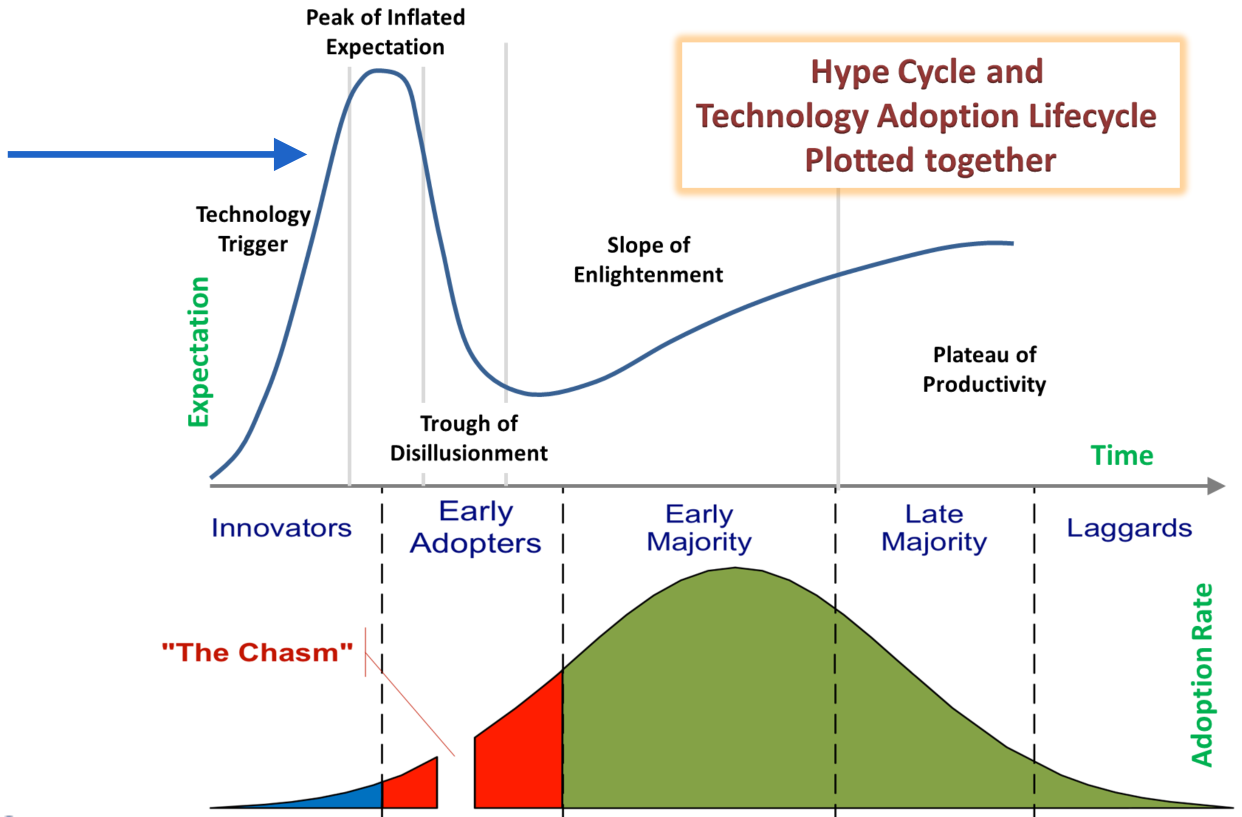
Customer perspective

Best PET scanner possible at reasonable price

Society perspective

As many PET scanners as possible





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Current TB PET

+

Very sensitive
Fast scan times
One bed position
Dose of PET can be reduced

-

Expensive
Slow patient positioning
CT dose
Amount of data

EXPECTED INCREASE IN PET(-CT) PATIENTS

Why ?

- New tracers for imaging with large number of patients: PSMA, Fapi….
- Not only detection but more and more (expensive) therapy prediction and follow-up
  - Early detection → improved therapy outcome
  - First PET scan (60%, 20 % normals)
  - Follow-up (40%)
- Future maybe selected screening: genetic, blood test, patient history

  → Fast evolutions towards early diagnosis of cancer
- Even with selected screening there will be a high number of patients and repeat scans

- **How** to deal with this:
  - Lower dose imaging (screening, other populations)
  - Faster imaging + Throughput
  - Lower cost imaging (systems + procedure)
  - Less personnel per scan

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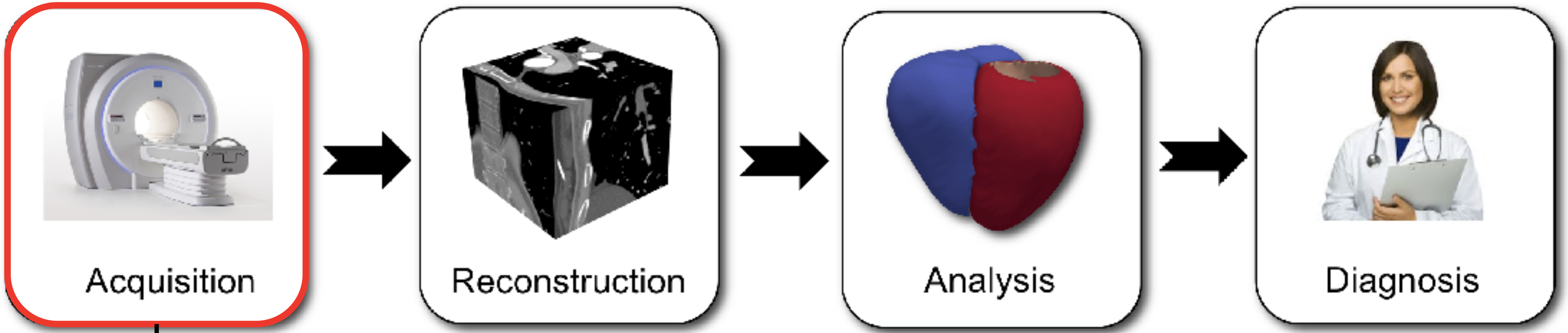

- Lower cost systems
- DL-TOF
- Improve detector performance

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Slide layout courtesy of FM Muller

DEEP LEARNING BASED SYSTEM DESIGN

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MEDIUM COST TOTAL BODY PET

Thin crystal TB PET

Improved TOF (?)
Limited DOI
50 % less scintillator

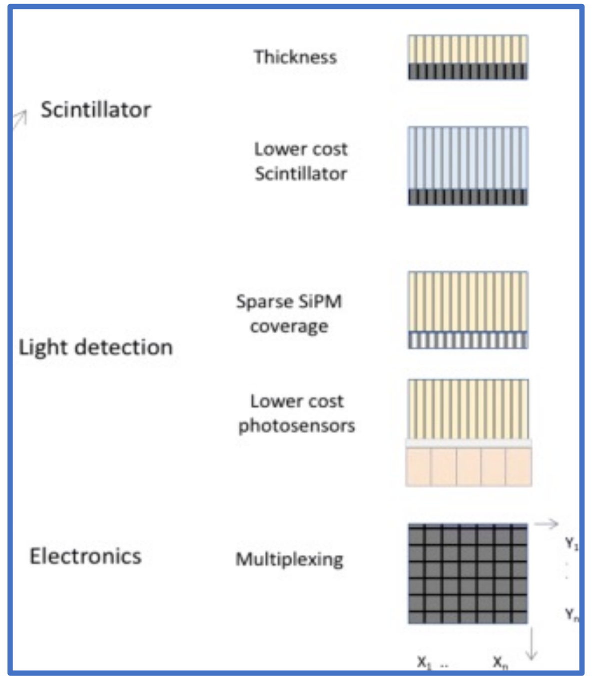
Total body PET

~ 4 x less counts than full TB PET
But still 3-4x more than PET

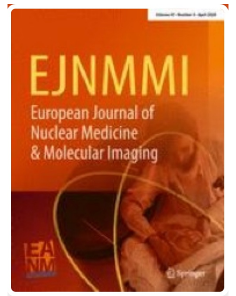
50 % less detectors

Sparse crystal TB PET

Lower cost detector options



Lower cost TB PET
4-6 Meuro range
With 2x - 3x higher througput financially interesting for most centers

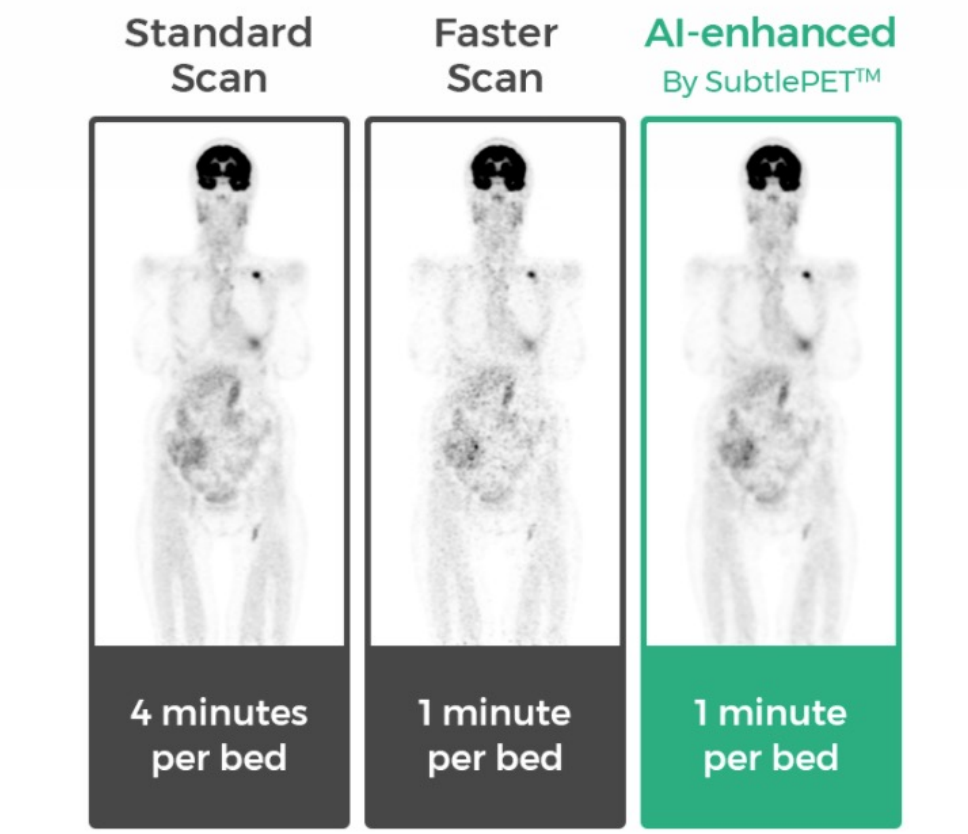


The potential of a medium-cost long axial FOV PET system for nuclear medicine departments
Stefaan Vandenberghe Nicolas A. Karakatsanis Maya Abi Akla, Jens Maebe Suleman Surti Rudi A. Dierckx Othmane Bouhalie Joel S. Karp, accepted for EJNMMI

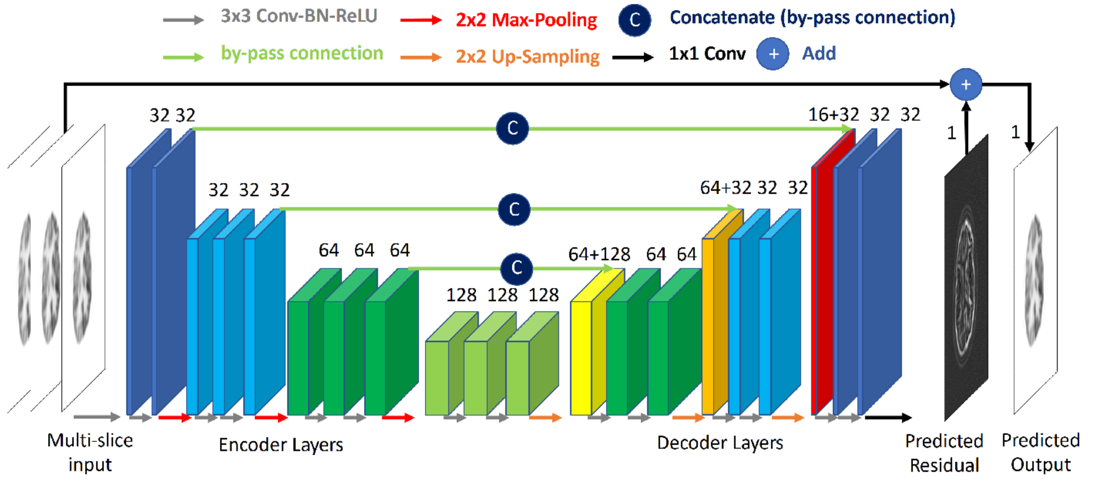
ARTIFICIALLY 'BOOST' LOWER COST (TB)-PET

AI
TO THE
RESCUE

LOW NOISE
'RECONSTRUCTION'
USING DEEP LEARNING
Train low dose-high dose pairs



Convolutional Neural networks



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Total Body PET

Deep learning
Detectors
Denoising
Data analysis

Gradual changes
Longer Axial FOV
Improvements in iterative recon and scatter correction
Increase in computing power, memory and storage

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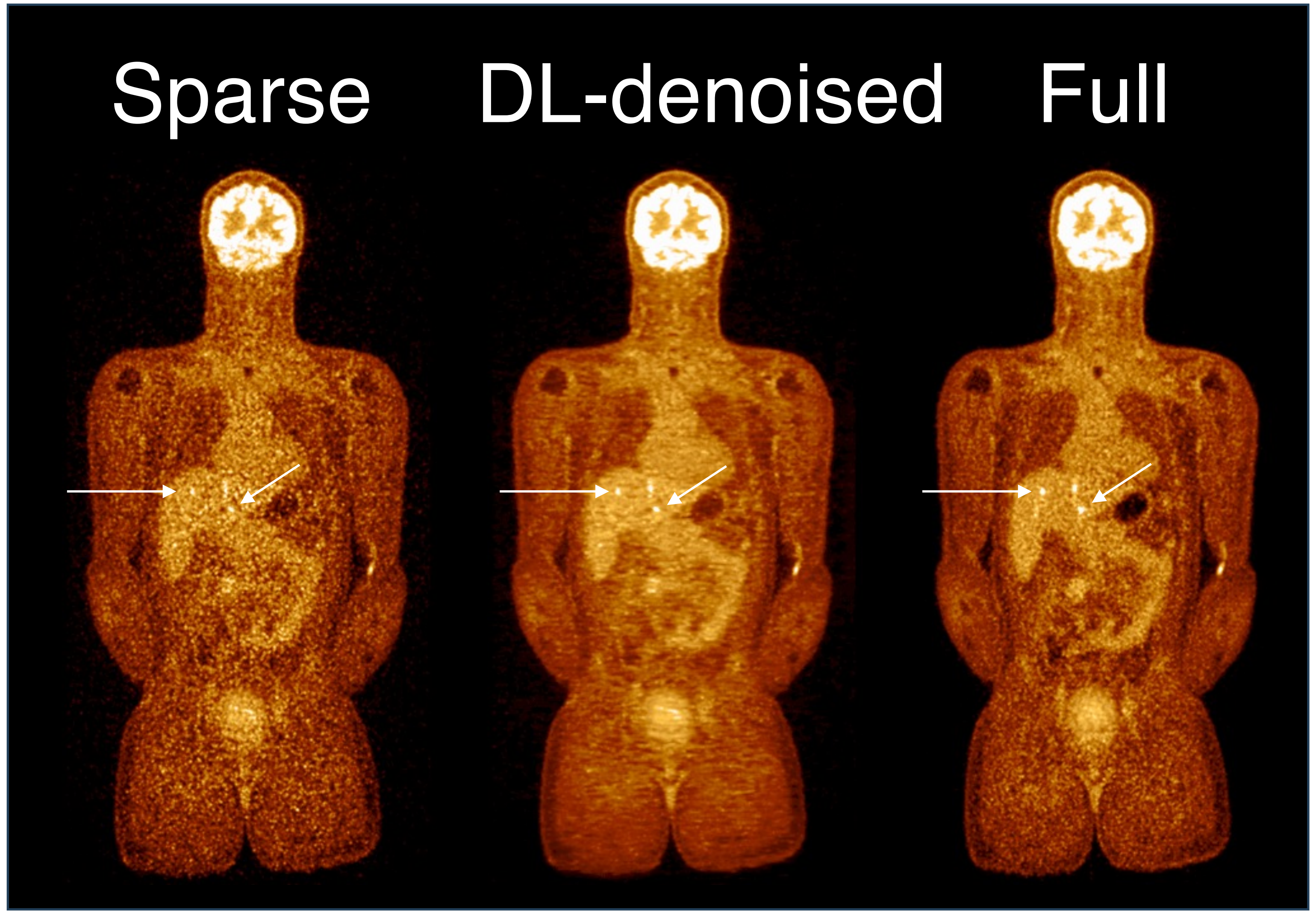
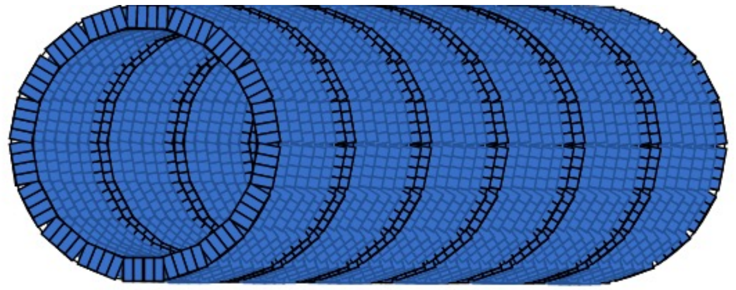
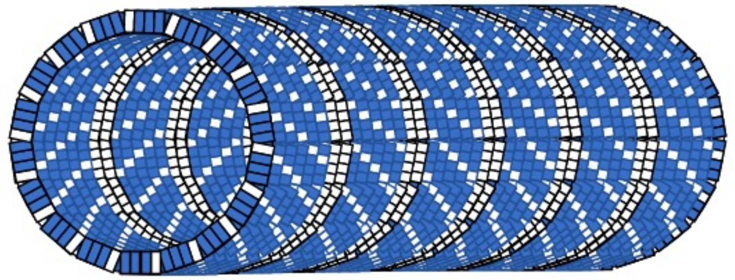
Deep learning denoising of sparse configurations

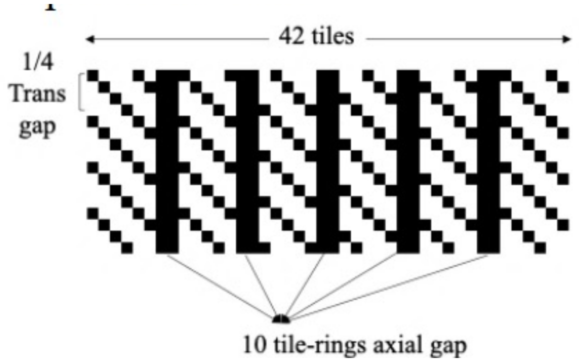




Full PennPET configuration



Sparse configuration



Around 2/3 of LORs are removed

➔ 43% detector savings

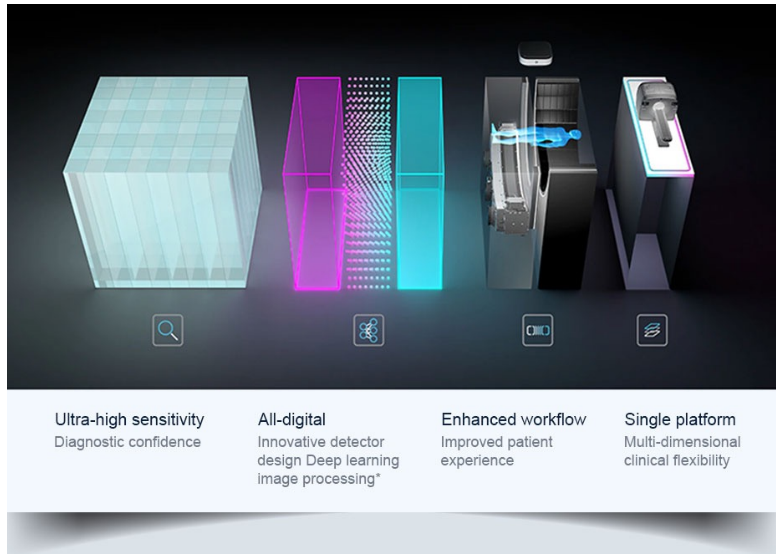
Cost-effective Total-Body PET with Axial and Transverse Gaps

Min Gao, Florence M. Muller, Margaret E. Daube-Witherspoon, *Fellow, IEEE*, Joel S. Karp, *Fellow, IEEE*, and Suleman Surti, *Senior Member, IEEE*

Presented at IEEE MIC 2023

AI to enhance system performance

GE Omni Legend
30 mm thick BGO-non TOF

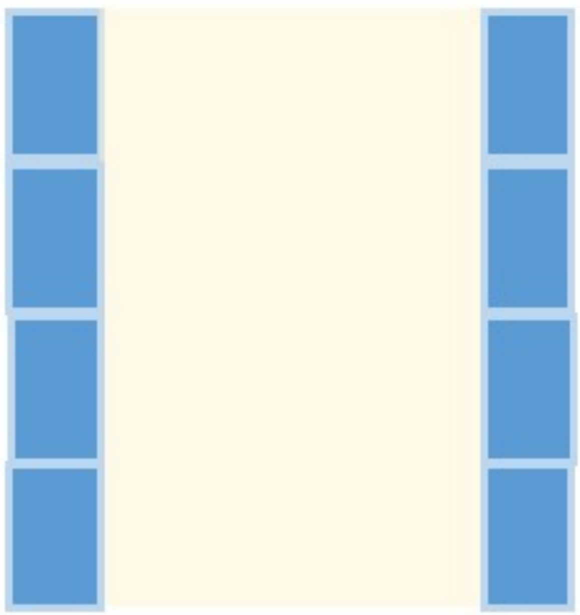


Non-TOF → lower cost detector/electronics

BGO of 30 mm → superior non-TOF sensitivity

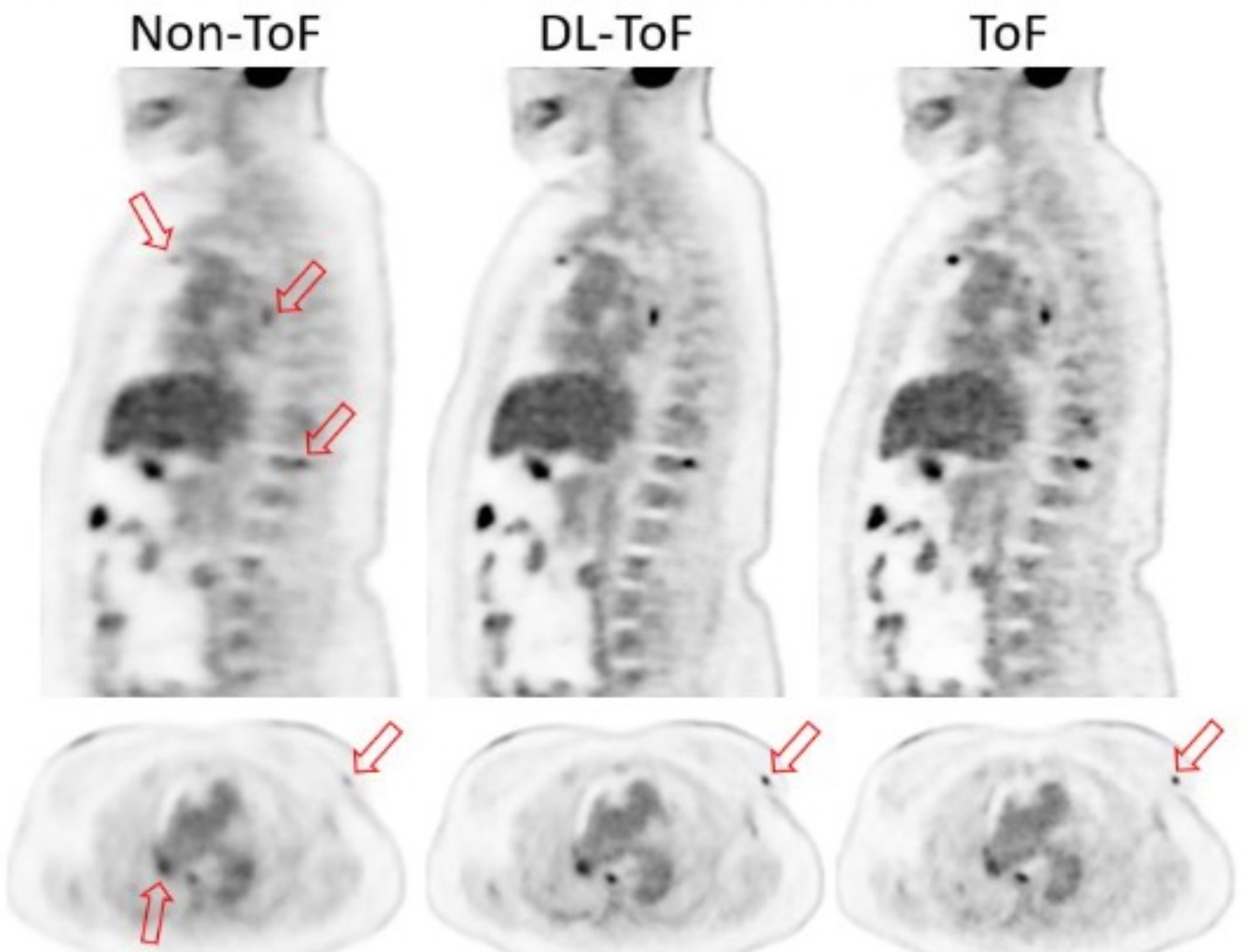
DL network trained on non-TOF images and TOF images

