
The future, AI, and dosimetry

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“Dose(s)” as an artificial construct

- When we think dosimetry, we may think assessment / measurement of some ***objective physical property***
- However, with the exception of Absorbed Dose (and a few more), “doses” are ***human-centered artificial constructs***, not immutable quantities existing in nature
- **Definitions** of those quantities can *change*, and, with them, the modality by which we **assess/measure** “dose(s)” can also *change*, as our understanding and our technology evolve

Effective Dose, as an example

LET LSS sex age at exposure
RBE epidemiology EAR/ERR sensitivity
particle energy radiobiology population
track structure animal studies latency lifestyle
field structure cancer incidence data baseline cancer incidence
tissue type cancer fatality data
biological endpoint radiation interaction mechanisms
heterogenous energy deposition medical care data comorbidities

E

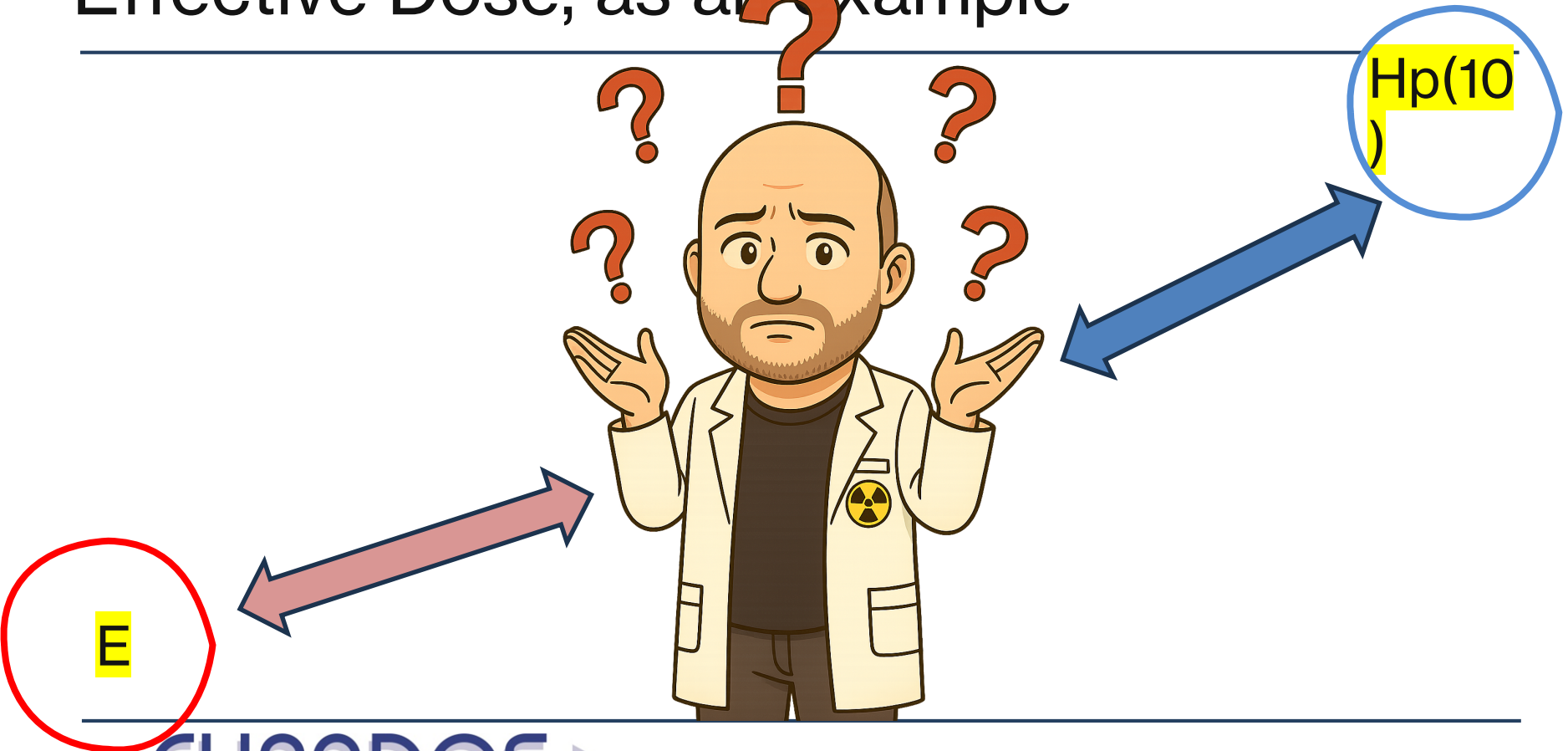
Effective Dose, as an example

reference male
reference female
reference irradiation conditions
every organ
exposure in unknown geometry
every particle energy
a myriad conversion coefficients
exposure in an unknown radiation field
a physical calibration phantom (different than the CP!)
exposure to unknown radiation

reference calibration beams
reference person
reference computational phantom
every particle/rndcl
reference radiation field
an imaginary sphere, you said?
“a” calibration factor