32 cm or
64 cm or
96 cm or
128 cm or
Axial length
Future Upgradeable



No time of flight (ToF)? No problem ;)
In our recent paper, we developed a deep learning based ToF (DL-ToF) algorithm that improves the lesion detectability and diagnostic confidence of non-ToF PET images. Check it out here https://lnkd.in/eqWVjNa3

#gehealthcare #oxforduniversity #NCIMI #deeplearning

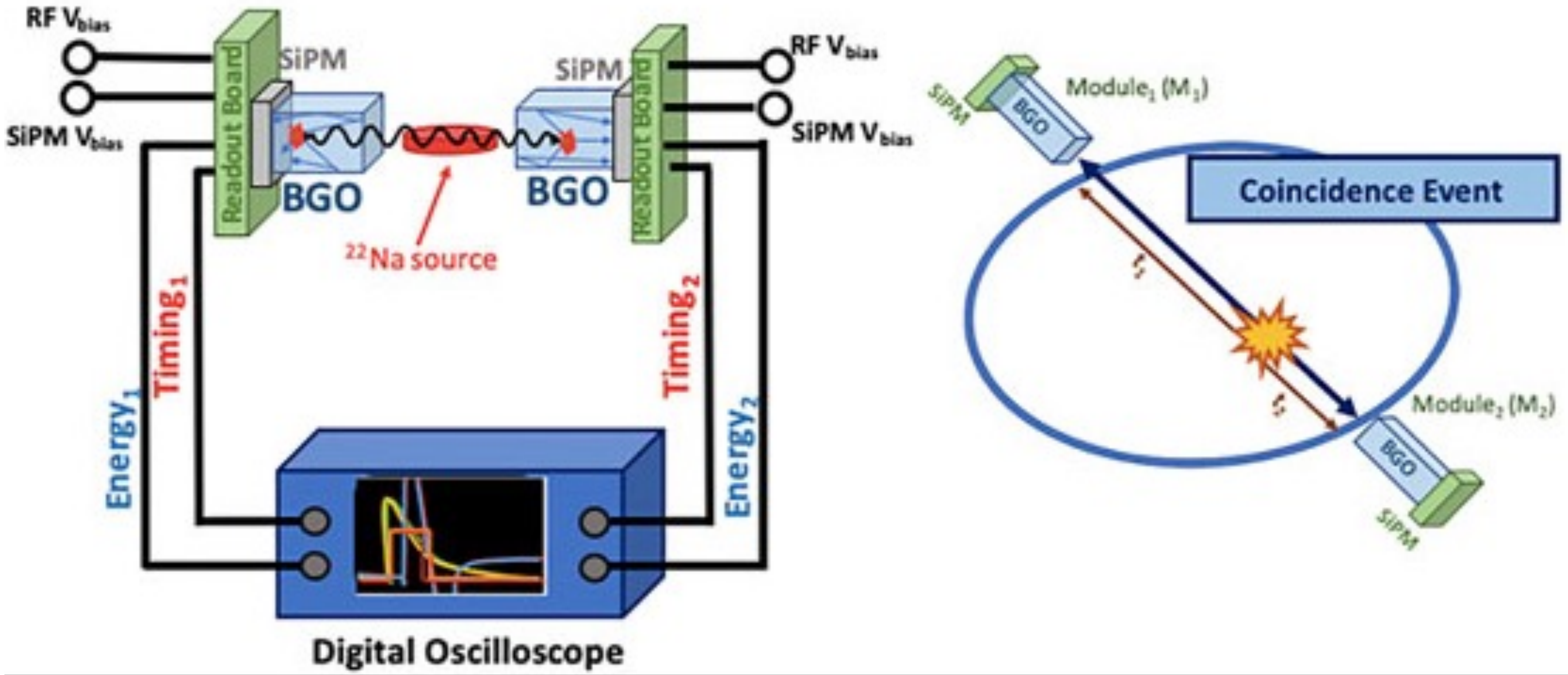


AI TO THE RESCUE

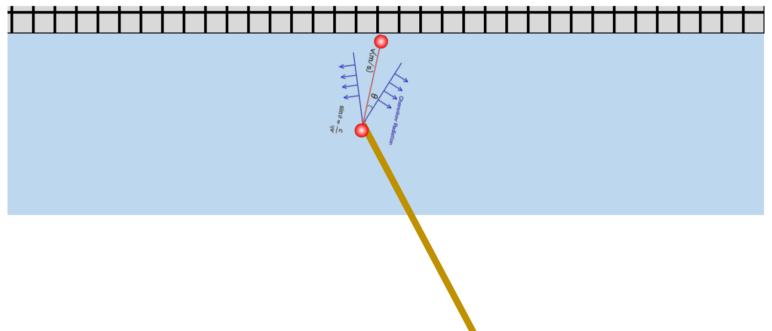
"The proof of the pudding is in the eating"

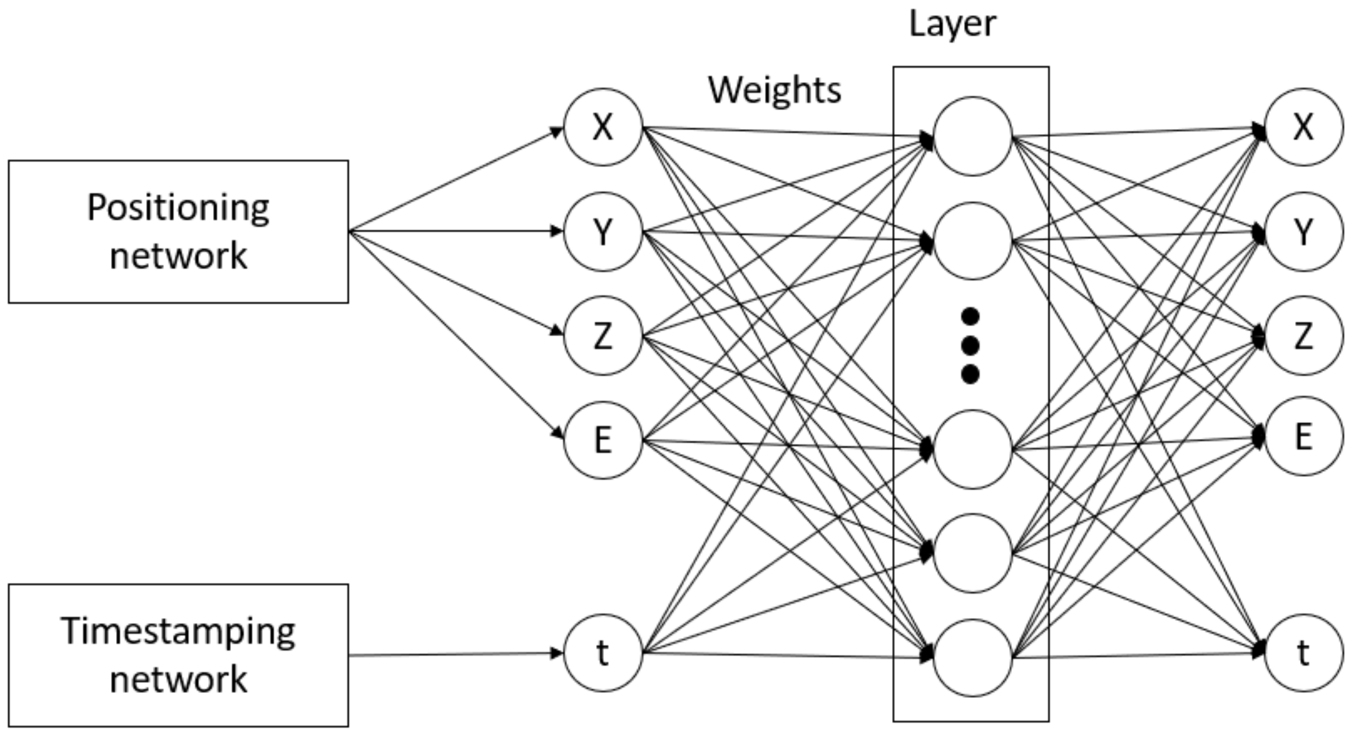
AI to enhance lower cost detector performance

TOF FROM BGO



Cherenkov light = only 0.2% of the scintillation light
But instant light (20 photons)
SiPMs around 50-60 % PDE
Low noise SiPMs





Deep learning based TOF and position
15 % energy resolution
1.3 mm spatial resolution
327 ps TOF
6x6 mm SiPMs → less channels
12 mm BGO: 3 x cheaper
ASIC Barcelona

OVERVIEW

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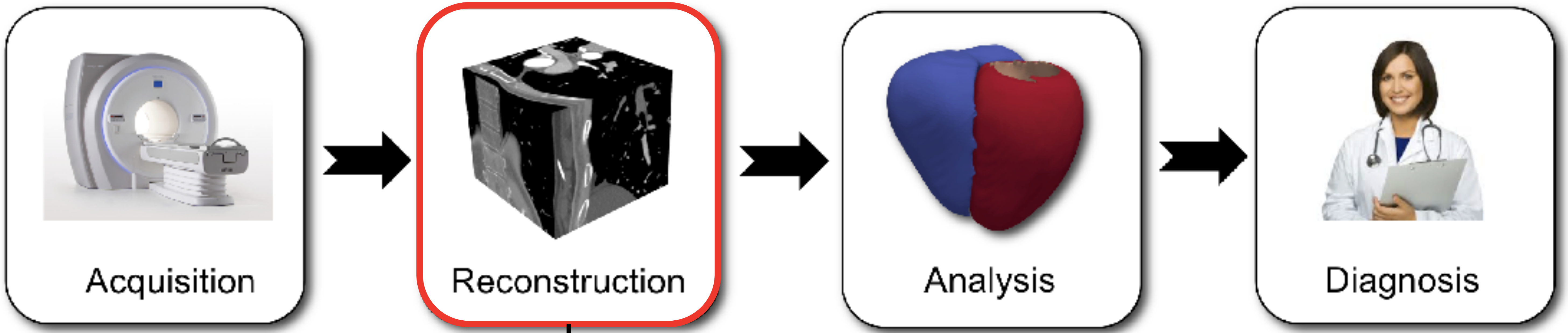

- DL-based Image Reconstruction
- DL for Data Corrections
- DL for Image Quality Enhancement

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DL BASED IMAGE RECONSTRUCTION

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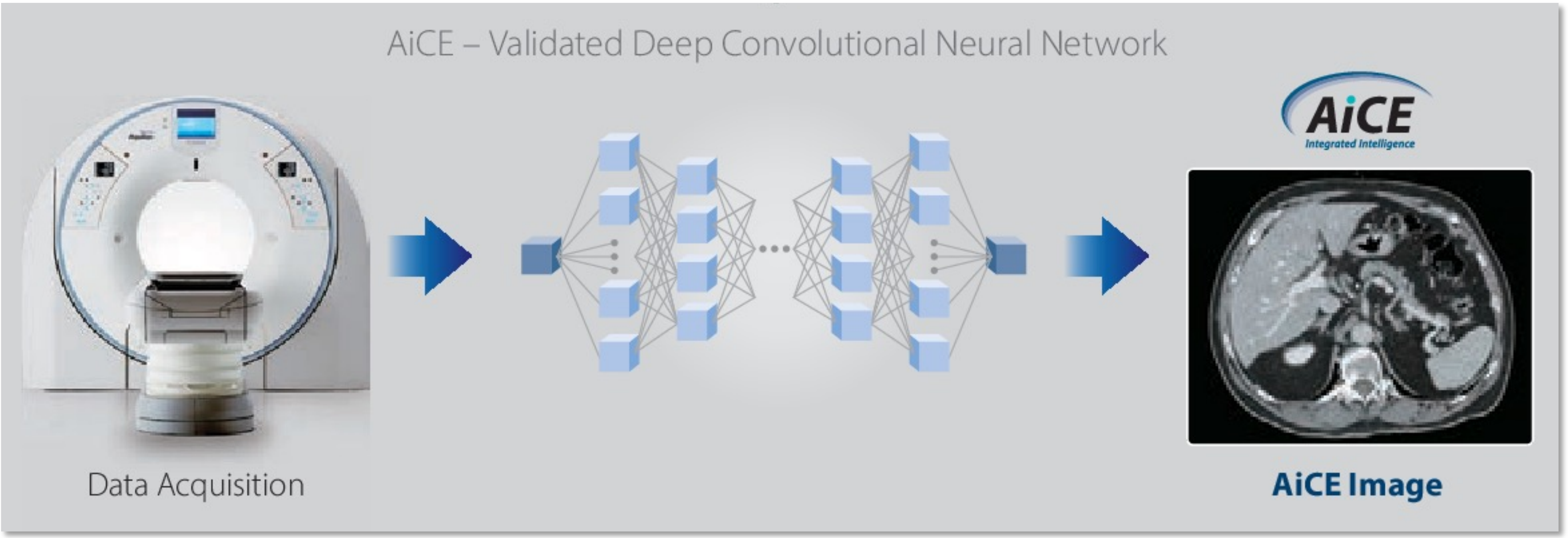
DL FOR CT IMAGE RECONSTRUCTION

FDA Clears AiCE Image Reconstruction on Canon Aquilion Precision CT



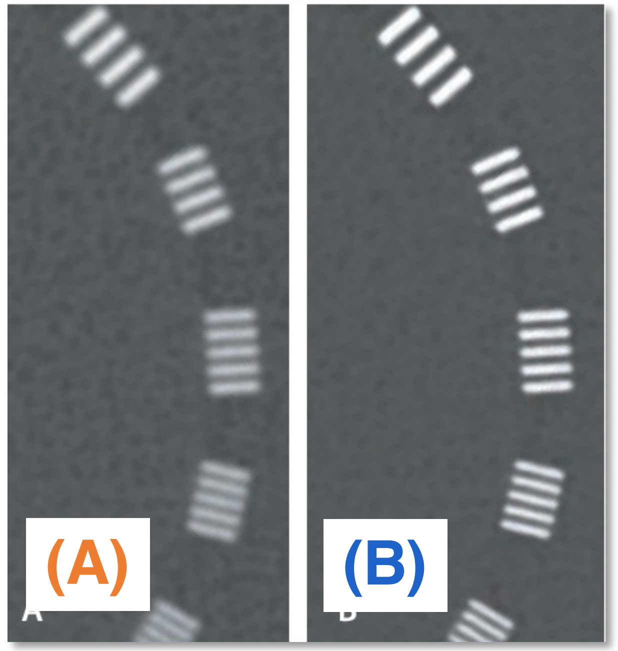
- *Singh R, et al.* ***Image quality and lesion detection on deep learning reconstruction and iterative reconstruction of sub millisievert chest and abdominal CT****. American Journal of Roentgenology. 2020 Mar;214(3):566-73.*
- *Arndt C, et al.* ***Deep Learning CT Image Reconstruction in Clinical Practice****. Rofo. 2021 Mar;193(3):252-261.*

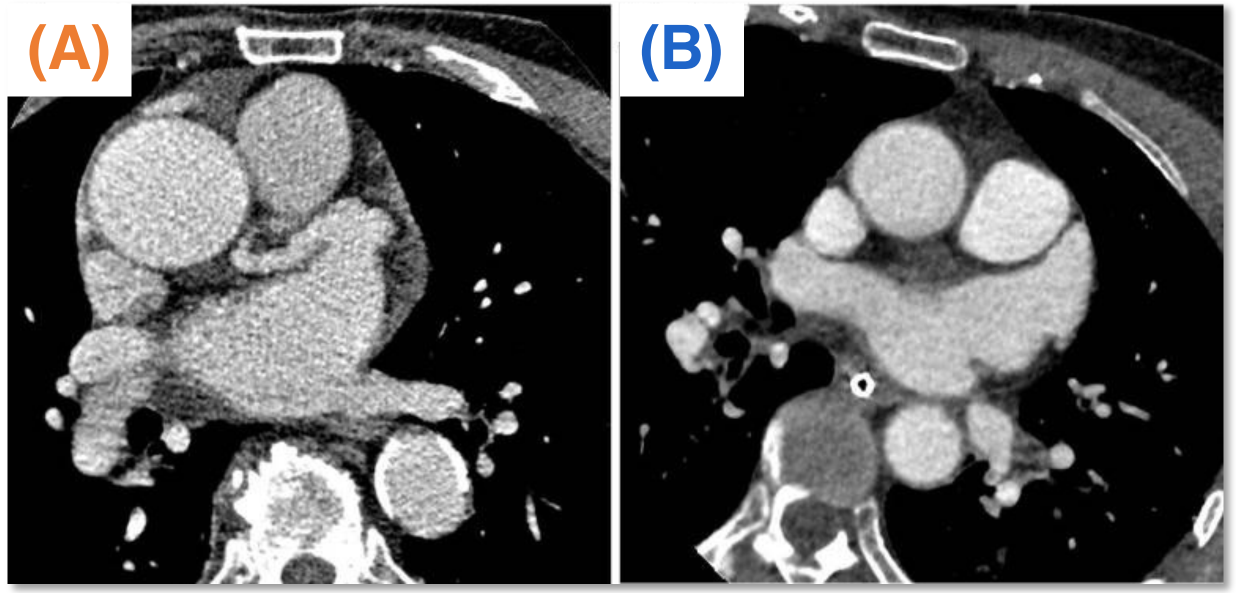
RESULTS FROM AICE

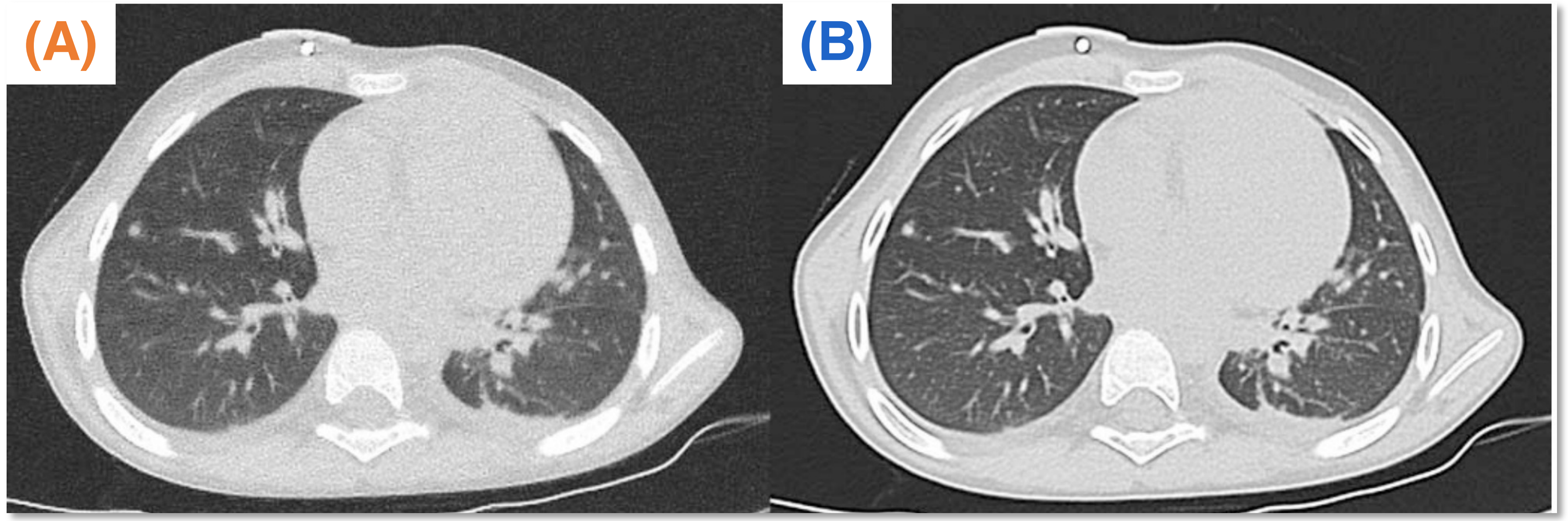
(A) Low dose CT reconstructed with **iterative algorithm**

(B) Low dose CT reconstructed with **deep learning algorithm**

- Improved contrast spatial resolution
- Reduced noise







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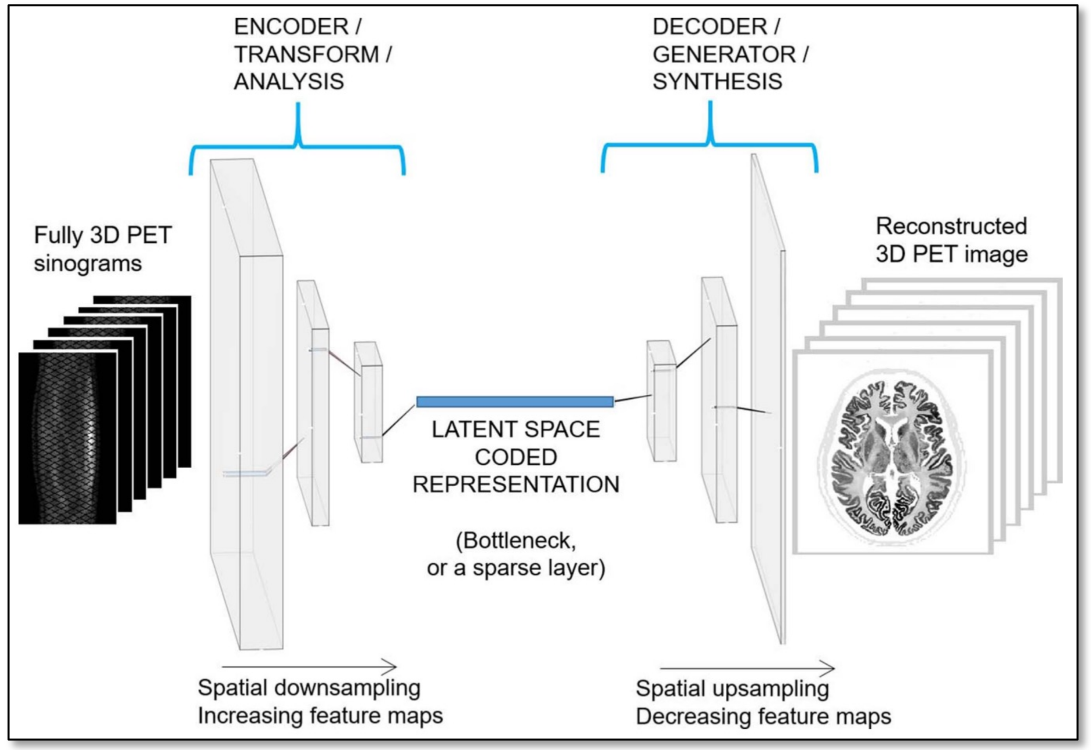
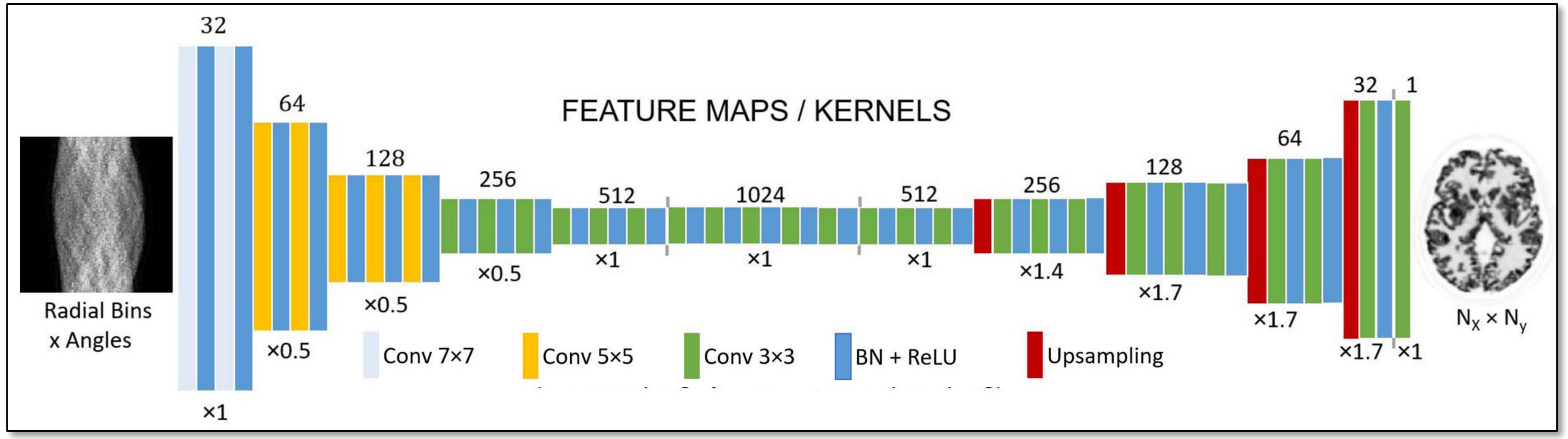
DL FOR PET IMAGE RECONSTRUCTION

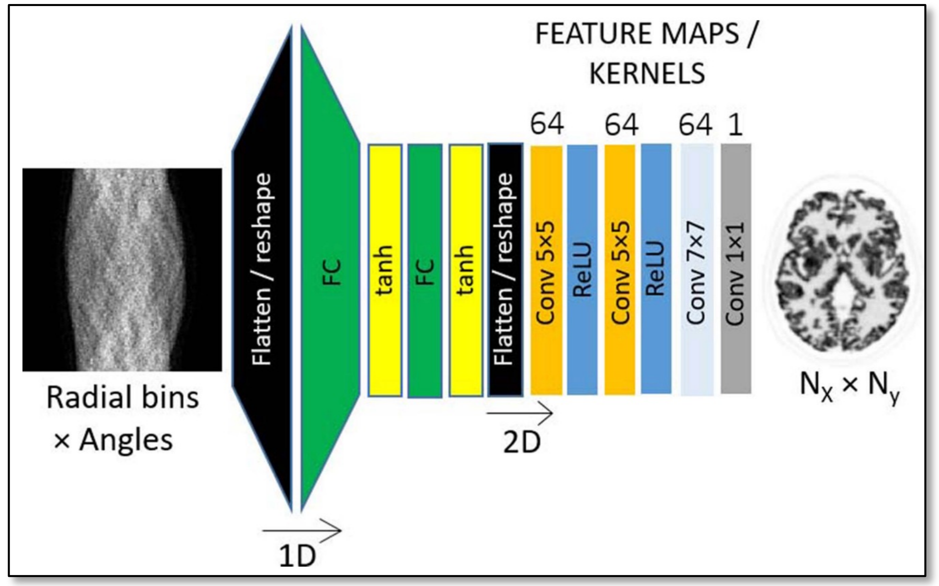
- Multitude of CNN architectures are developed and investigated but the neural network always aims to directly reconstruct an image from acquired data.



Encoder-decoder (Reader A. *et al.*)



DeepPET (Häggström I. *et al.*)



AUTOMAP (Zhu B. *et al.*)

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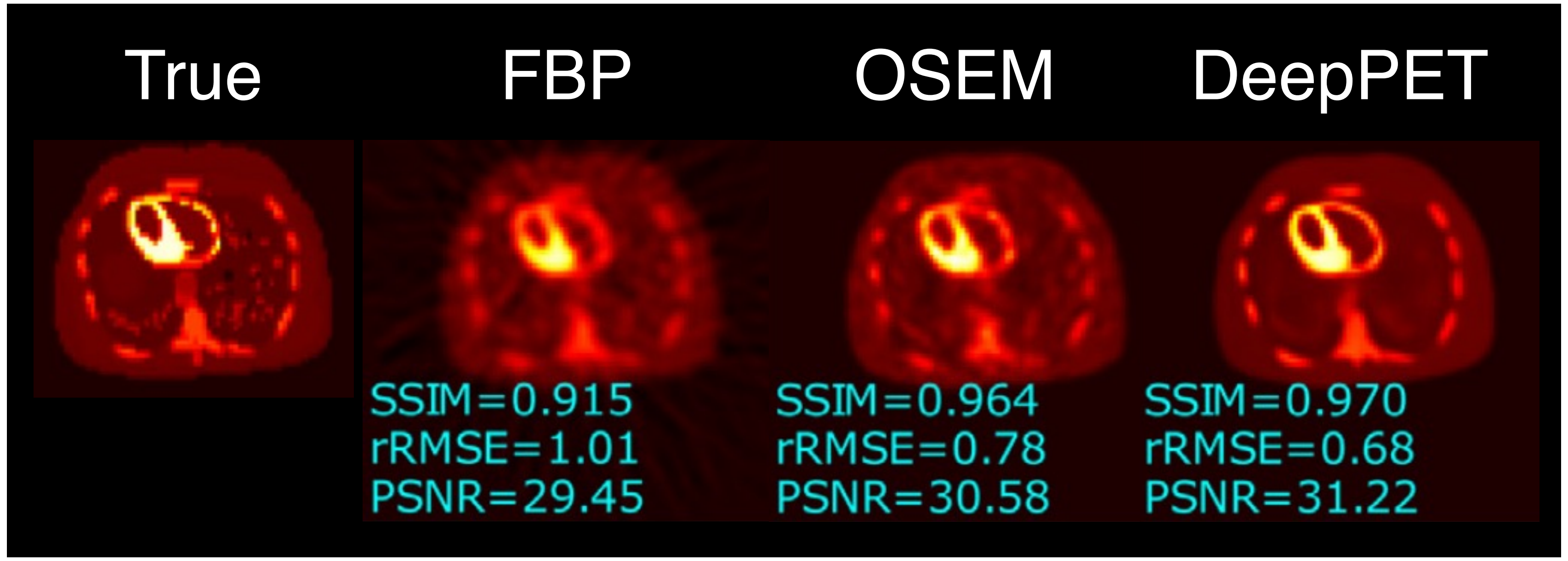
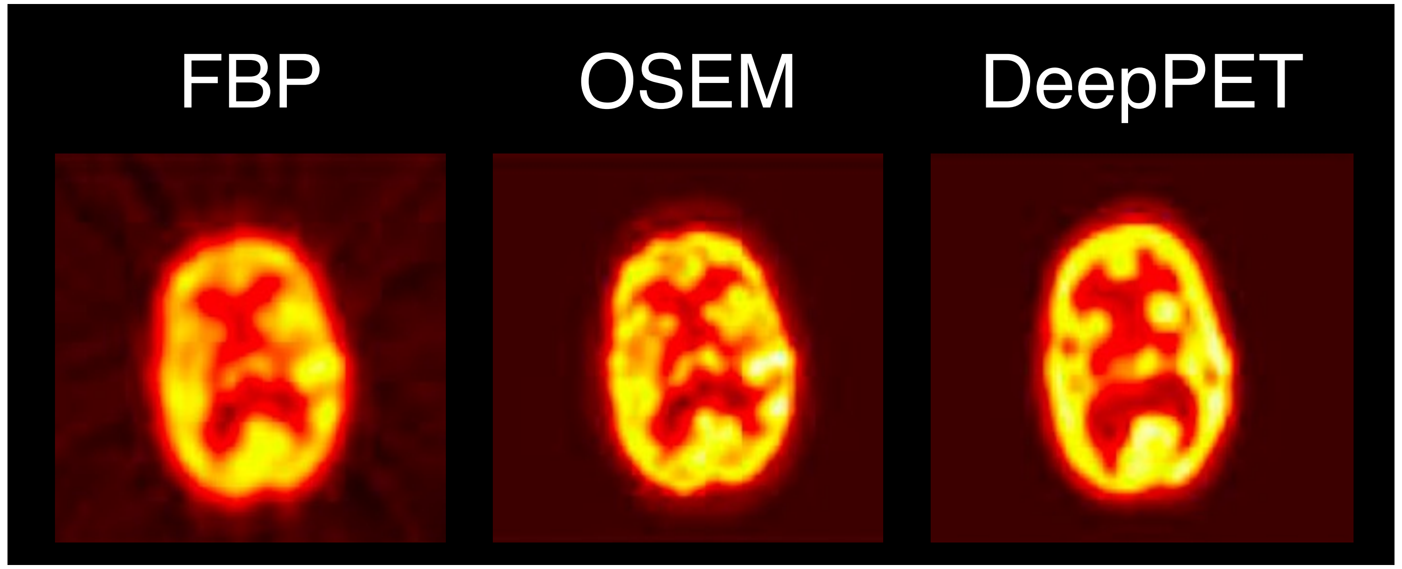
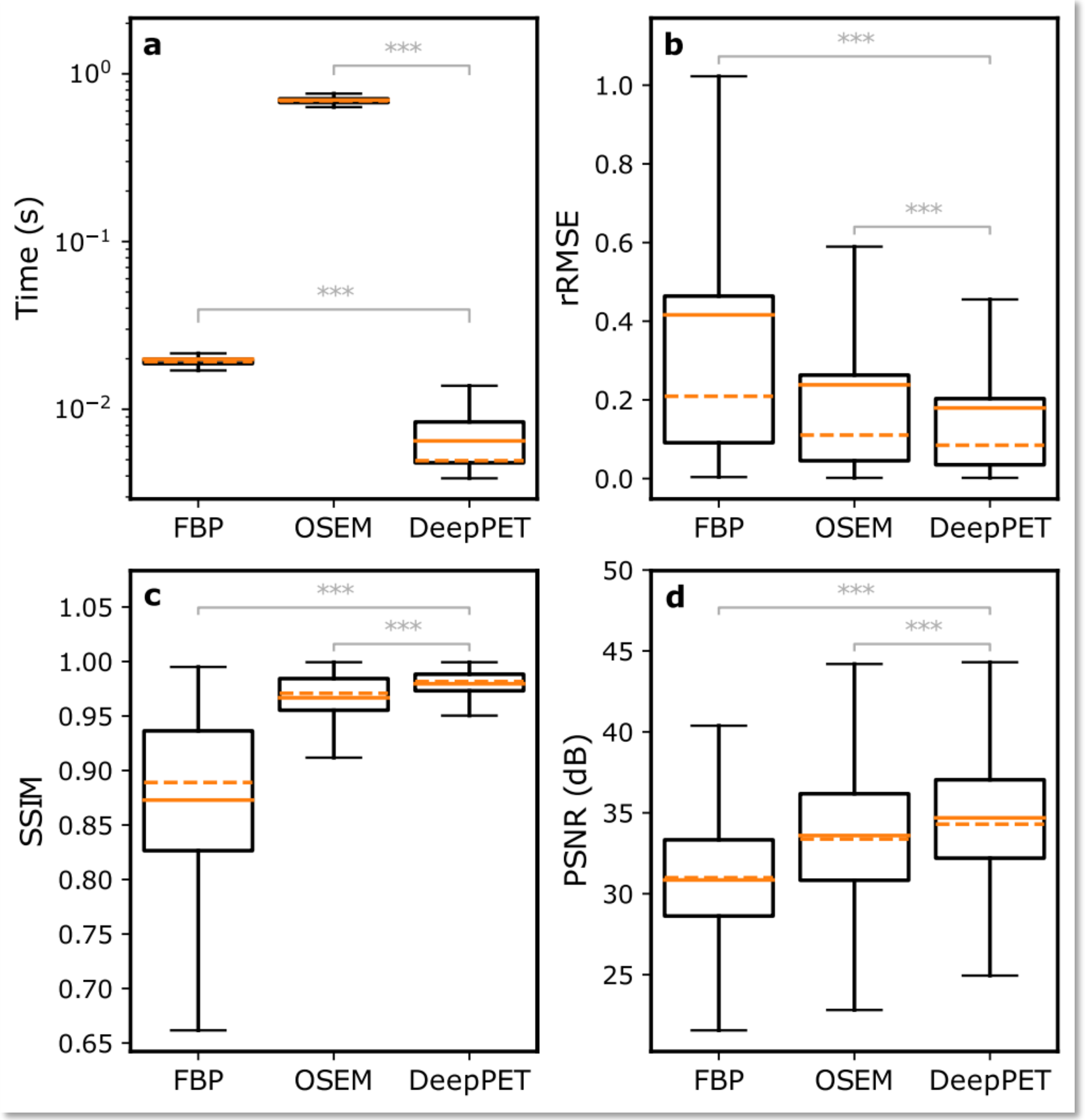
RESULTS: DEEPPET

Simulated data



Real data





~**10% lower noise** (RMSE) than OSEM

~**10x faster** than OSEM

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DL FOR DATA CORRECTIONS

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Deep learning (DL) methods have shown promising potential to result in **more accurate and faster** performance of **(CT-less) attenuation and scatter correction (ASC)** in PET imaging [1-3].

[1] Lee JS. (2021) IEEE TRPMS. [2] Chen, X., Liu, C. (2023) J Nucl Cardiol. [3] McMillan AB, Bradshaw TJ. (2021) PET Clin

Non-corrected PET image

DL-prediction of a CT-like image

Transmission image (mu-map)

used to derive the ACF needed for PET image reconstruction

Anatomical image: not of diagnostic quality, but sufficiently realistic to minimize reconstruction bias

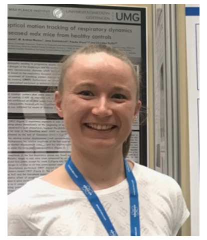
Extra recon steps with (SSS) scatter estimate → **Time-consuming**

DL-prediction of a fully corrected PET image

Attenuation- and scatter-corrected (ASC) PET image

Very fast: directly predicts the final PET image (only requires NAC recon)

One network to jointly predict AC and SC → **Challenge to handle a variety of tracer studies**: needs large training



Joint Ugent-UPENN PhD
Florence Marie Muller

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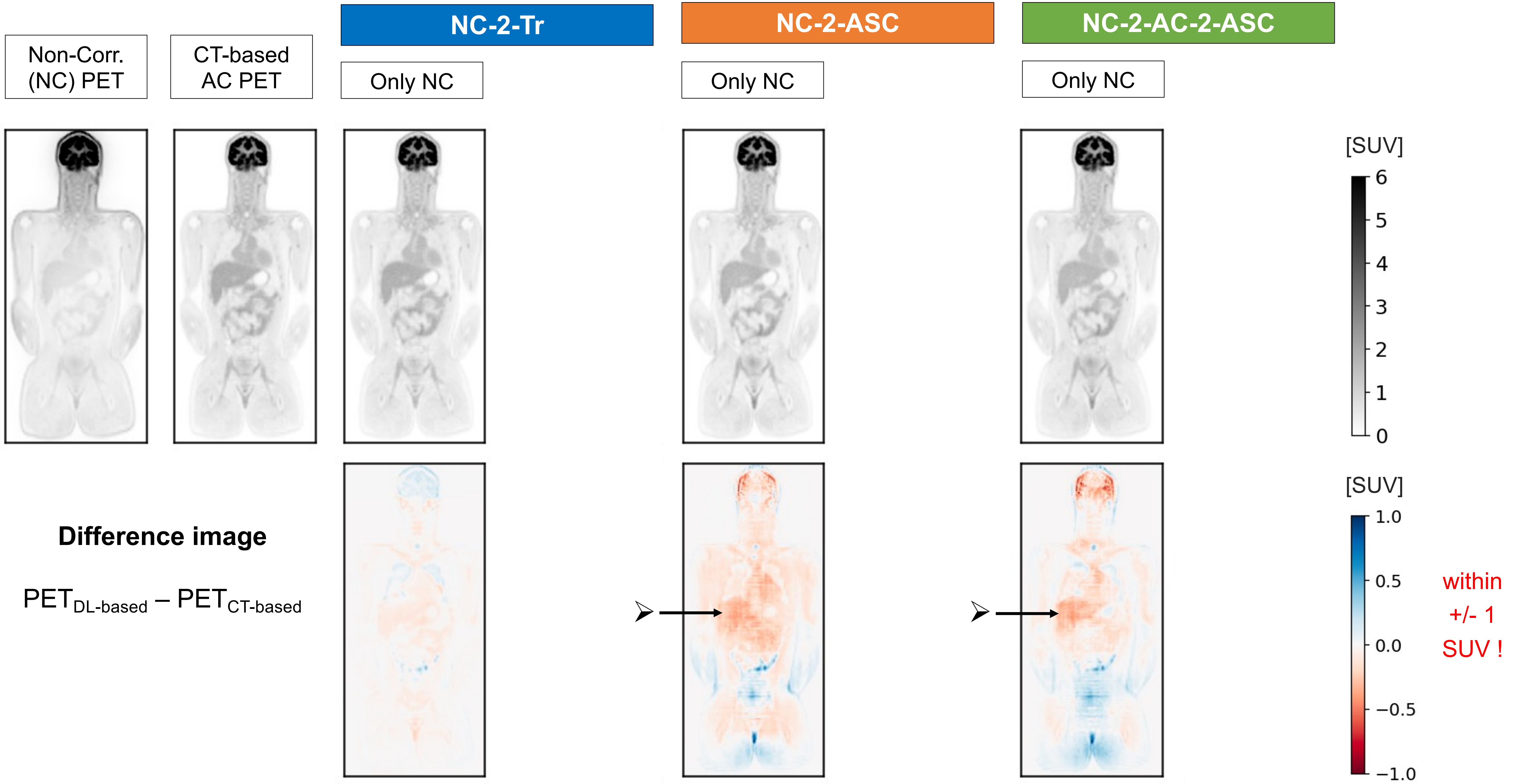
University of Pennsylvania

Courtesy of FM Muller

^{18}F-FDG



NC-2-Tr model: much lower bias (< 0.2 SUV difference: 3%) compared to the other two DL models (< 1 SUV difference: 15%)

- Liver: Negative bias (DL-based < CT-based)
  → Undercorrected for attenuation

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Courtesy of FM.Muller

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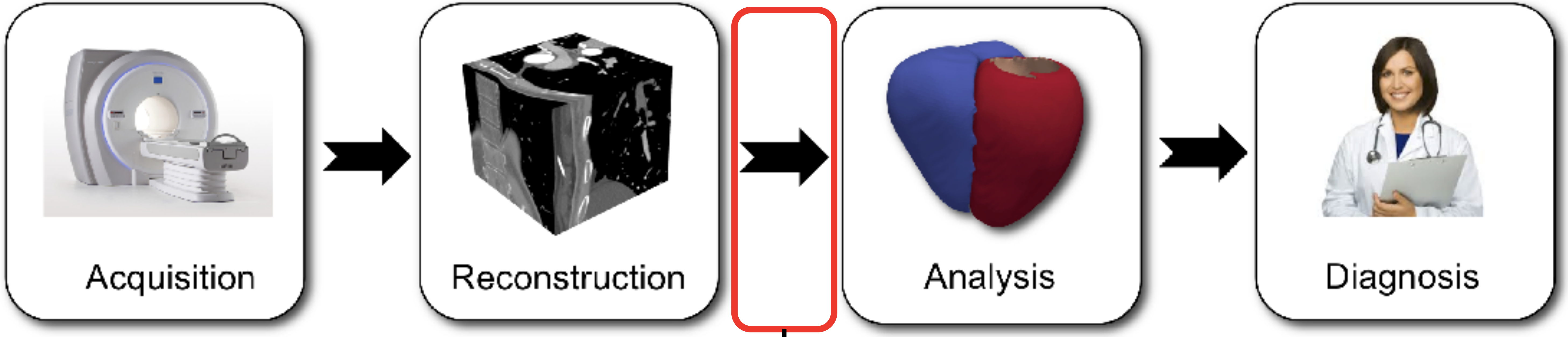

- Denoising of static data
- Denoising of dynamic data

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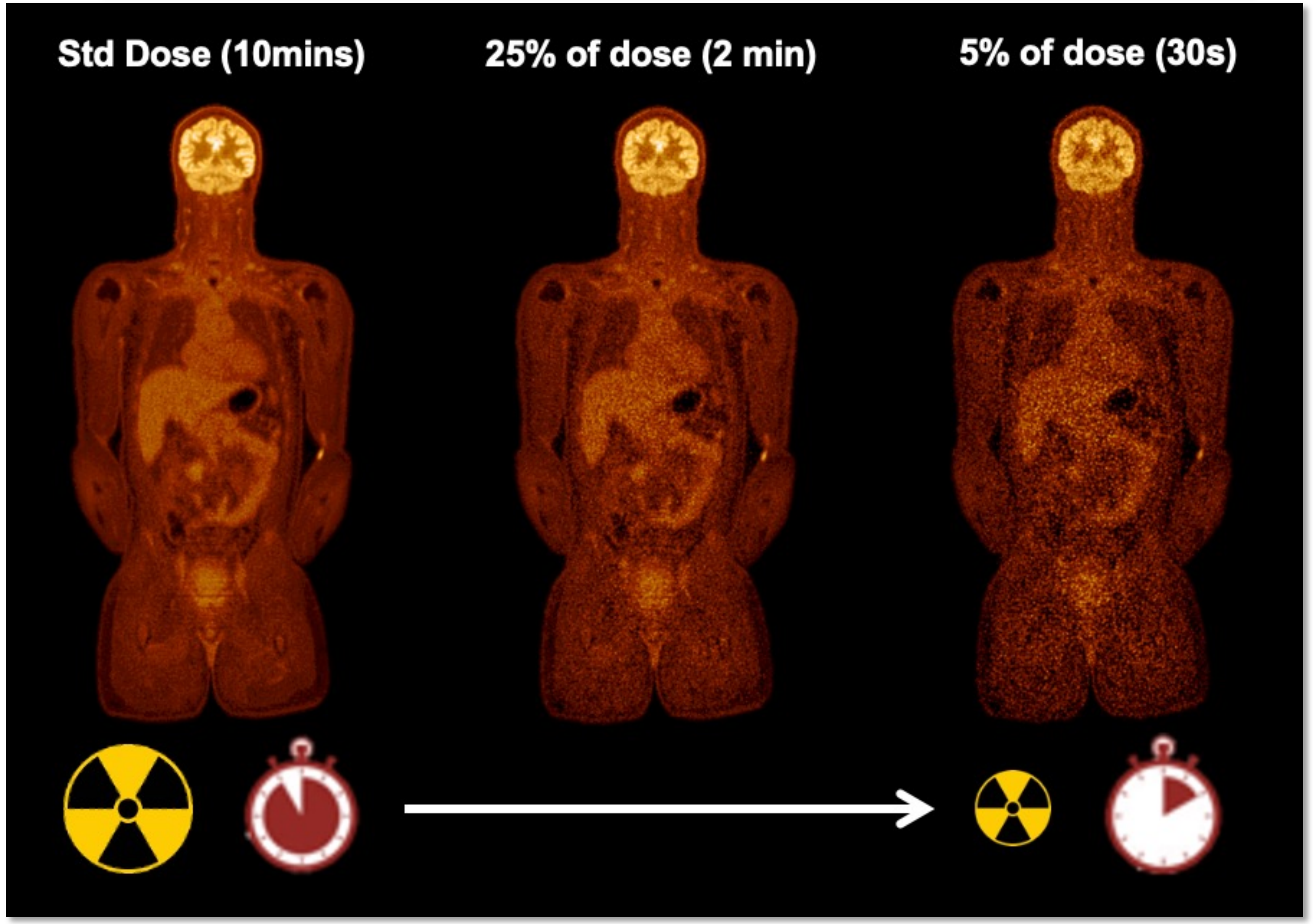
WHY DENOISING?

Noise inversely related to dose and acquisition time



- Lower radiation dose
  - especially for paediatric and non-cancer patients
  - Non-standard tracers for PET can be very expensive
- Faster imaging
  - Increased patient throughput
  - Patient moves more during longer scan (-> artefacts)

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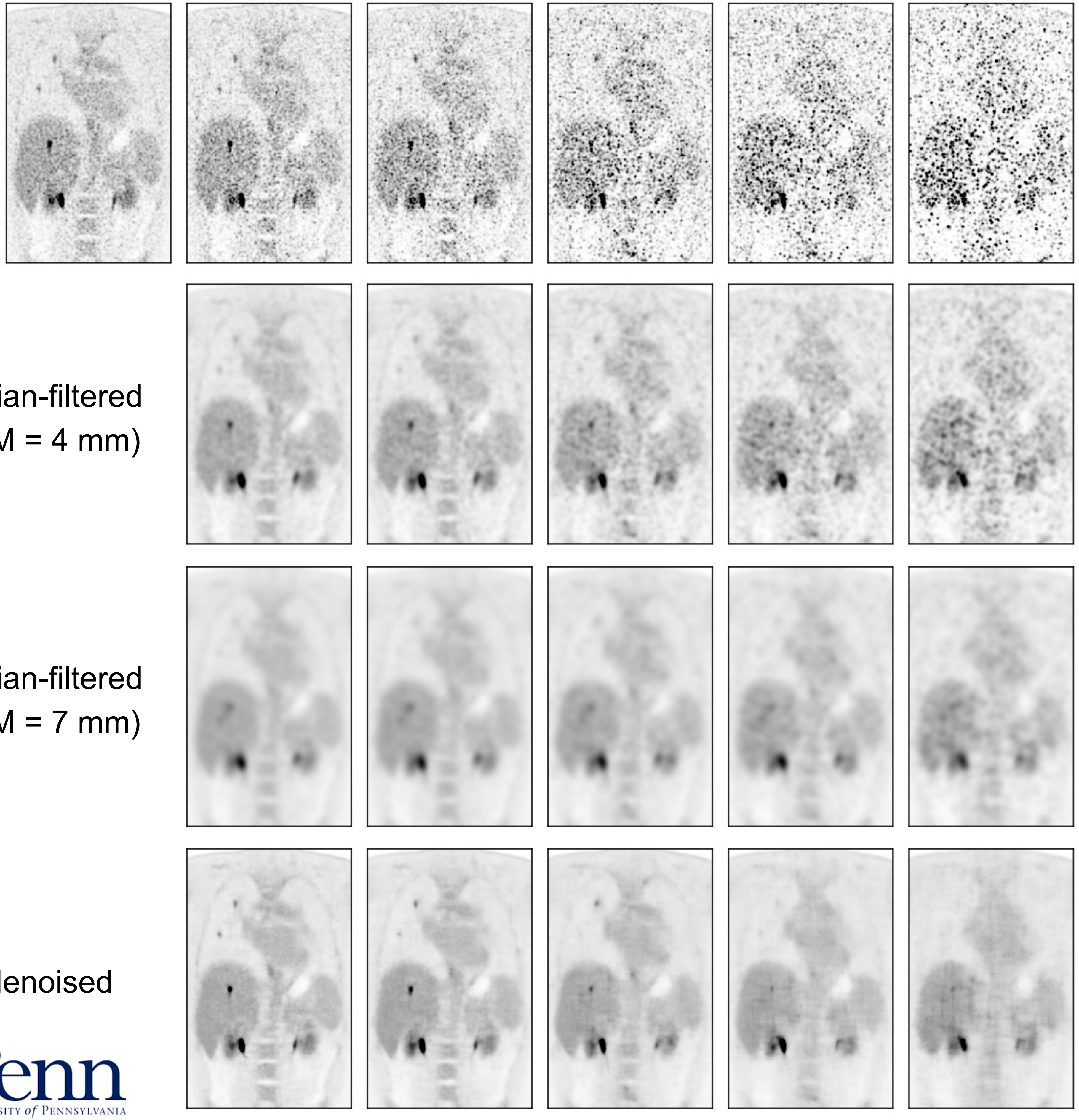
3 mins | 1 min | 30 s | 10 s | 5 s | 2 s

Gaussian-filtered (FWHM = 4 mm)

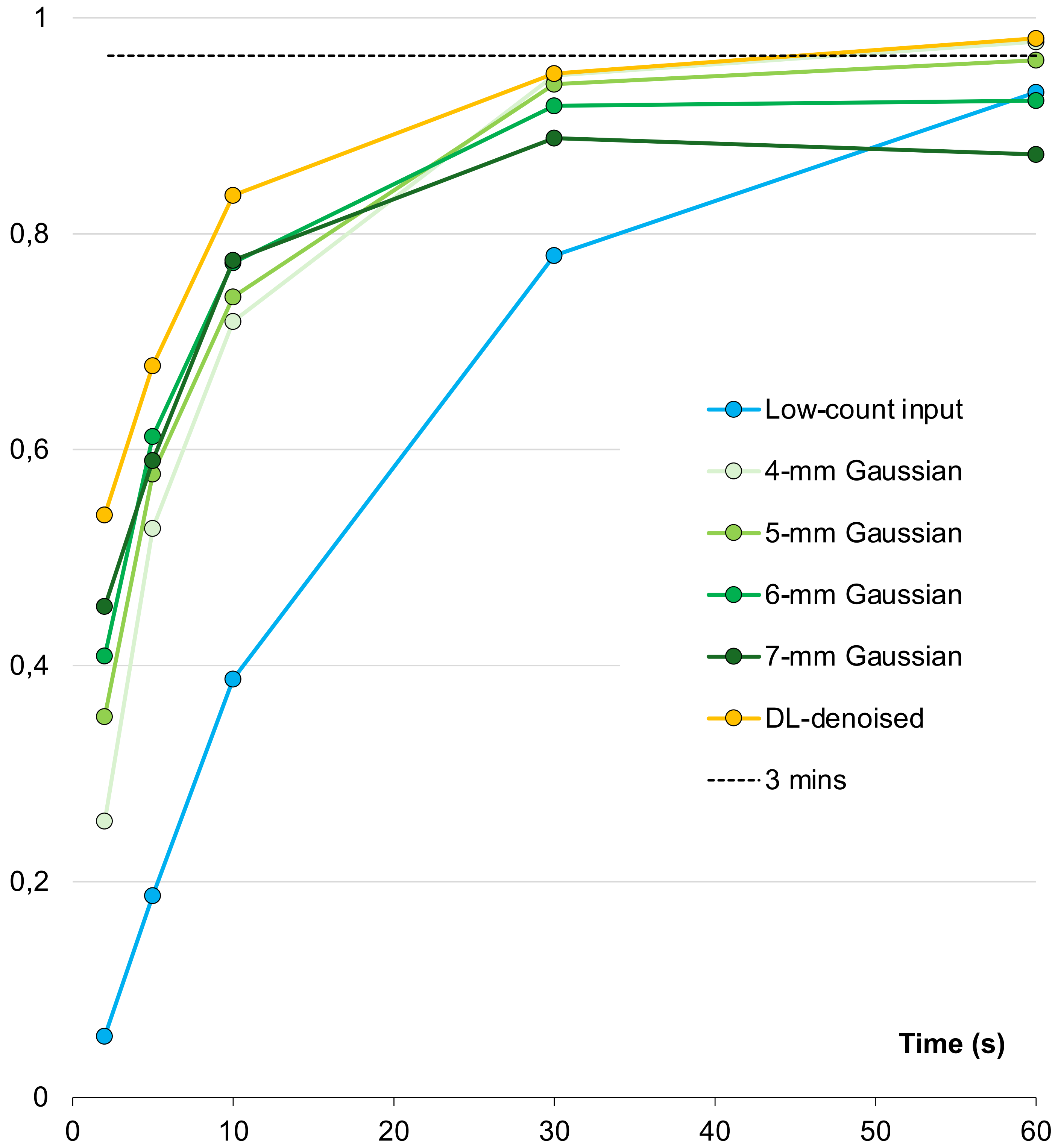
Gaussian-filtered (FWHM = 7 mm)

DL-denoised



Lesion Detectability (Numerical Observer)

Lung ALROC



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Dynamic ^{18}F-FDG Dataset

	Standard-dose (9.3 mCi)	1/2 dose	1/10 dose
Input			
DL-denoised			

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Coronal slice is shown

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FACULTY OF MEDICINE AND HEALTH SCIENCES

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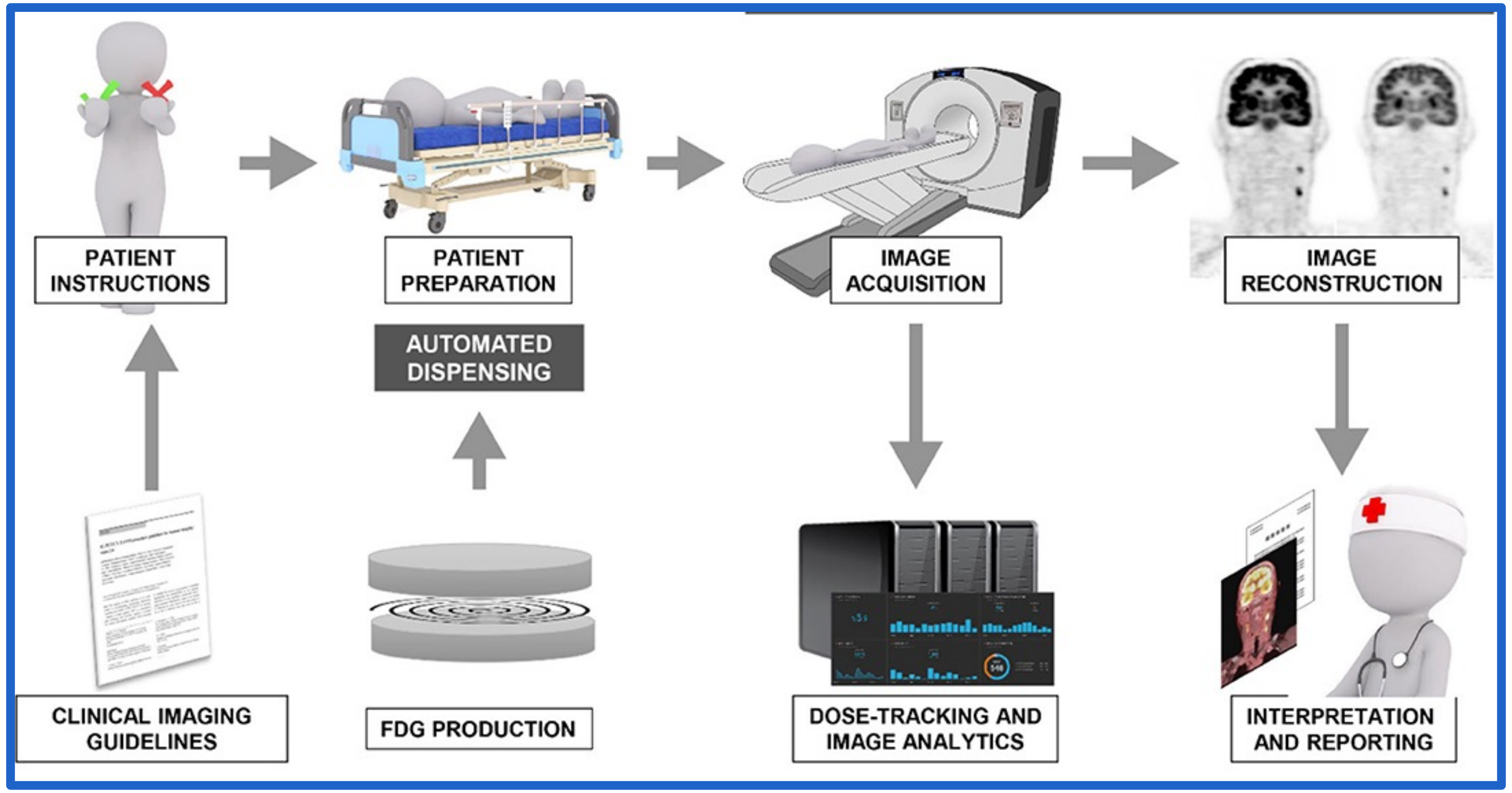
WHAT IS THE CURRENT CHALLENGE IN IMAGING

- Very good systems available but quite expensive

- Real world challenges (indicated by NM physicians and radiologists)
  - Accurate quantification (therapy prediction/follow up) ~ spatial resolution
  - Cost reduction of the systems without loss of quality
  - Personnel availability
  - Enhance the throughput/ number of patients
  - Aid the physician in handling all the data



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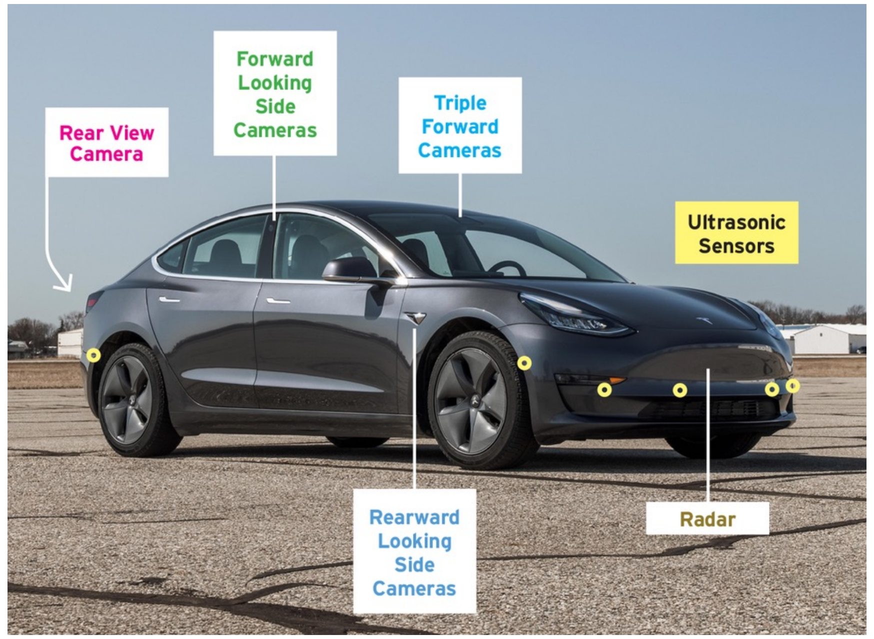
INTRODUCTION OF AI

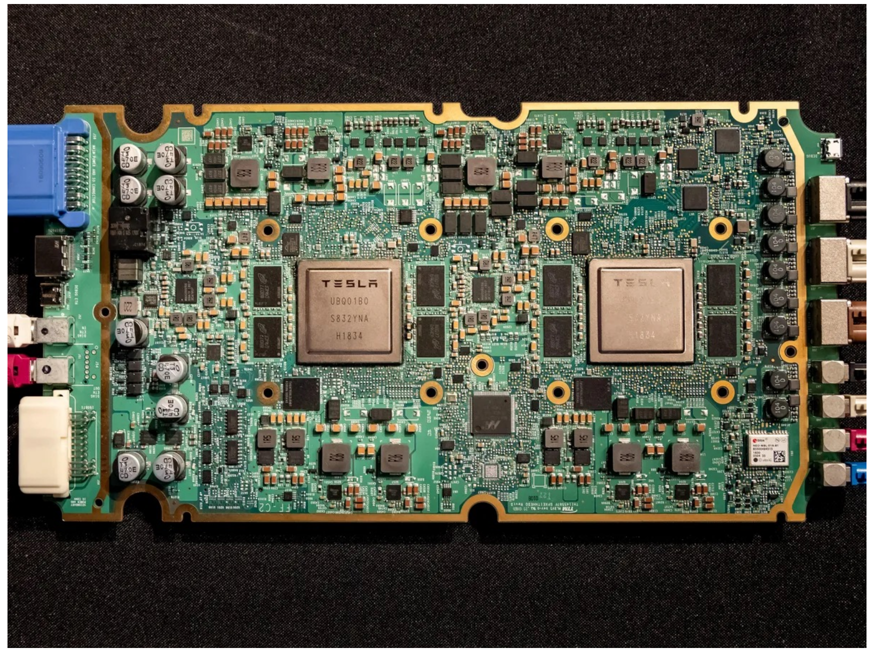
AI is an essential component for new cars

Noisy

No updates

Only hardware problems





More quiet

Can (must) be updated

Almost self driving

Software and hardware problems

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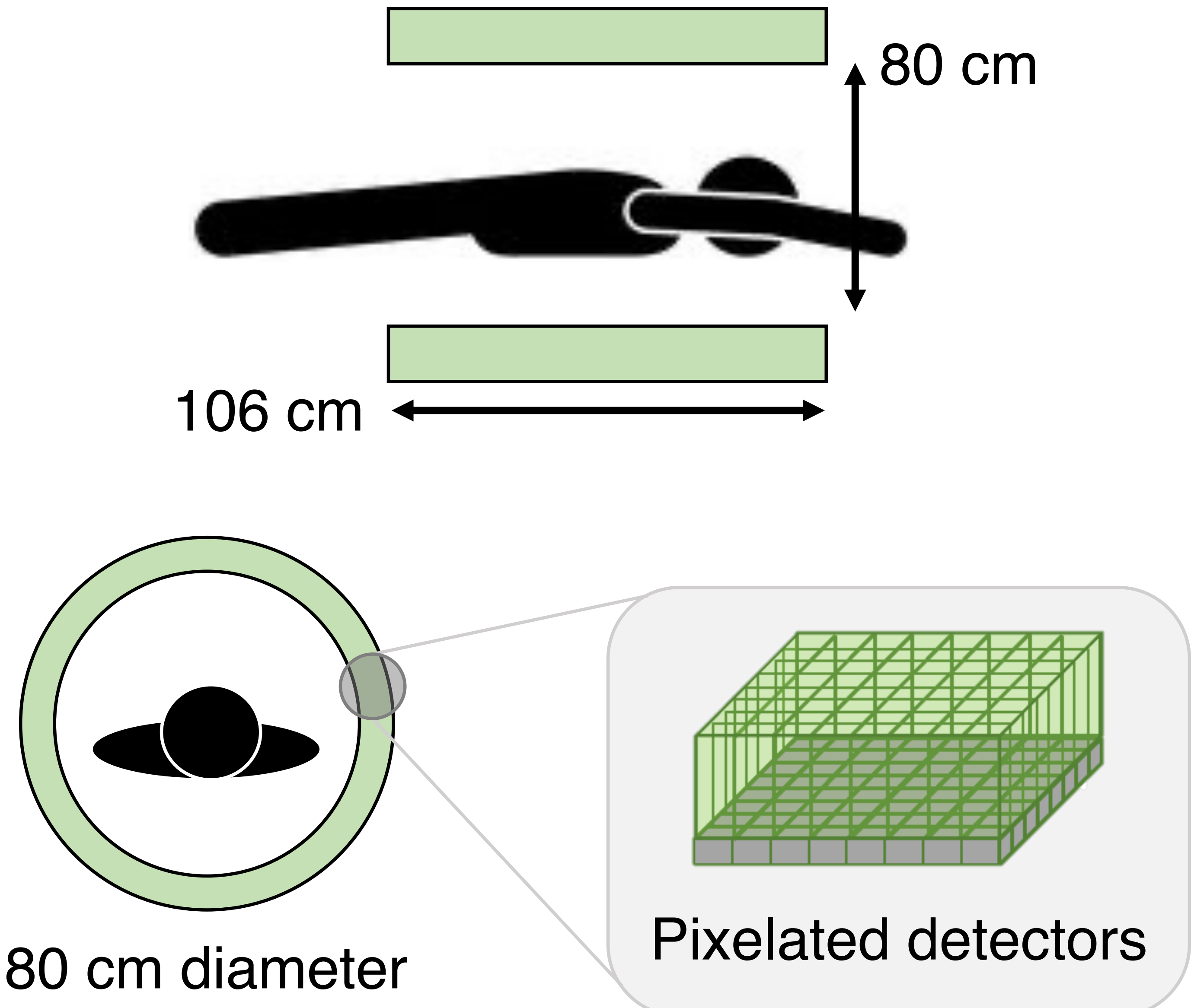
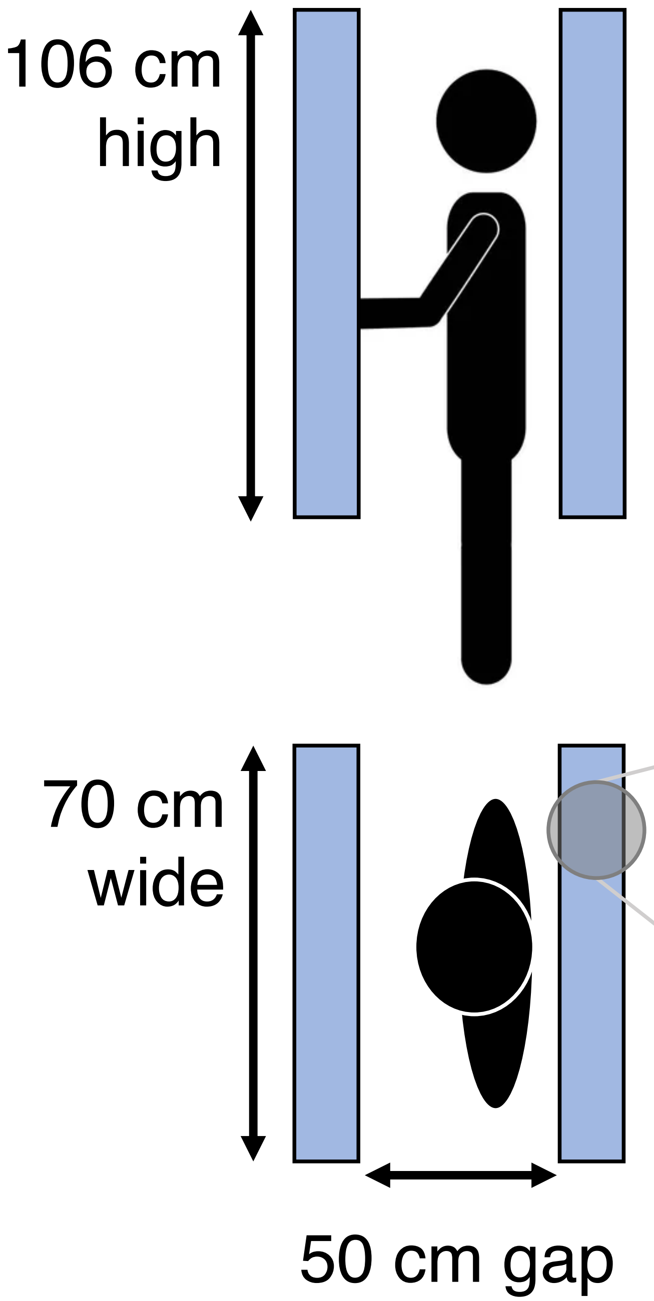
Walk-Through Total-Body PET

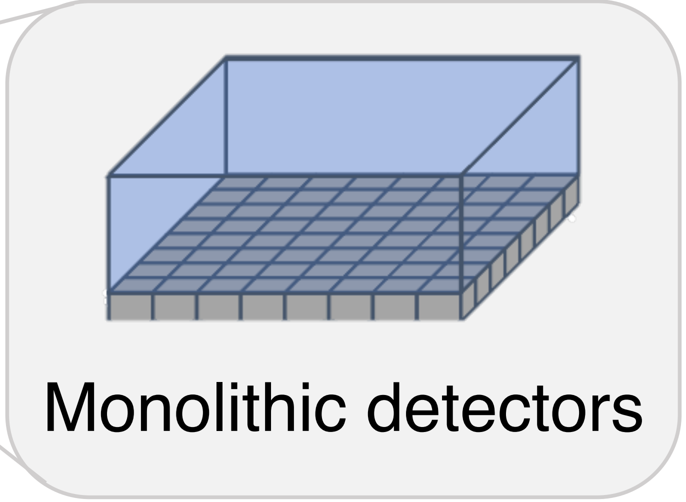
Cylindrical long AFOV PET (Siemens Quadra)



Walk-Through Total-Body PET (WT-TB-PET)



- Detectors much closer to patient
  - **Smaller footprint**
- Fewer detectors with same AFOV
  - 1.9x less detector surface
  - **Lower system cost**



PATIENT CENTERED DESIGN

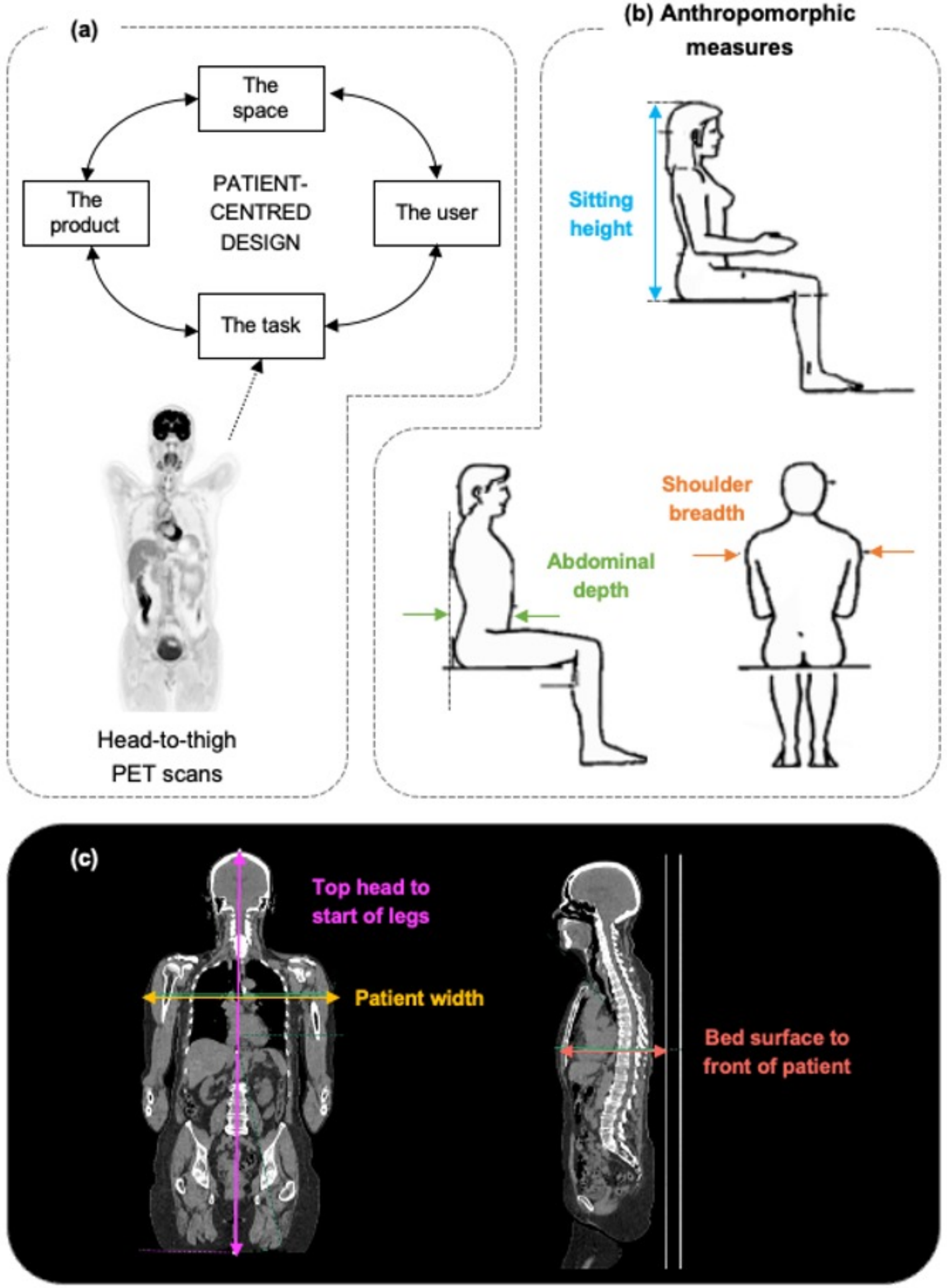


Fig. 1 **(a)** System design concept **(b)** Anthropomorphic measures **(c)** Measures from CT of PET-CT patients

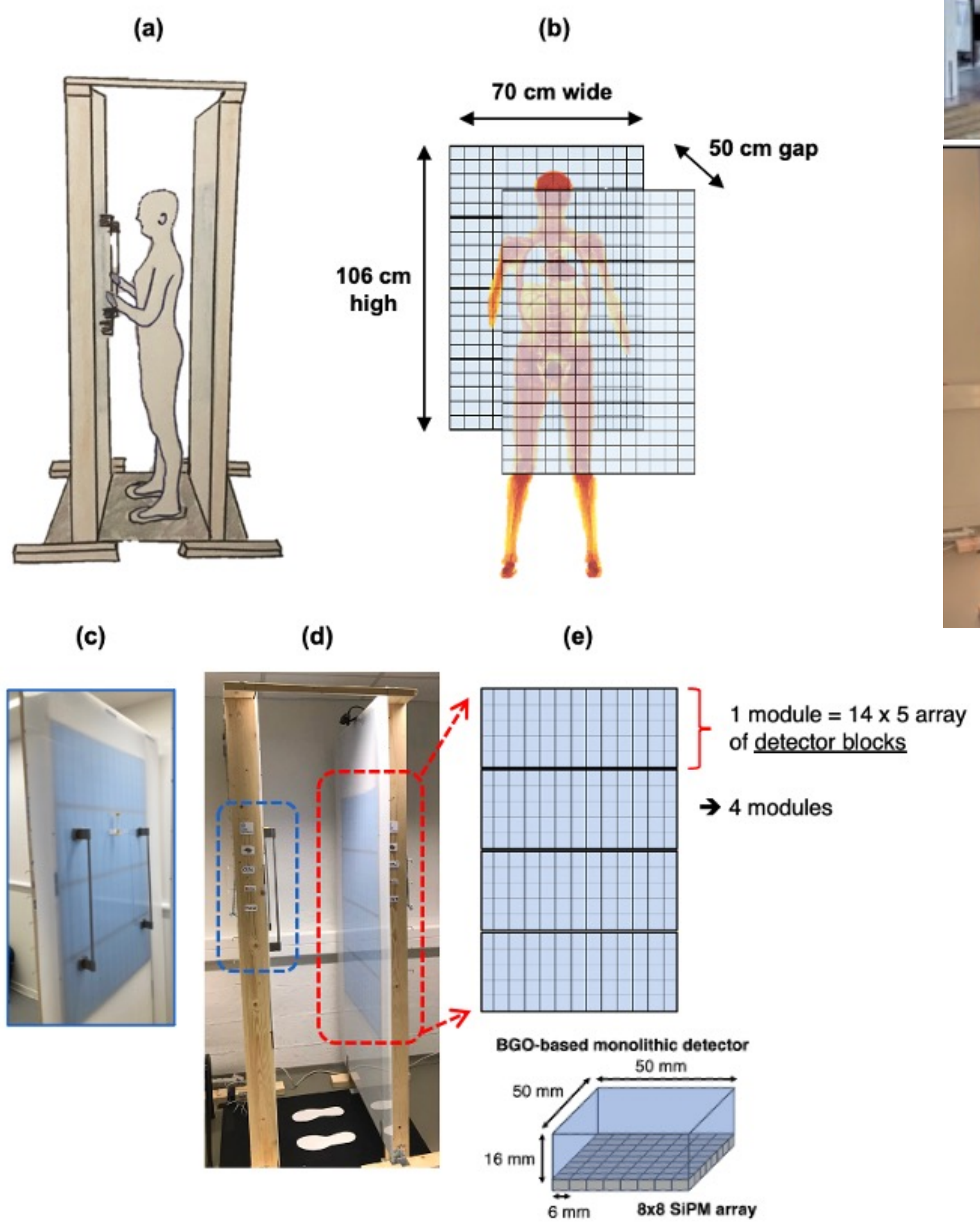


Fig. 2: **(a)** Artist view of the Walk-Through TB-PET **(b)** Flat panel dimensions and design **(c)** One side of the mock-up with the handlebars installed to reduce the body motion. **(d)** Side view of the WT-TB-PET mock-up used for patient throughput measurements. Prints of feet are used to let the patient position themself between the flat panels. **(e)** The four blue modules on each panel side can manually be adjusted to the right height.

COMPARISON QUADRA VS WT-PET

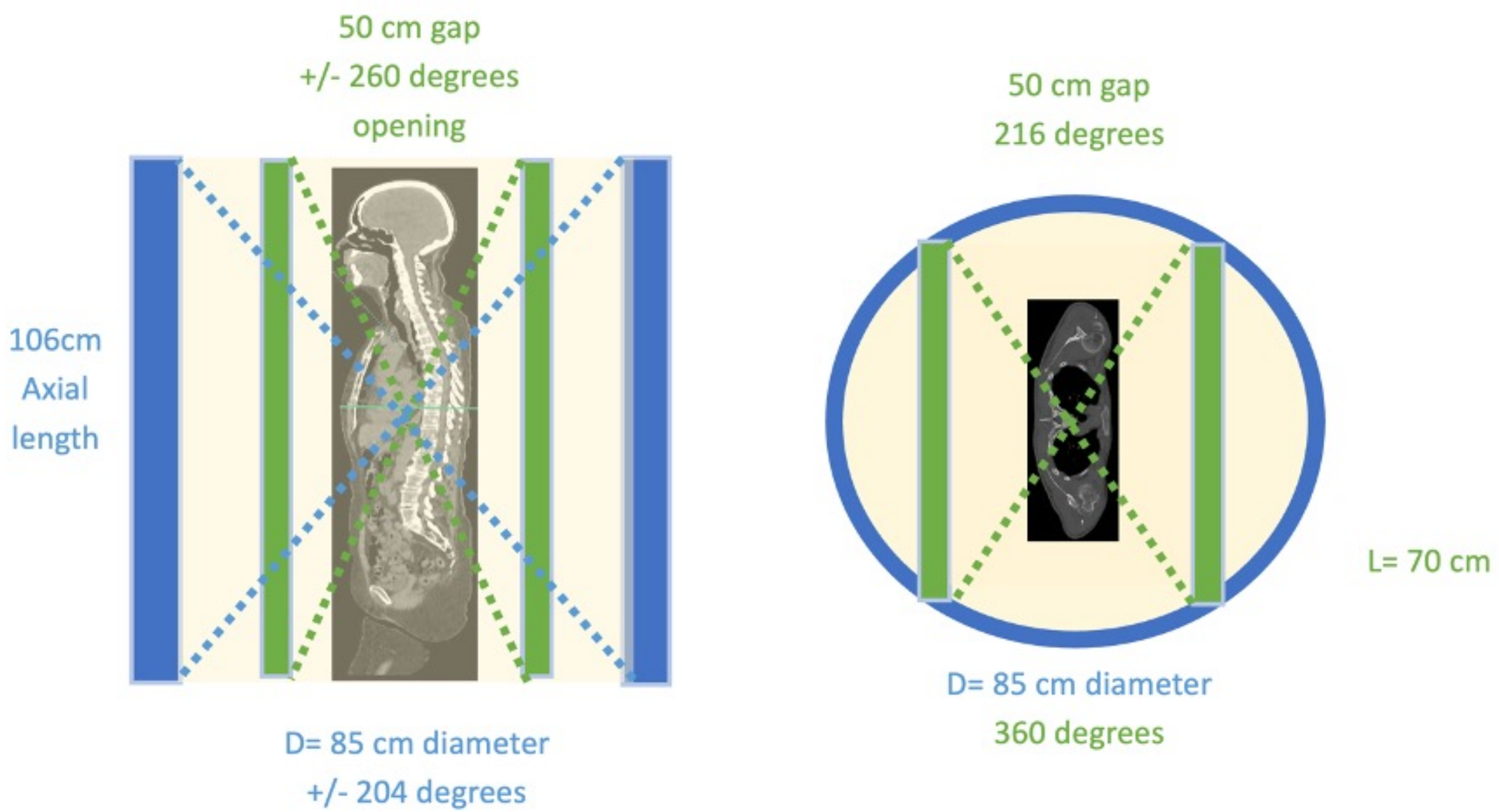
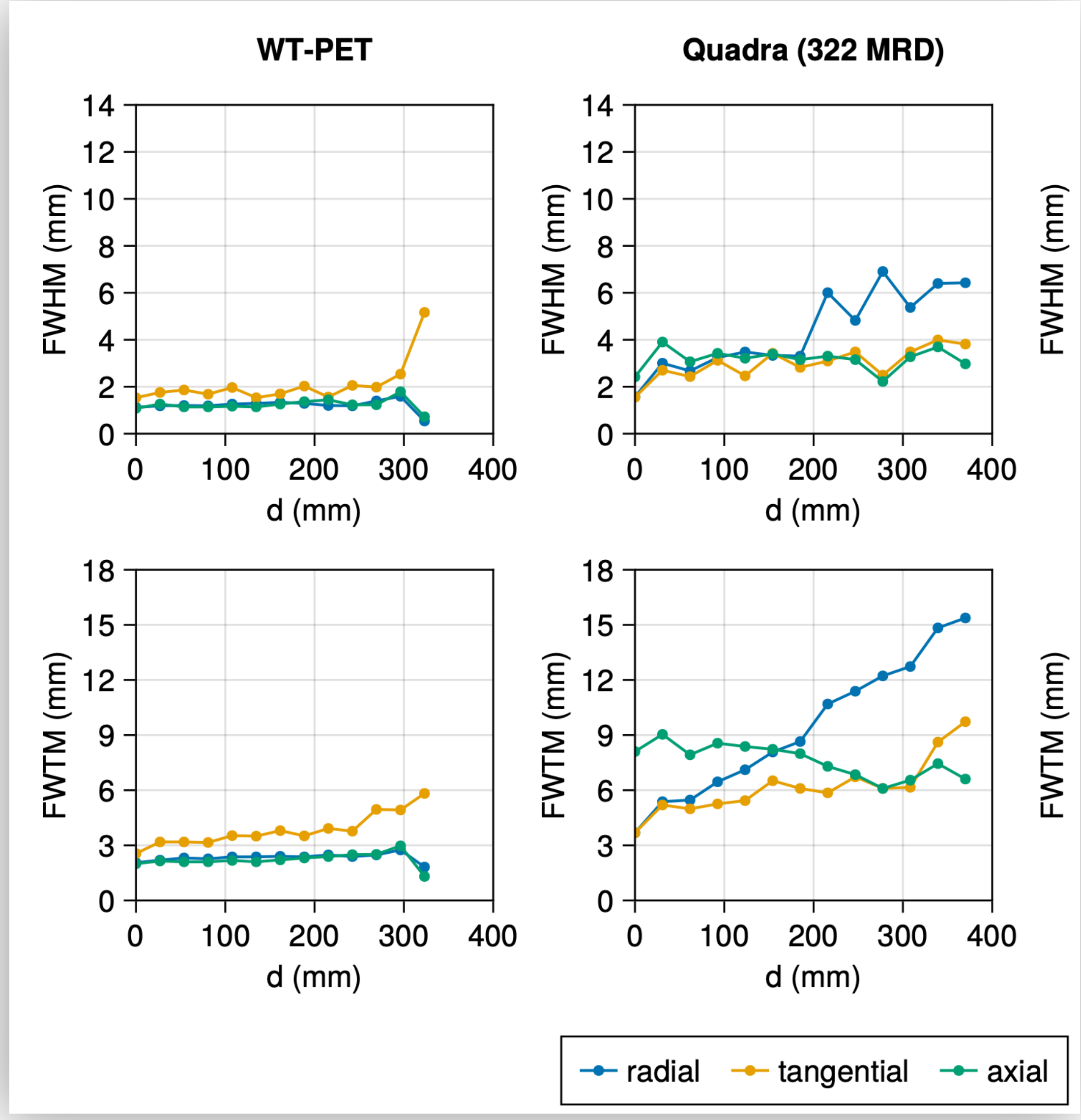
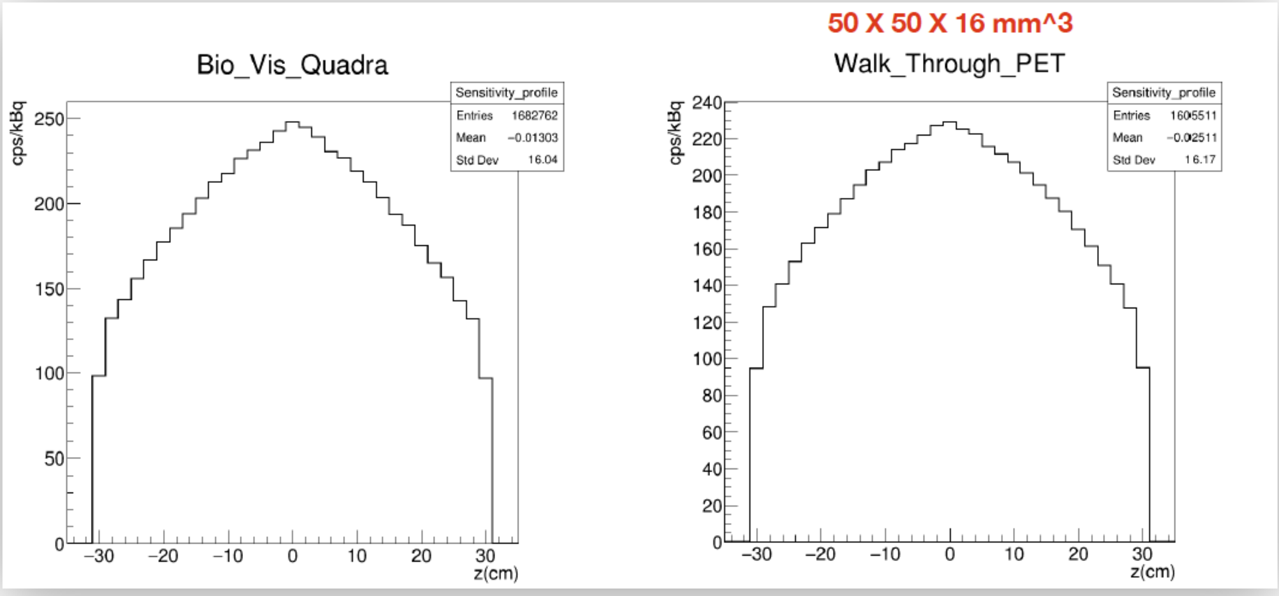


Fig. 3: Comparison between the Siemens Vision Quadra design in blue and the Walk-Through TB-PET design in green.

2-3 x better spatial resolution



Comparable sensitivity



Excellent spatial resolution:

- High intrinsic resolution of monoliths
- 6 layer DOI
- Large opening angle in transverse and axial direction

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FULL SYSTEM SIMULATION/RECON

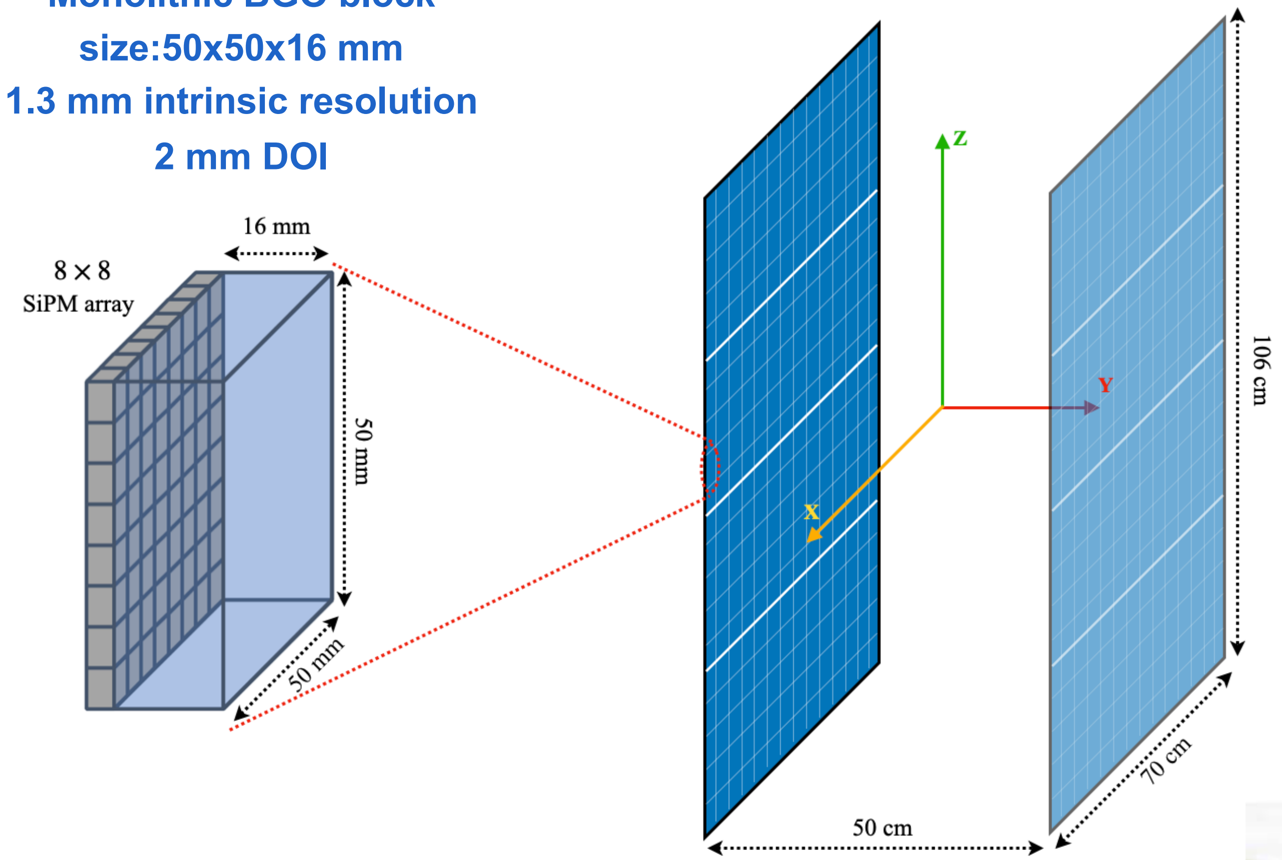
GATE MC-SIM
Xcat 3 MBq/kg - 56 kg
1m72 cm height
Lesions of 10, 7 and 5 mm
8:1 contrast
30 sec stationary acquisition !!

RECON
TOF-listmode ML-EM
2 mm voxels
327 ps
10 iterations

Transverse/coronal/Sagittal slice show excellent contrast/image quality

Two opposed panels with 280 Monolithic BGO Blocks

Monolithic BGO block size:50x50x16 mm
1.3 mm intrinsic resolution
2 mm DOI

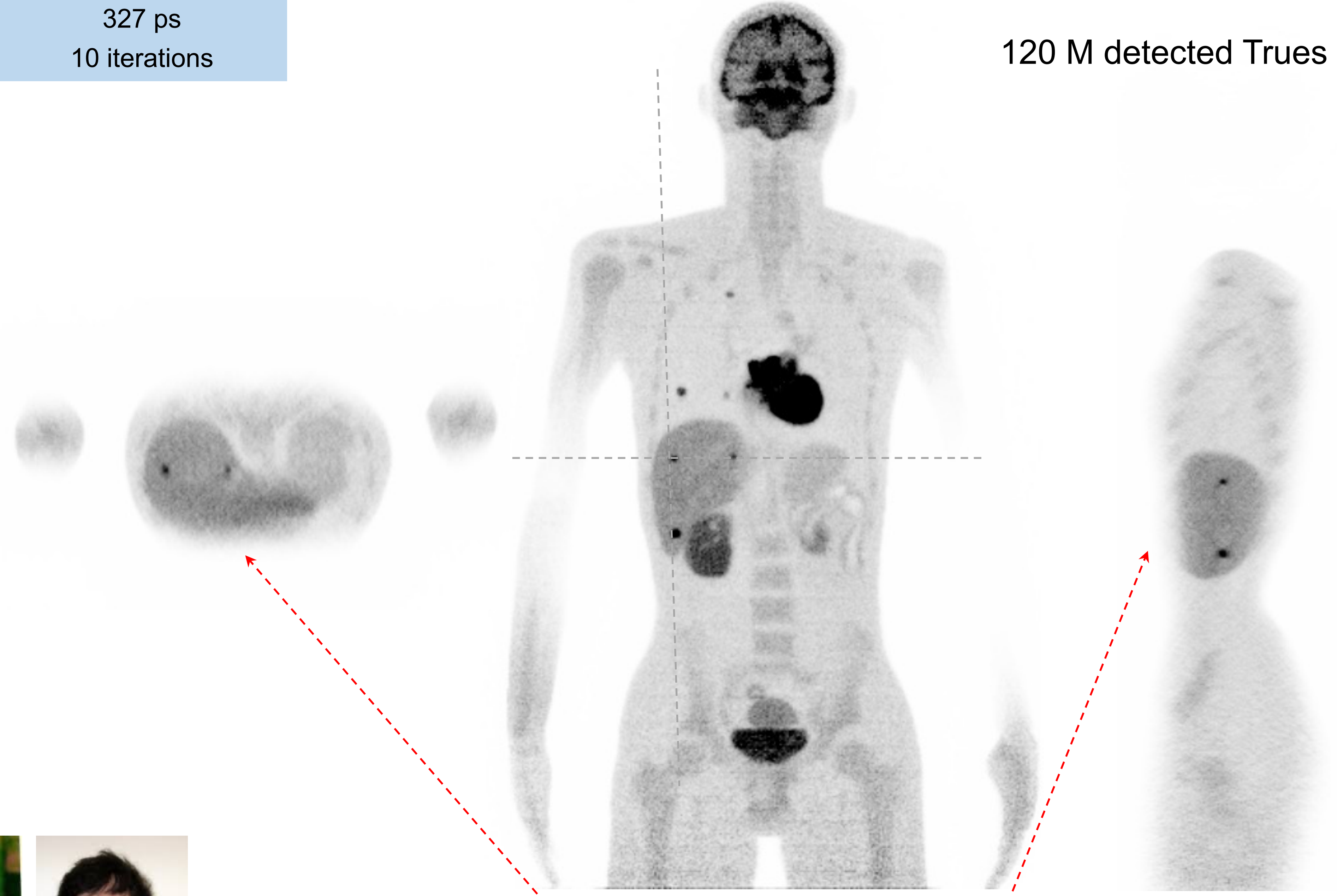


50 cm gap, 70 cm wide,106 cm high


Gate Simulations
Meysam Dadgar


LM-MLEM Julia-GPU
Jens Maebe

120 M detected Trues



Some limited angle artefacts close to detectors

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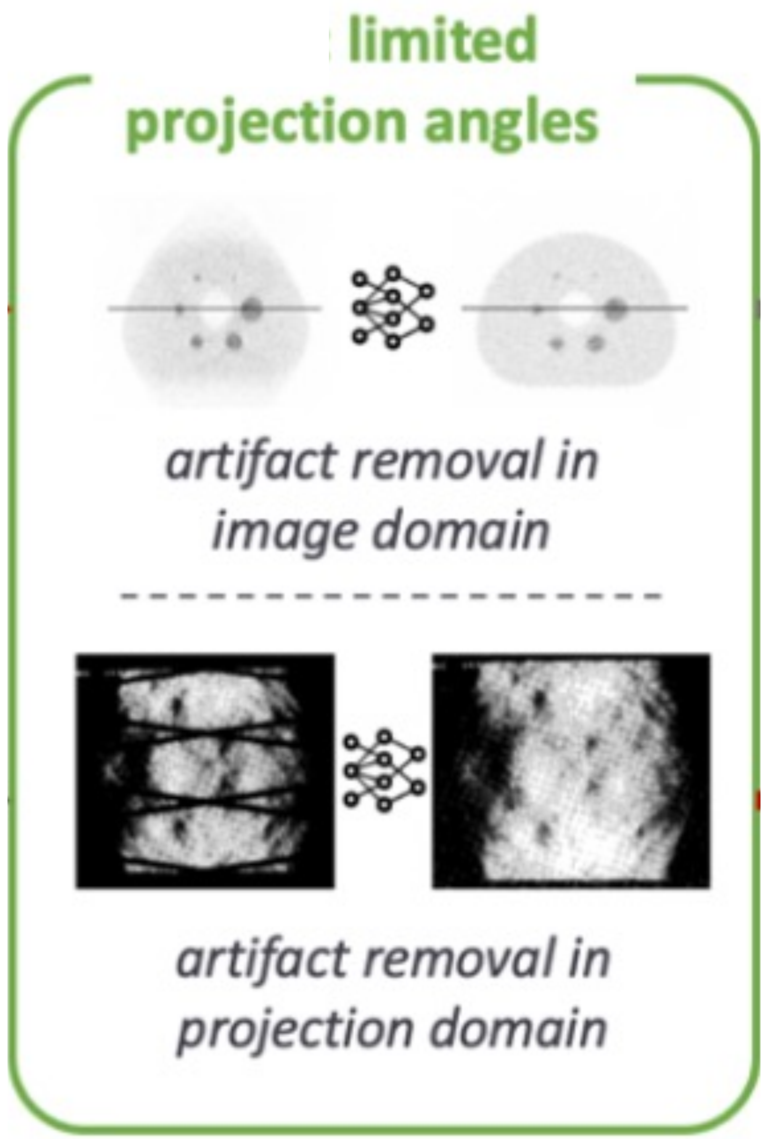
LIMITED ANGLE EFFECTS

AI TO THE RESCUE



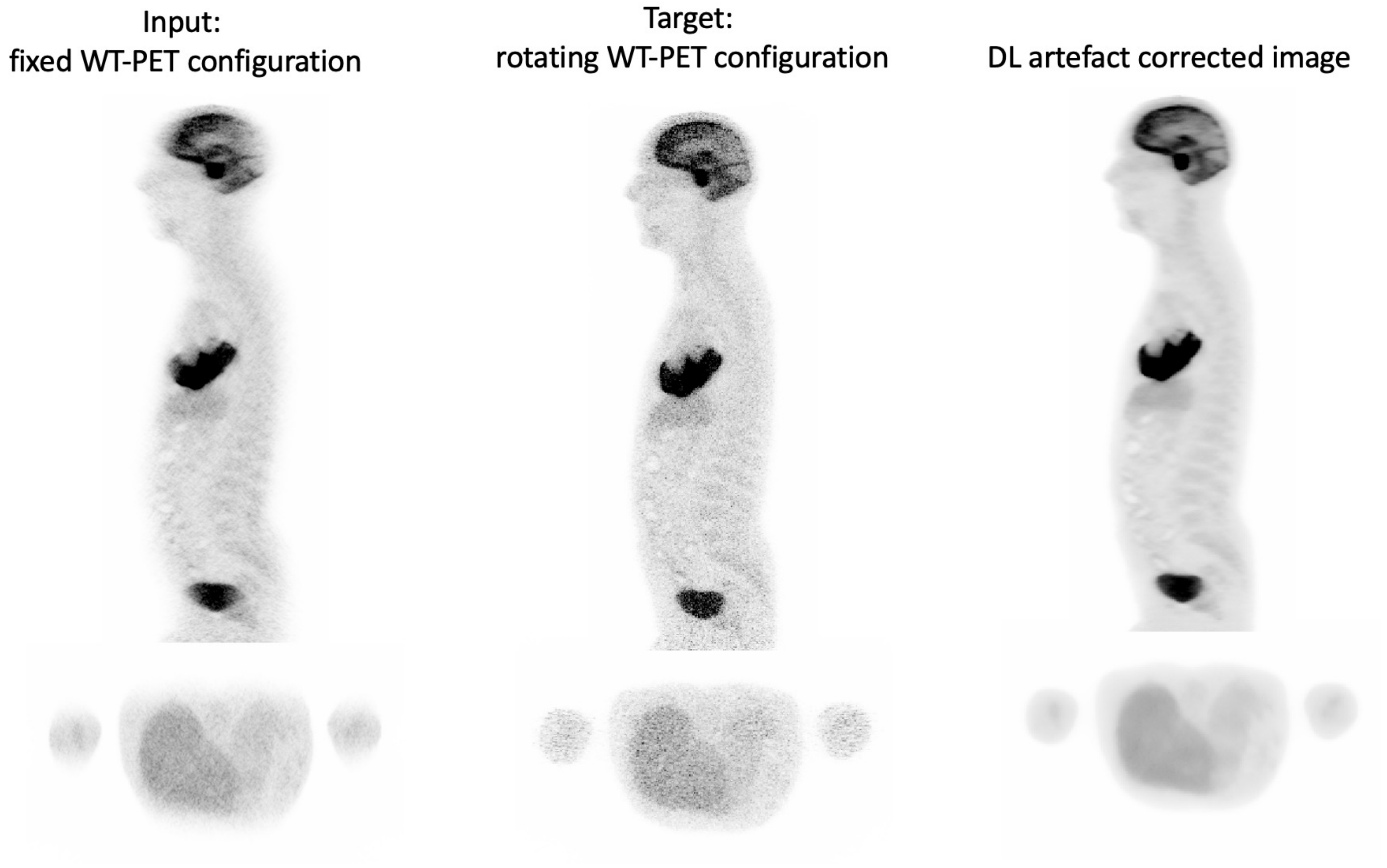
Approaches

Sinogram completion with Fourier methods

Deep learning based image restoration

Learn from image pairs of complete/incomplete data

Deep learning image restoration inside recon



First results for
IEEE MIC 2023
Jens Maebe

Training pairs
from simulations
→ Deep Learning-CNN

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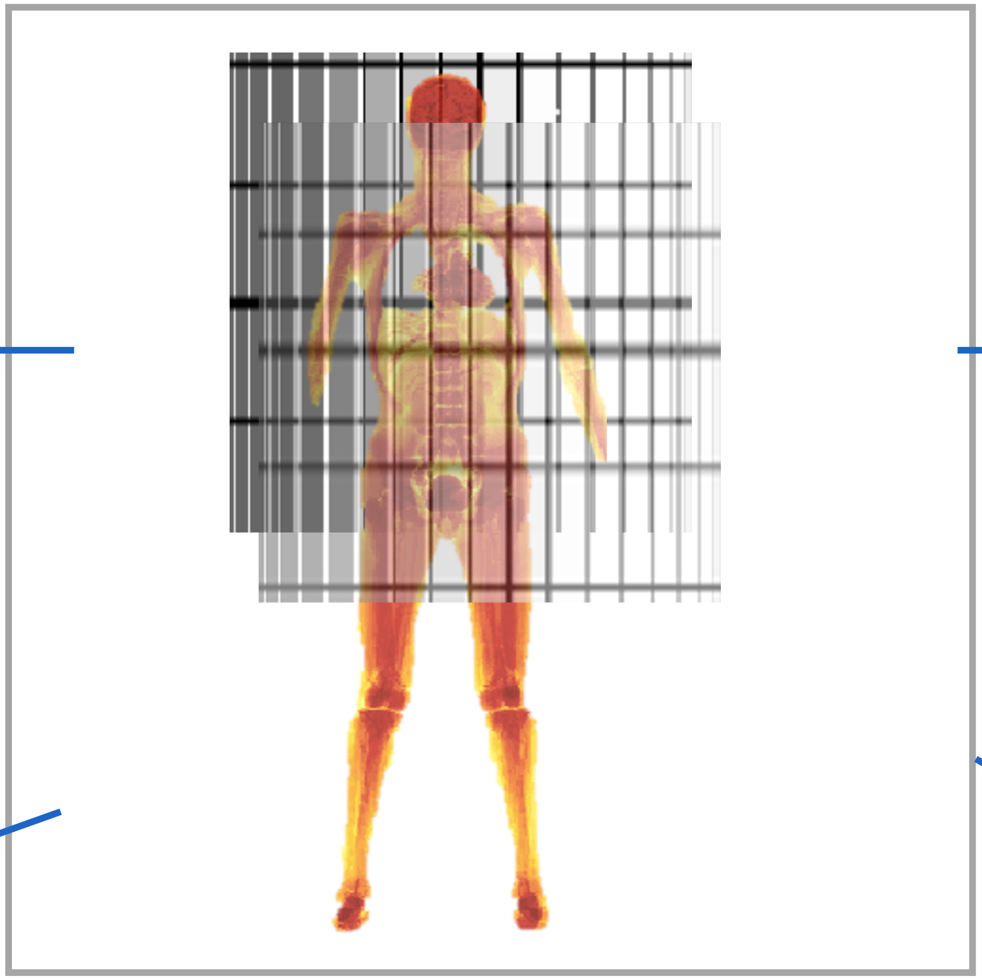
BENEFITS OF WALK-THROUGH PET

Lower cost
BGO is 1/3 price of L(Y)SO
BGO: 30 % more coincidences
BGO 2x worse TOF
Close to the patient
1.9 x Less detectors



Patient throughput
Avoids patient positioning+ scout-view and CT
Aim:
PET in breath-hold of 30 sec
Patient throughput of 3-5 min

Very compact footprint
About 2-4 m2
Semi-mobile
More space for patients in dept

Spatial resolution
Monolithic detectors
Uniform over whole FOV thanks to 6-layer DOI
Less motion of patient

Less personnel
Most patients can position themselves

Disadvantages
No anatomical CT quality
How to scan bedridden patients?
WIP 😉

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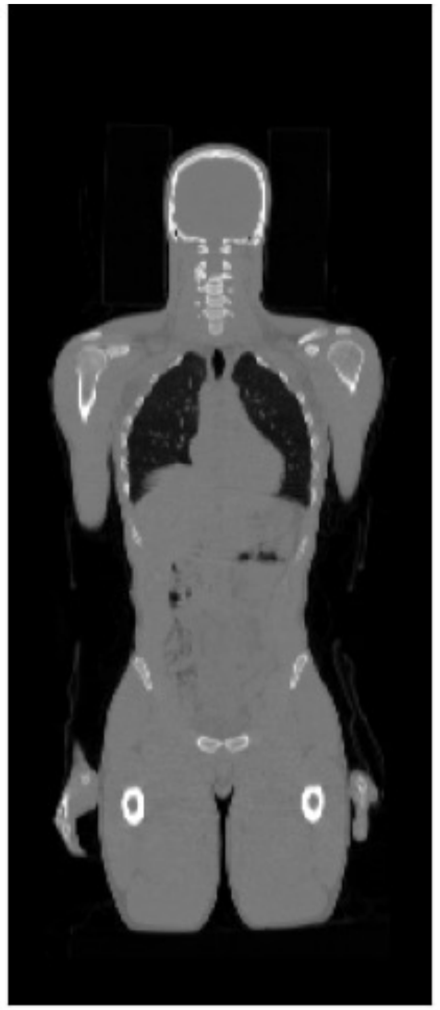
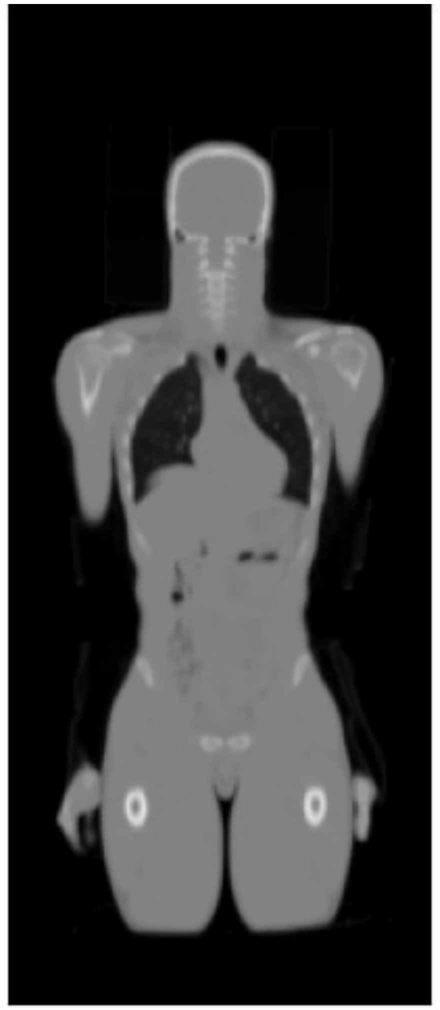
QUANTITATIVE PET WITHOUT CT

AI TO THE RESCUE





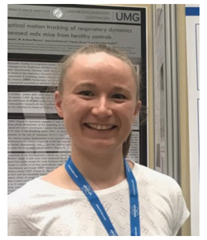
Input-output training
Pairs of NAC-PET and
CT of patients

DL-generated
transmission
image

Quantitative
reconstruction

To Be checked
Robustness ?
Other objects ?

Penn-PET LAFOV Explorer



Joint Ugent-UPENN PhD
Florence Marie Muller

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Using domain knowledge for robust and generalizable deep learning-based CT-free PET attenuation and scatter correction

Rui Guo, Song Xue, Jiaxi Hu, Hasan Sari, Clemens Mingels, Konstantinos Zeimpekis, George Prenosil, Yue Wang, Yu Zhang, Marco Viscione, Raphael Sznitman, Axel Rominger, Biao Li & Kuangyu Shi

Nature Communications **13**, Article number: 5882 (2022) | Cite this article

TOTAL COST OF OWNERSHIP IS KEY

– PET scanner is more than acquisition cost & service contract
  - Throughput !
  - Daily tracer/radiopharmacy costs
  - Personnel cost + hospital space

→Average cost per (quality) scan is what ‘counts’

(**Physicists think too often it are the number of counts or TOF that ‘counts**’)

2022 KELLEY BLUE BOOK OFFICIAL GUIDE 5- Year Cost to Own Awards

2022 Tesla Model 3

Electric Luxury Vehicle

AUDI A4

Quoted Price
488 £
Energy Cost
118 £
TCO Price
607 £

Higher lease cost
But lower consumption
and service costs
and higher resell value

Tesla Model 3 SR+

Quoted Price
520 £
Energy Cost
39 £
TCO Price
559 £

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HOW TO ESTIMATE EXPECTED THROUGHPUT ?

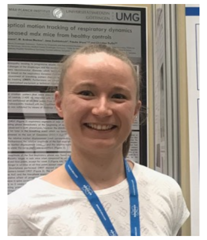
Prof N.Withofs
NM CHU

One day of recording on Siemens Vision at CHU-Liege
Average PET scan/transfer/scout/CT times for 3MBq/kg patients

Steps in this process

1. **Measure throughput** in a real setting on an existing Siemens Vision
2. **Simulate** systems to determine **sensitivity** difference
3. Use Simulated sensitivity + TOF to **predict scan times** on other systems
4. **Estimate setup/transfer time of WT-PET** with a mockup
5. Calculate throughput based on PET scan times and setup/transfer time
6. Calculate the component cost of systems (based on quotes)
7. Calculate how much tracer is required to inject all patients
   - Account for time between patients
   - Account for decay

Gate Simulations
Meysam Dadgar



Mockup measurments
Florence Muller,

System config	SAFOV LSO 210 ps	LAFOV (limited) LSO 210 ps	LAFOV LSO 210 ps	WT-PET BGO 400 ps
Sensitivity	15 kcps/MBg	83 kcps/MBg	176 kcps/MBg	152 kcps/MBg
PET acquisition time	600 sec	108 sec	51 sec	112 sec
Time for Transfer/setup/CT	420 sec	420 sec	420 sec	210 sec
# of possible scans in 8hr	28	54	61	89
Relative cost of PET system	1	4	4	1.4
Reduction in tracer cost vs SAFOV	0%	39 %	46 %	66 %

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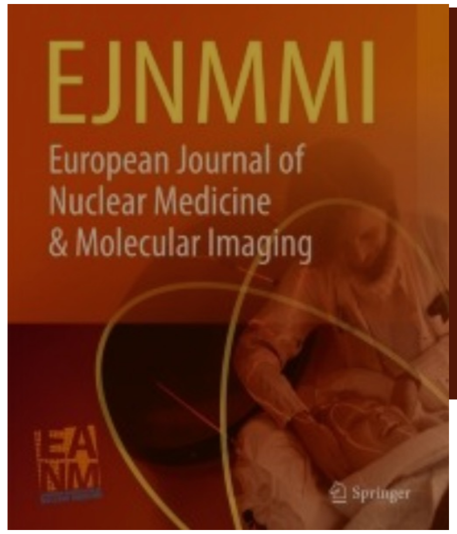

Walk-through flat panel total-body PET: a patient-centered design for high throughput imaging at lower cost using DOI-capable high-resolution monolithic detectors

Original Article | Open access | Published: 19 July 2023 | 50, 3558–3571 (2023)

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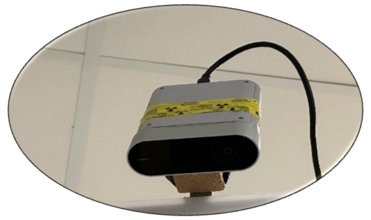
Stefaan Vandenberghe, Florence M. Muller, Nadia Withofs, Meysam Dadgar, Jens Maebe, Boris Vervenne, Maya Abi Akl, Song Xue, Kuangyu Shi, Giancarlo Sportelli, Nicola Belcari, Roland Hustinx, Christian Vanhove & Joel S. Karp

WT-PET

- 2.85 x lower component cost than Quadra
- Lower sensitivity + TOF than Quadra
- But has potential to scan
  - 1.3 x more patients than Quadra
  - 3.1 x more patients than Vision
- At 66% lower dose cost/patient than Vision

ONGOING WORK: STANDING MOTION CHALLENGE



Support from back + handle bars

Projection from back → instruct minimal motion

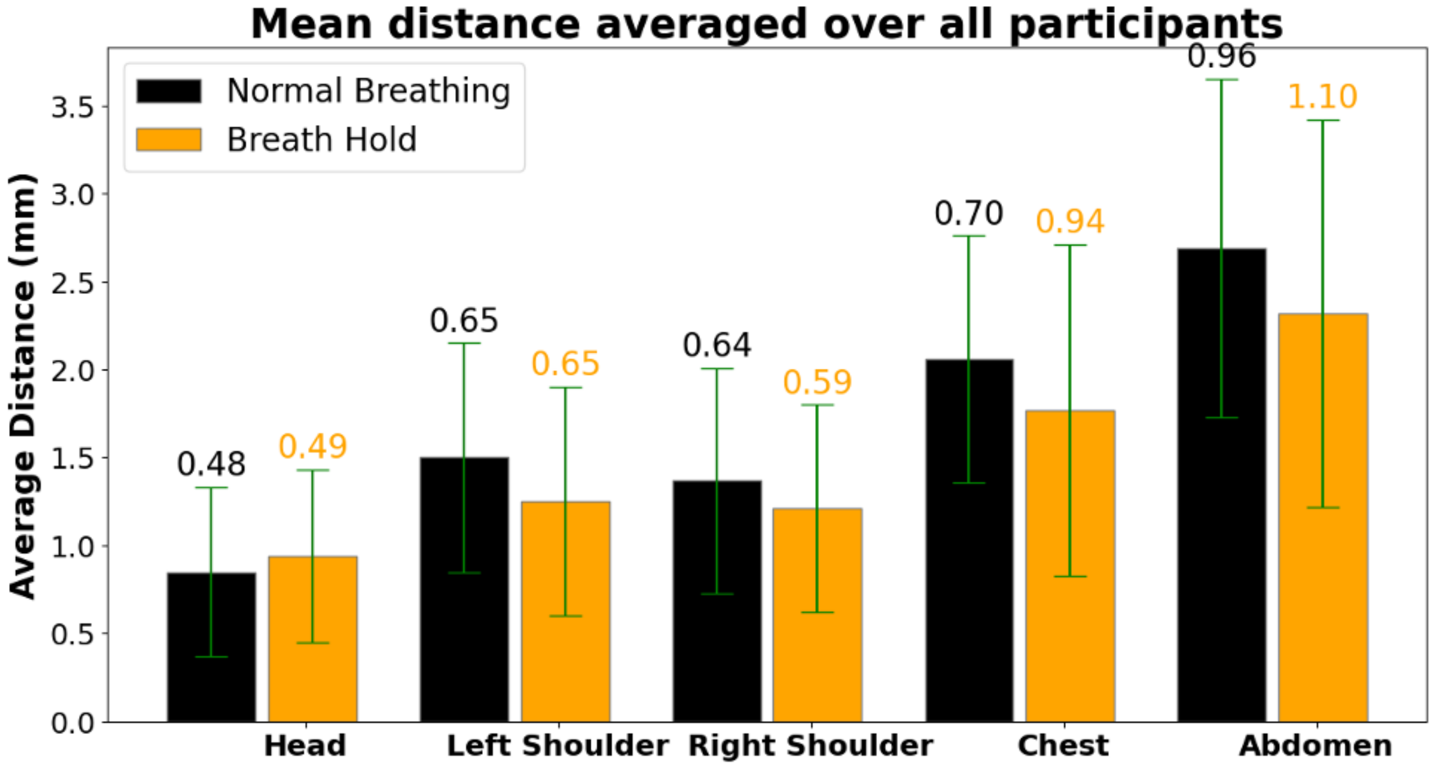
Scan fast (30 sec) to minimize motion

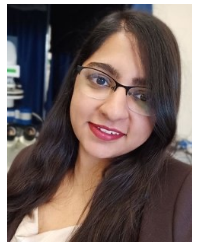
Camera to capture patient motion

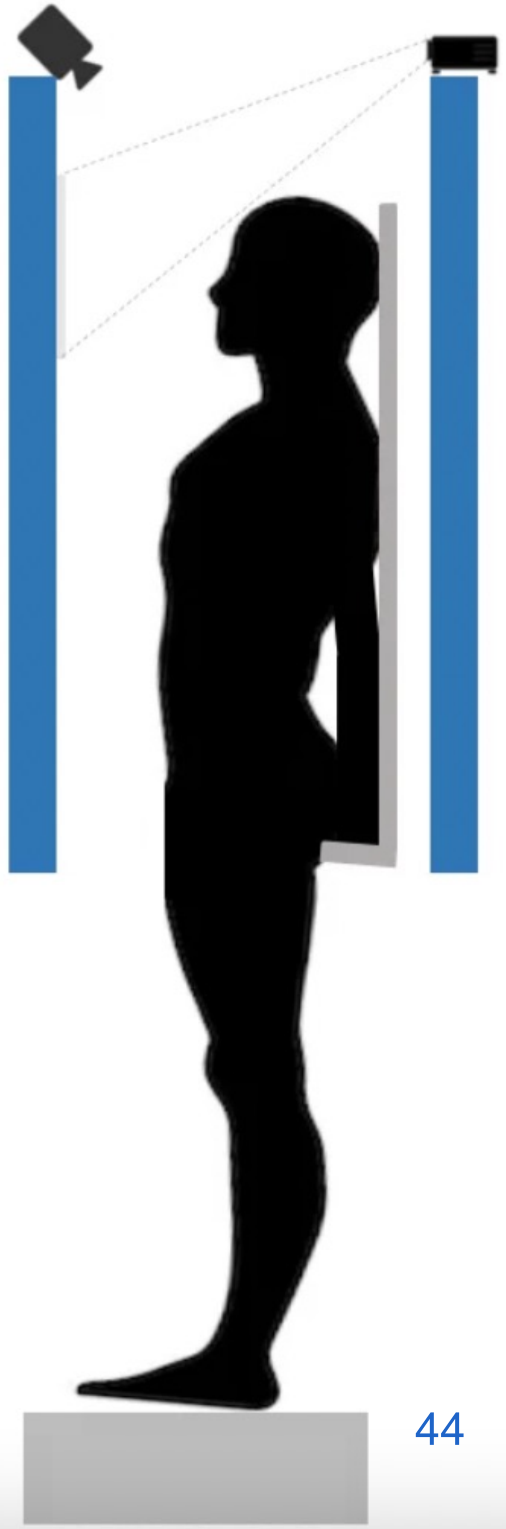
Track motion during 30 sec

IR markers on head/shoulders/chest/abdomen

Normal breathing vs breath-hold

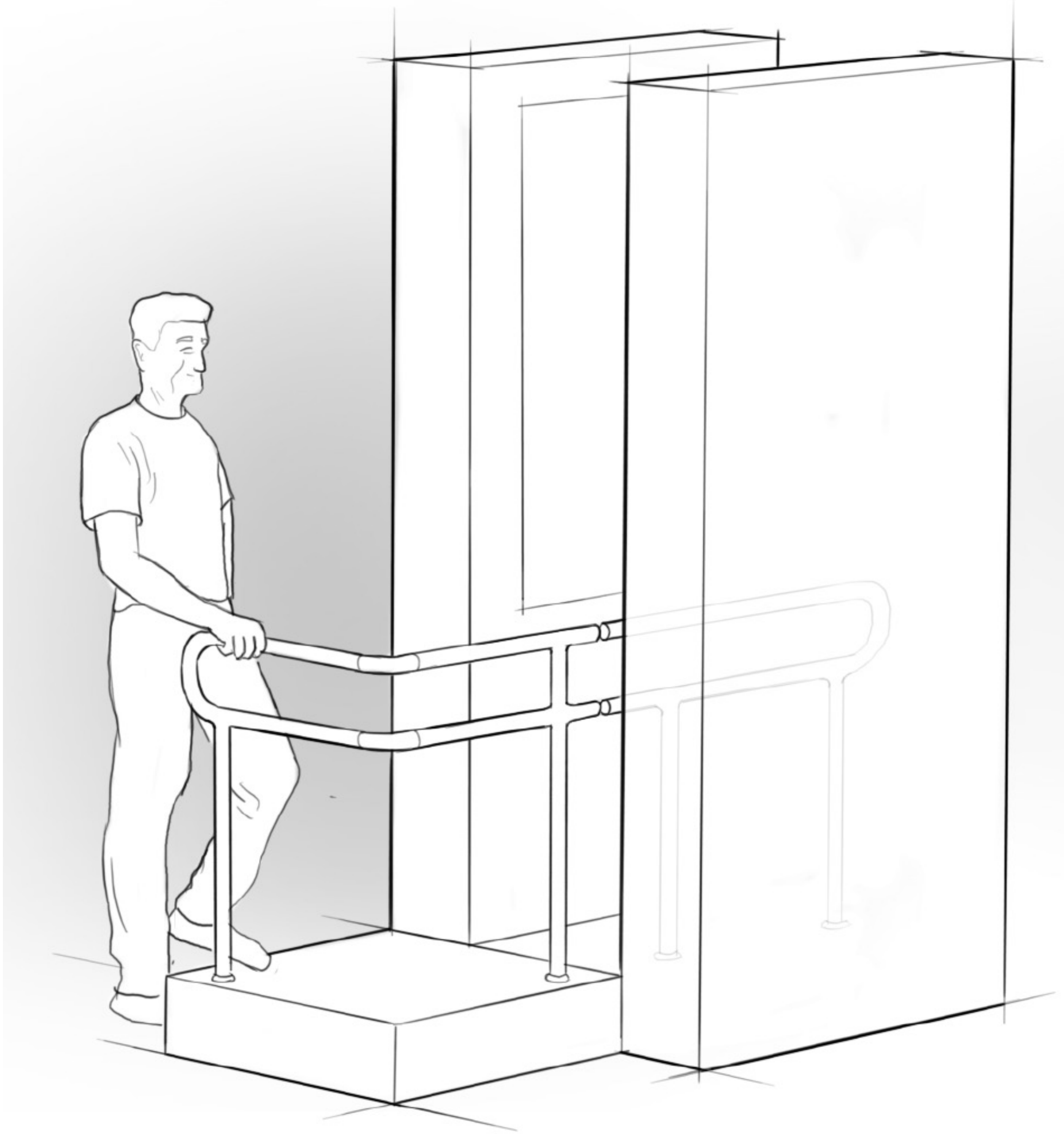


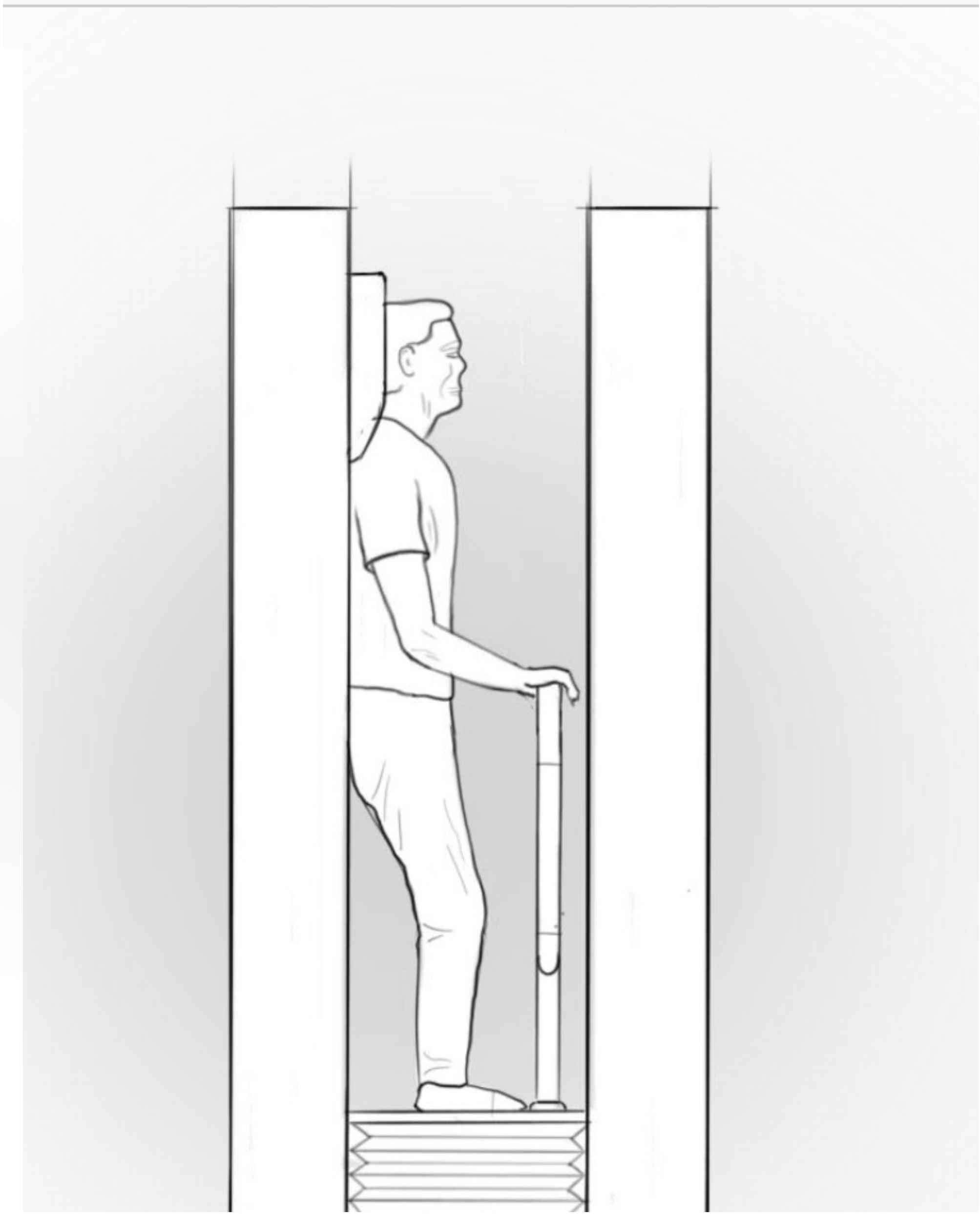


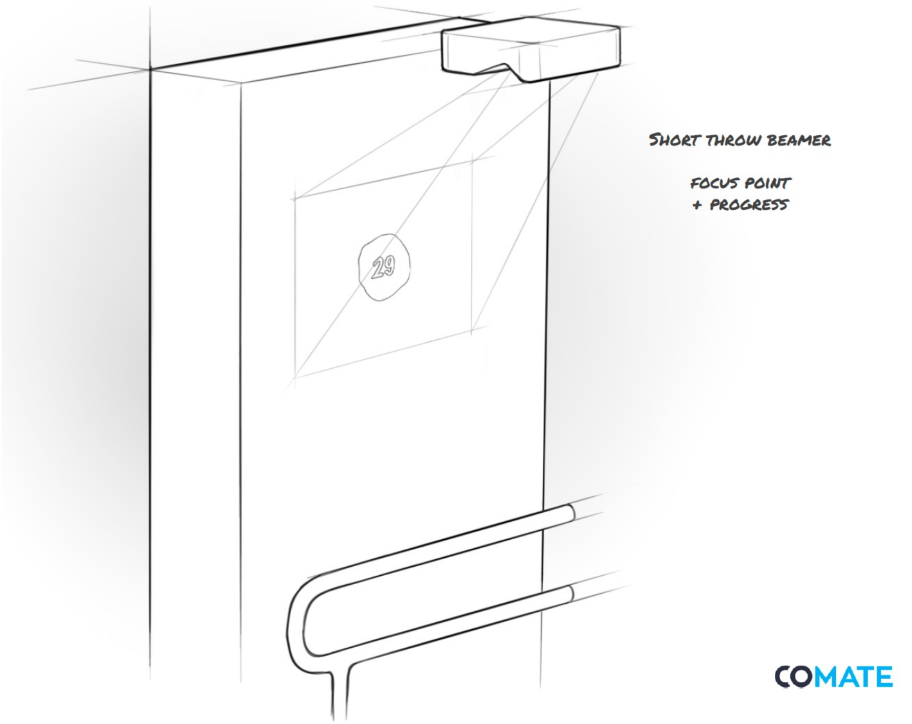


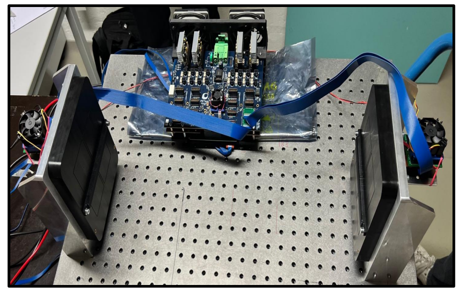
PhD Rabia Aziz: AI for motion correction

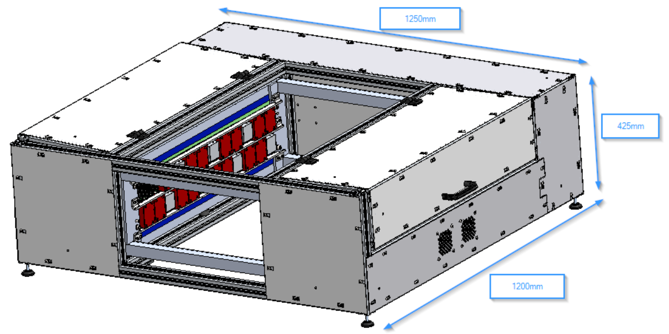
FIRST DESIGN CONCEPTS











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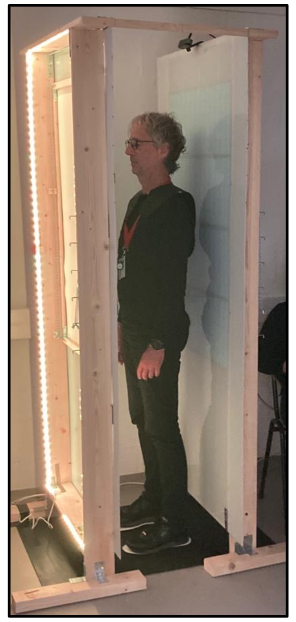
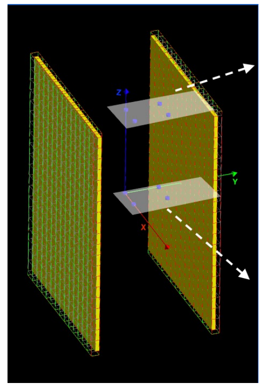
COMATE Engineering & Design

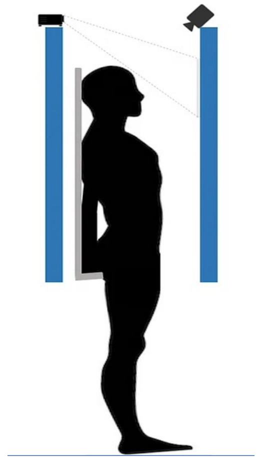
Project timing (2022-2025)

Concept &
Early tests
Q3-Q4 2022

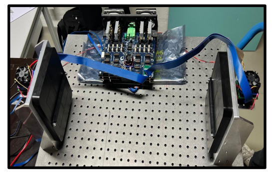


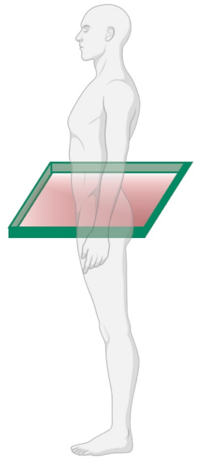
Simulations & Recon& Motion
Q1-Q4 2023



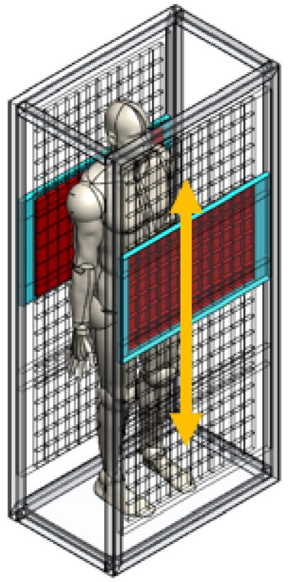


Detector & CT design
Q1-Q4 2024





First prototype
Q1-Q2 2025



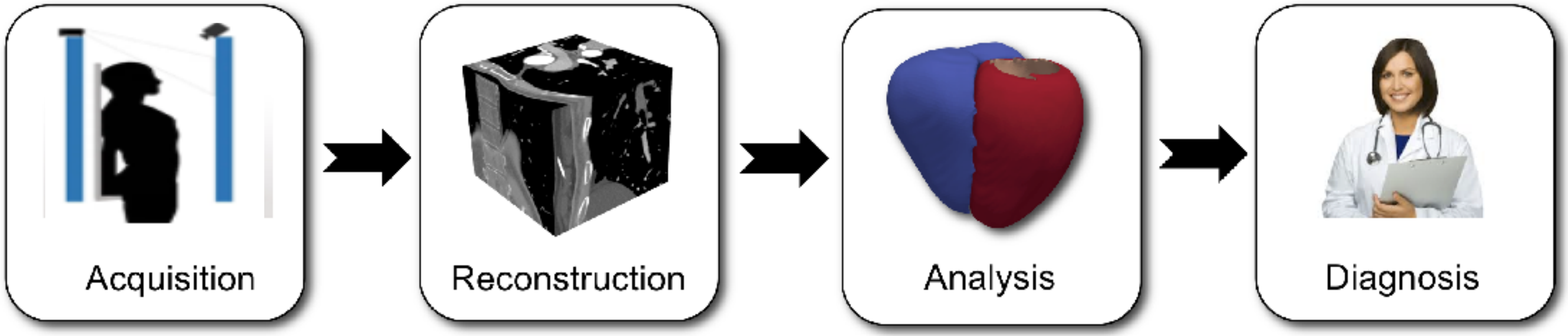
Project Partners

ST Engineering

WT PET
THE FAST LANE

OVERVIEW

AI will be employed into the entire imaging pipeline.



DL for TOF
and positioning

Motion detection

CNN for ultrafast
reconstruction
and corrections

Image
denoising

Efficient reporting

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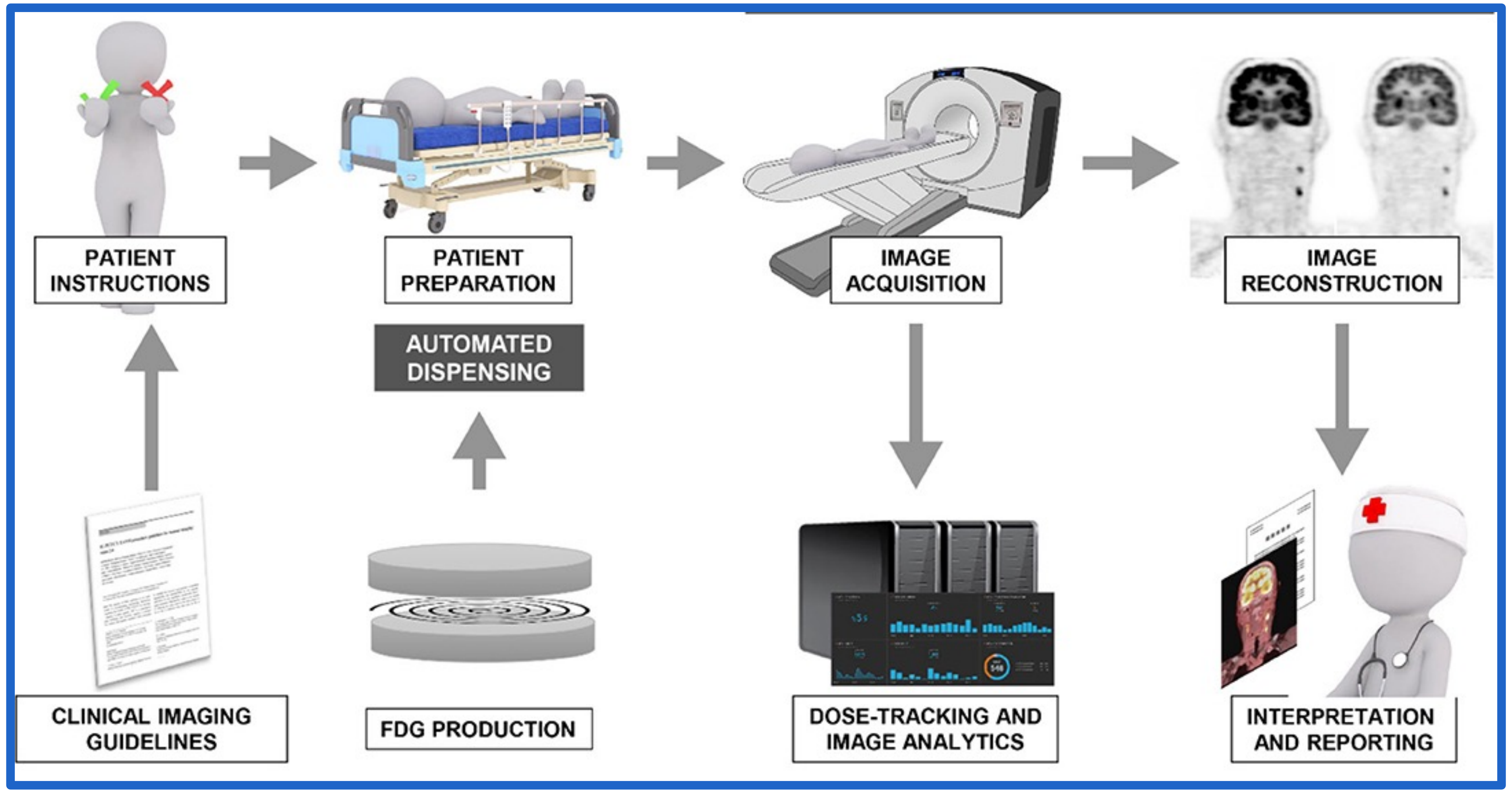
Gains in chain may enhance each other → Faster molecular imaging systems



Not only scanner but whole chain needs optimization

Upgrading every car to a Ferrari does not solve traffic jams

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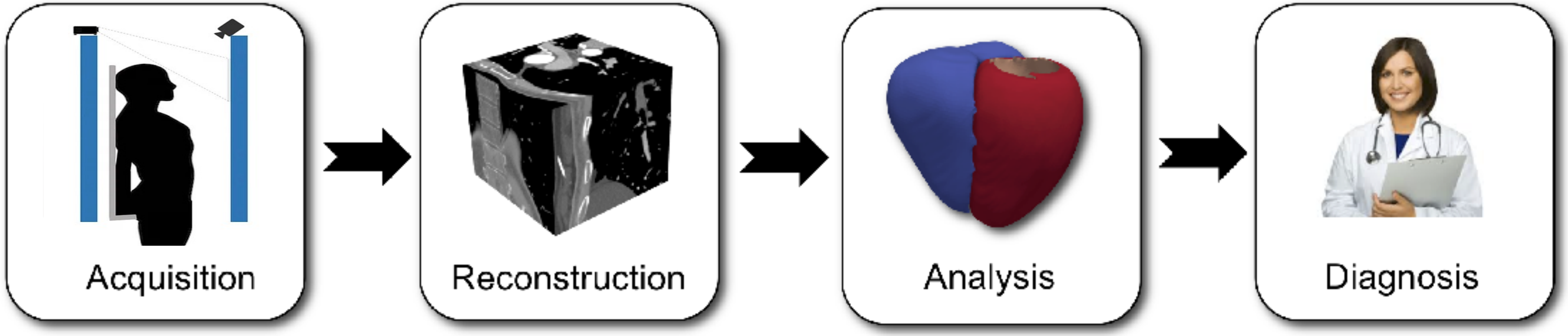
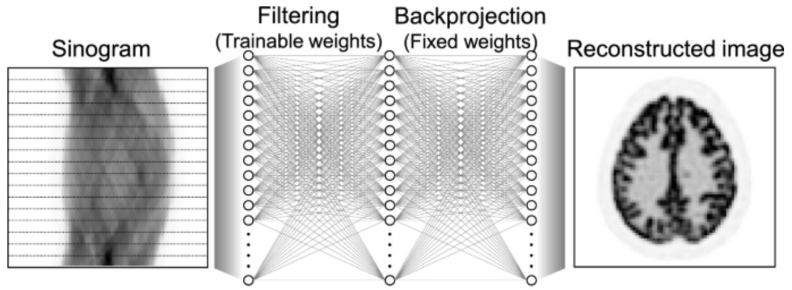
AI TO THE RESCUE

Long term vision:

Make nuclear medicine more efficient, less personnel, more accurate and lower cost

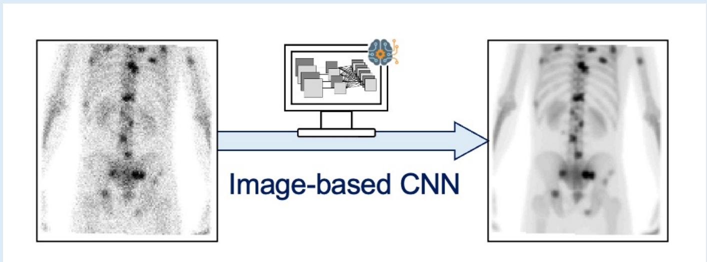


Deep Learning based TOF+ positioning



Large Language Models in Healthcare

CNN denoising



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Shifting tasks of nuclear medicine physicists

Manual quality control

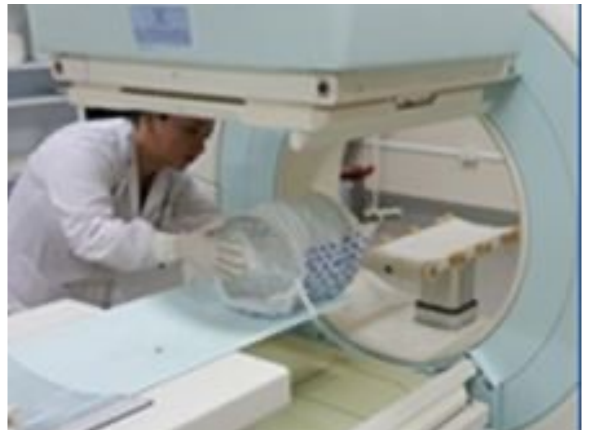
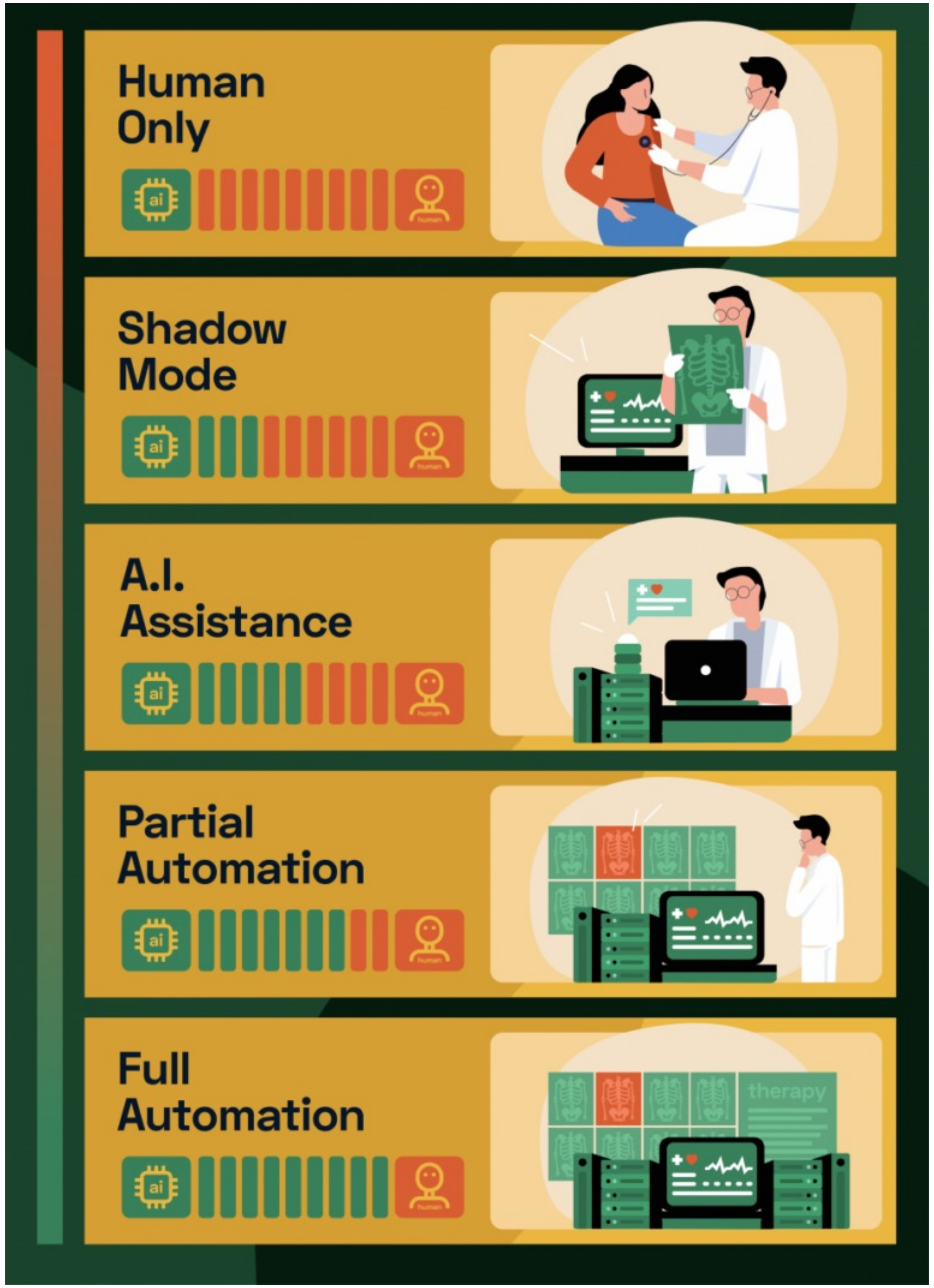
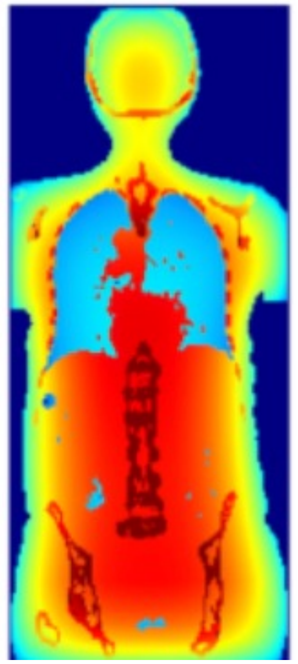


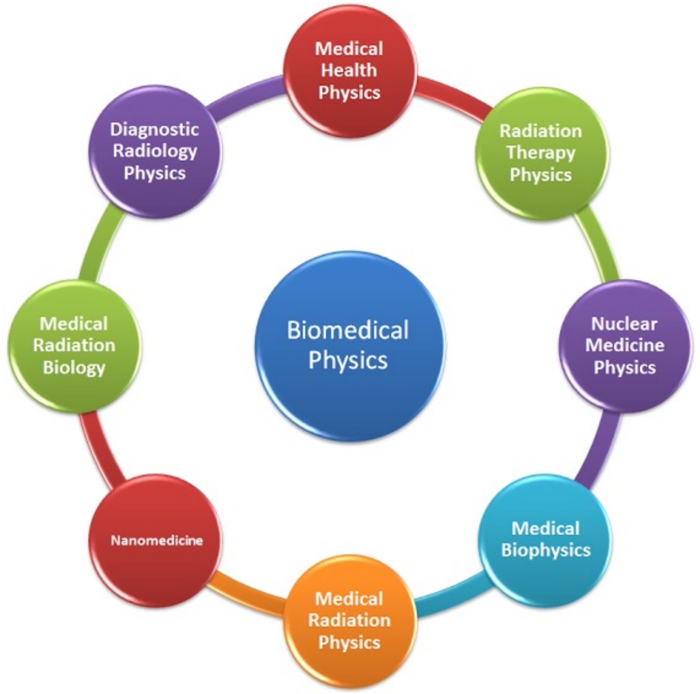
Image processing



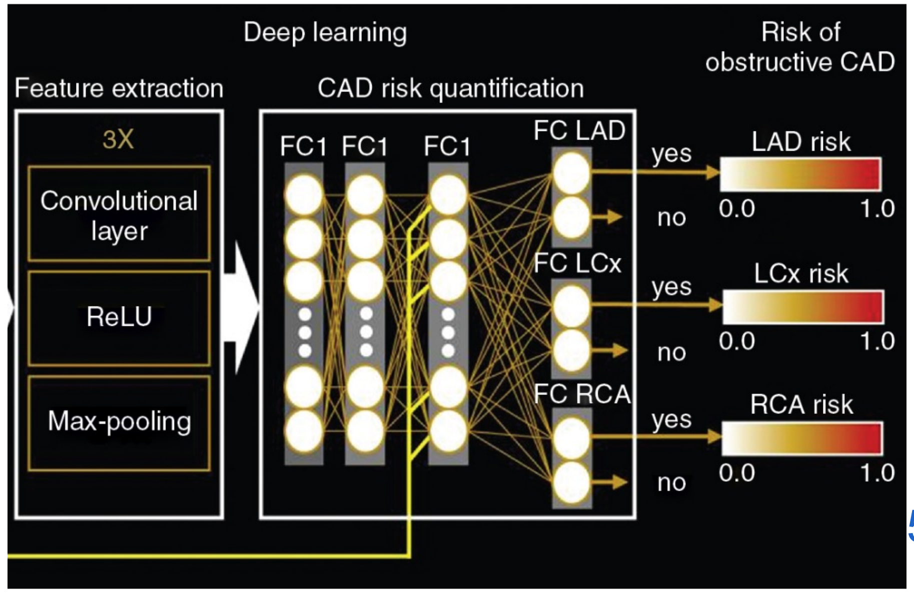
Voxel based dosimetry



Data exchange with other departments) (Radiotherapy, radiology, oncology..)



AI training and testing



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Shifting tasks of nuclear medicine physicians

Patient care

Reading scans

Training staff members

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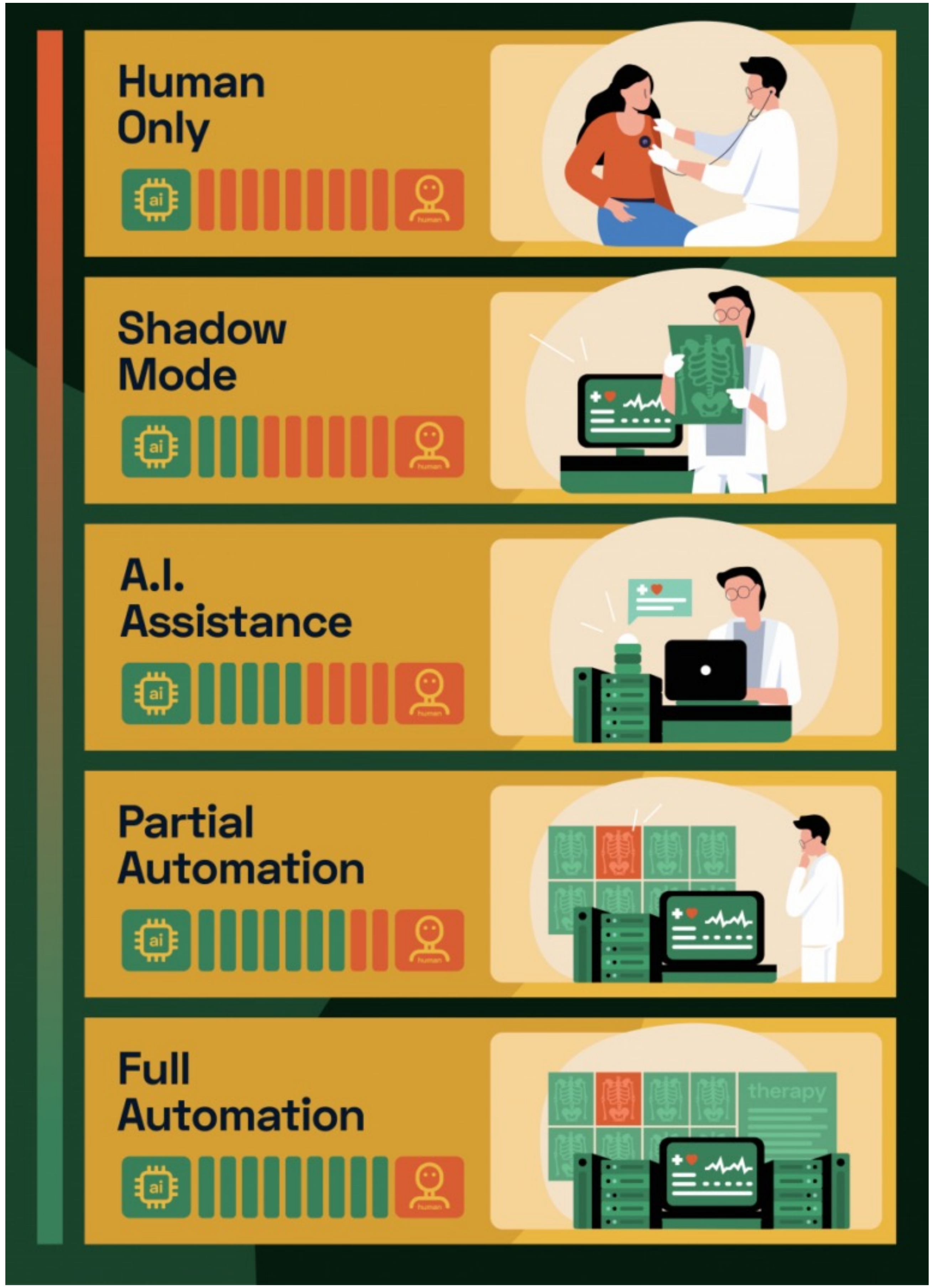
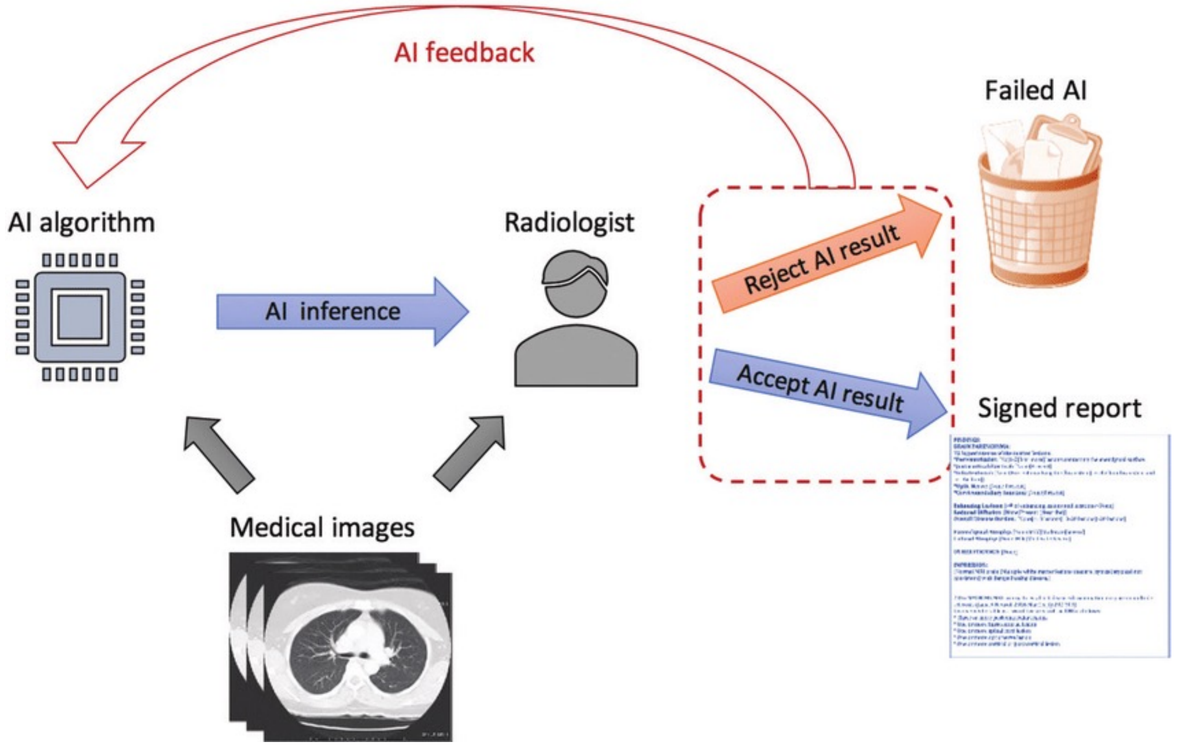
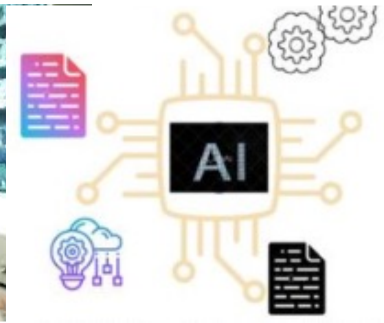


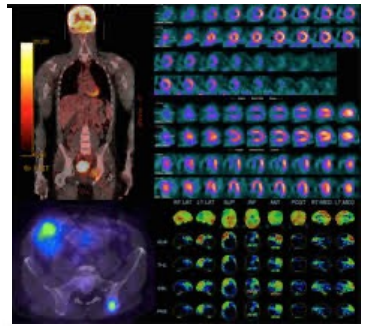
Patient care

Testing/learning to use AI



Training AI for diagnosis and prediction

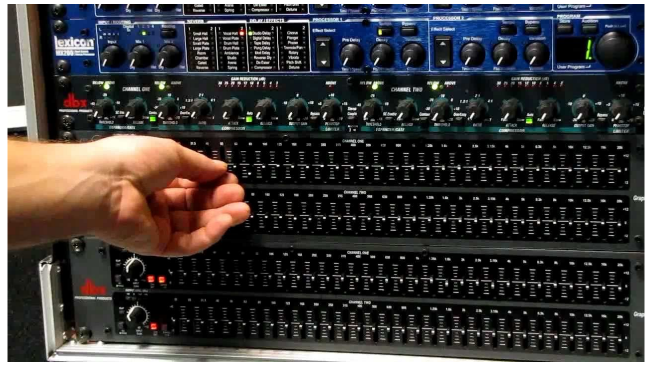




SUMMARY/DISCUSSION

- AI has the potential to speed up imaging and impact system design
- Quite safe and predictable for simple tasks (positioning, denoising)
- AI seems to be used gradually in reconstruction and denoising (CT, MRI, PET, SPECT)
- Future higher throughput/low-cost design based on Walk-Through PET with AI
- AI can/should be used for diagnosis/prediction but carefully especially for complex tasks
- Clear standardized training data with gold standard for training are key for further progress

AI is like a complex toolbox/equalizer
with many knobs and settings
to train input to output, it does it faster
and probably better but maybe also
sometimes worse and unpredictable.



AI-powered object detection just identified
the longest cow on earth

Thanks!

Prof Dr Stefaan Vandenberghe
Expert in molecular imaging, PET system development.

Ir. Jens Maebe, Master of Science in Engineering Physics: Expert in the use of artificial intelligence in PET and CT

Ir. Florence Marie Muller, Master of Science in Biomedical engineering:

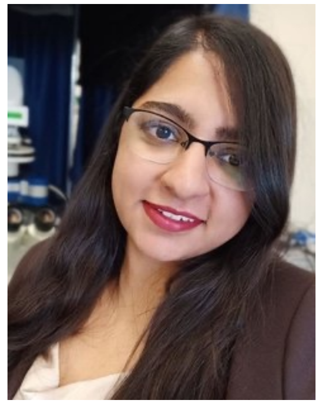
Expert in ultra low dose PET and CT

Msc. Maya Abi Akl,

Master in Physics: Expert in Total body PET optimisation

Prof Dr. Nadia Withofs

Nuclear medicine clinician
Patient centered design



Msc Rabia Aziz

Motion minimization, detection anc correction

Prof Chris Vanhove

Lab leader

Prof Joel Karp
Senior advisor
Experience in bringing clinical PET prototypes to market (UGM/ADAC/Philips)

ST Engineering

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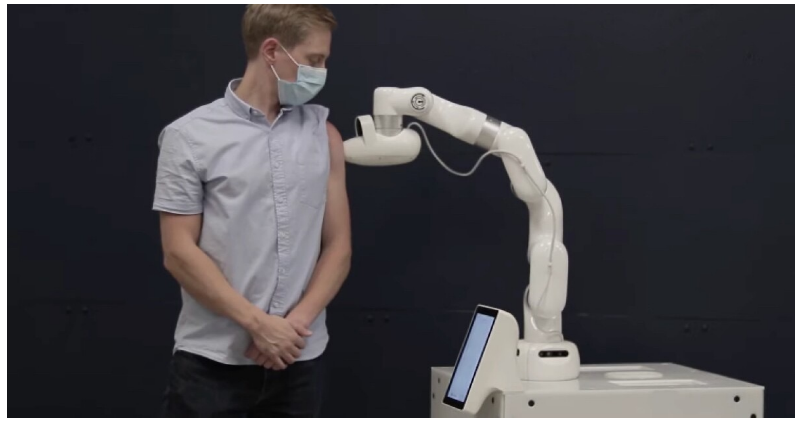
Top level international Clinical Advisory Board

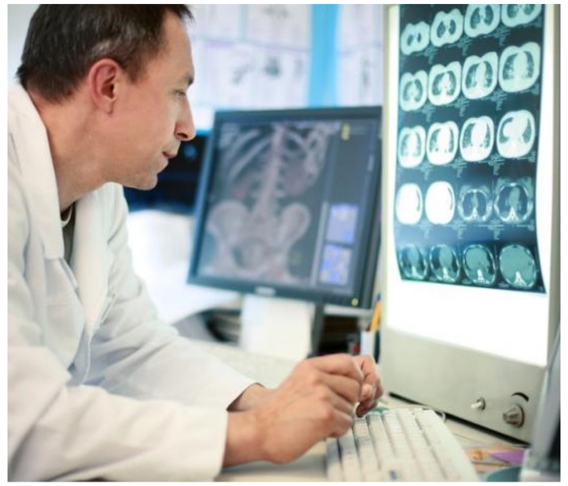
- Rudi Dierckx (EANM president)
- Arturo Chiti (Editor-in-Chief EJNMMI)
- Ken Herrmann (Essen Hospital)
- Rominger Axel (Insel Hospital Bern)
- Alexander Hammers (KCL London)
- David Mankoff (UPENN)
- Christophe Deroose (KU Leuven)
- Francois Benard (Vancouver)

Website: WT-PET.org

Possible future for efficient NM



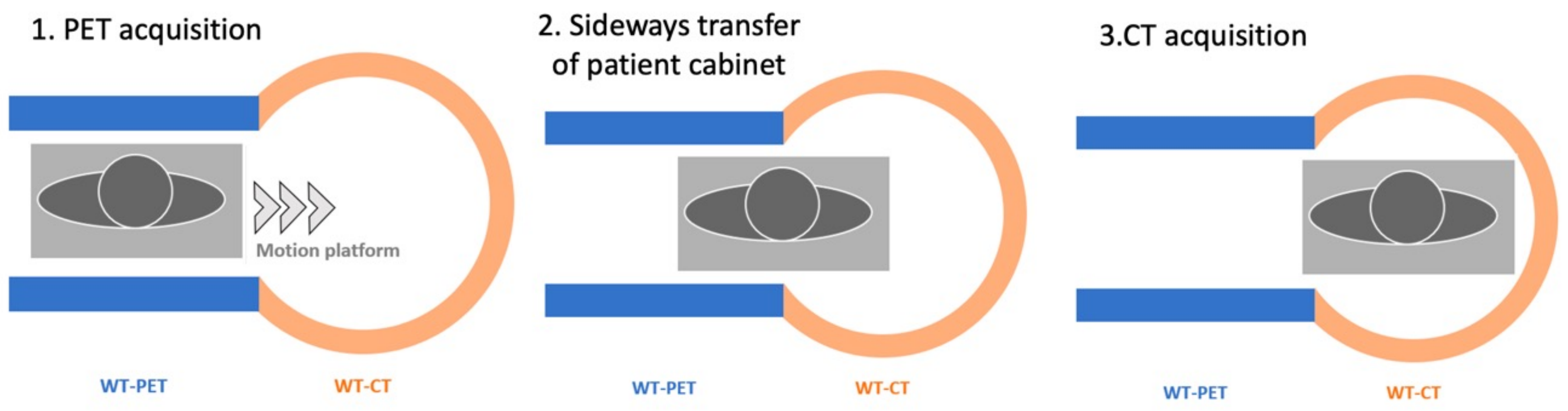
- Patient preparation/injection
- Walk to waiting rooms
- Video instructions for patient scan
- Patients walk in the scanner.
- Fast positioning and acquisition
- High throughput
- Fast deep learning based
    - Image reconstruction
    - Motion correction

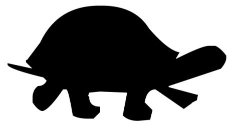


FUTURE WORK: ADD DIAGNOSTIC CT

Making the Invisible Visible

– PhD Boris Vervenne (1st october 2023)
– Design CT scanner for
  - Scanning torso while patients are standing upright
  - Sufficiently fast (< 1min for full torso)
  - Reliable detector technology

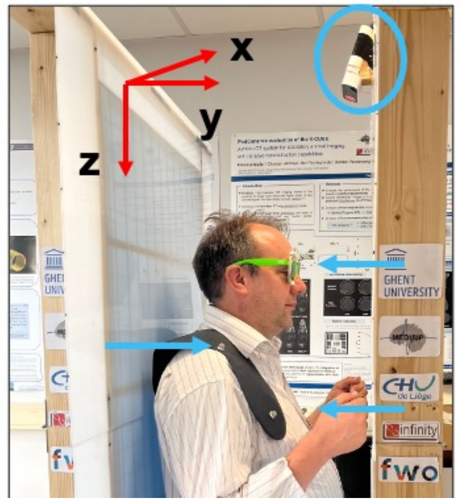




0.2 km/hr
=
about 10 s for 50 cm

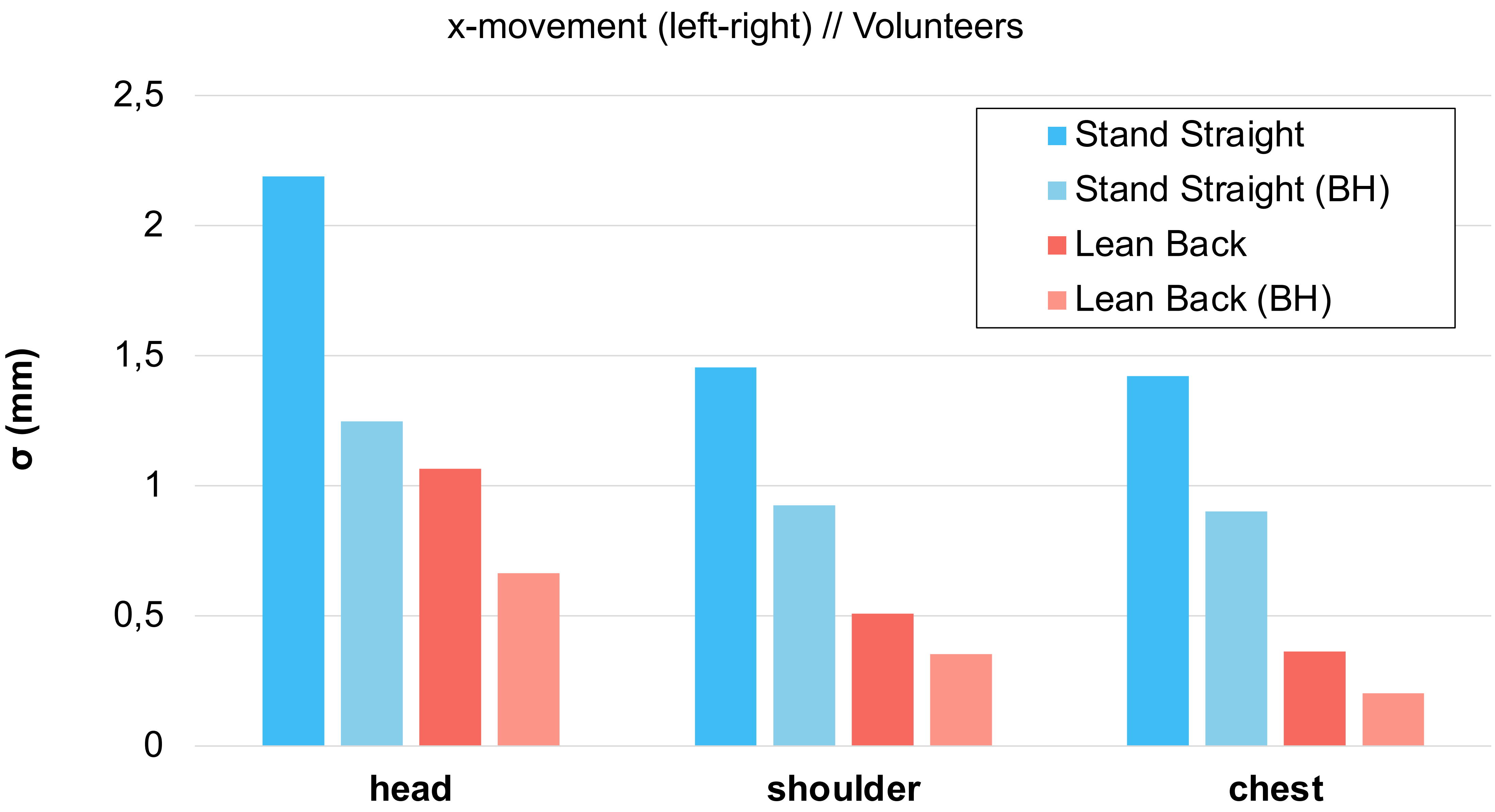
MOTION: LEAN BACK AGAINST SURFACE

- **Kinect camera**
- **IR markers** are positioned: on shoulders, on glasses (head), chest level, abdomen
- Record in x (left-right), y (front-back), z (vertical)



Mockup measurments
Florence Muller, Jens Maebe, Nadia WIthhofs,

Motion in standing position
→ Limited due to short 30 s scan
→ Mostly head forward and back



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