Hp(10)

Effective Dose, as an example



AI will transform, and possibly change:

- The **definition** of “dose(s)”, and which ones we will actually use (emergence of *new* “dose(s)”?)
- Their **calculation methodology**
- The techniques we use to **measure** them
- The processes for “dose(s)” **assessment**
- The **meaning** of “dose(s)” themselves
- The **use** of “dose(s)” in the practice, and specifically in the demonstration of regulatory compliance

AI will also transform the System for RP

- And, as the concept of “dose(s)” is deeply embedded in the ICRP System for Radiological Protection...
- ... AI will deeply transform the System for Radiological Protection* as well!

*S-RP, from now on

How AI will change the S-RP architecture

A more personalised RP approach

Assessing risks, not (only) doses

Computing doses in real-time

How AI will change the S-RP architecture

Synergy MC-AI

Introduction of individual elements in the S-RP

A new generation of wearables

Integration between wearables and real-time dosimetry
computations using personalised phantoms

A paradigm shift: from “dose compliance” to “risk compliance”

AI will change the S-RP architecture

- AI is already having an impact on radiobiology [02], [03], [04], animal studies, AOPs [01], LLS [09], detriment calculations,...
- There is tension between the current System, based on **static, average values, obtained from large population, animal and radiobiological studies**, and a **more personalised approach**
- This is currently driven by *precision medicine*, but its impact will reach outside medical exposure situations

How will AI change dosimetry

$$E = \sum_T w_T \sum_R w_R D_{T,R} \leq H_p(10) + \sum_{j,r} e_{j,r} \cdot I_{j,r}$$

- w_R
- w_T
- Detriment
- Computational Phantoms
- Operational Quantities
- Dose-meters and their calibration
- Usefulness of E
- Demonstration of regulatory compliance
-

How AI will change w_R

- w_R are informed by particles' RBE, and by $Q(L)$
- w_R are a **simplified, administrable construct**, conservatively established by ICRP via expert judgment, with an eye to practicality and to prudence [06]
- Radiation field → track structure/microdosimetric descriptors → biological damage/responses (cells/animals) → endpoints judged relevant to stochastic risk → w_R

How AI will change w_R

There is agreement that Linear Energy Transfer (LET) has inherent **ambiguities**, lacks consistent definition, and fails to capture the **stochastic, microscopic spatial distribution of energy deposition** relevant to biological effects [05]

- Recent efforts in **micro** and **nanodosimetry**
- New **descriptors** that we currently struggle to use

Why AI shines in dosimetry research?

- AI excels in uncovering **complex dose-response relationships directly from data**, finding correlations that may not be obvious to identify, effectively mitigating biases associated with pre-specified parametric model assumptions
- AI shines when used to address **complexities that linear models struggle with** – such as multi-dimensional lifestyle factors, deconvolution of mixed signals, pattern discovery, non-linear dose-responses, etc.

How AI will change w_R

- AI will bring **micro and nano-dosimetry** into the definition of w_R
- AI will support the ongoing **omics integration**
- There is a great potential for AI to support ongoing reviews and data mining of **animal studies**
- AI will support and impact how **AOPs** are integrated into the S-RP

How AI will change w_R

AI will change w_R calculation methodology by changing:

- **What descriptors of track structure are used**
- **How descriptors are obtained**
- **How biological evidence is extracted**
- **How evidence is combined**
- **How uncertainty and bias are quantified**

How AI will change w_R

AI will change w_R calculation methodology by changing:

- **What descriptors of track structure are used** (microdosimetry vs nanodosimetry vs hybrids)
- **How descriptors are obtained** (measurement + Monte Carlo + surrogate models)
- **How biological evidence is extracted** (automated phenotyping, image analysis, omics integration)
- **How evidence is combined** (hierarchical causal/meta-analytic models rather than narrative expert synthesis)
- **How uncertainty and bias are quantified** (including domain shift across labs, species, endpoints)

How AI will change w_T

- If w_R is a window towards “radiation interactions”, w_T is a window towards “**human populations in the world**”
- “**Radiation detriment**”, on which w_T values are based upon, integrates baseline cancer incidence data in various world populations (ERR/EAR), mortality, quality of medical care, degradation of quality of life, and years of life lost (severity adjustment)
- **Sex, populations, age at exposure** are among the factors influencing radiation detriment and nominal risk

How AI will change w_T

- While important variations are recognised, they are “**averaged out**” in the current S-RP
- A reflection started whether (and how) to integrate some of those elements in detriment calculations [08], [20], [07]
- The question is **not trivial** (the meaning of those quantities integrating non-reference parameters needs clarification), and an answer probably requires a **paradigm shift** (moving away from the current use of the Reference Person and computational phantoms)

How AI will change w_T

Multiple possible scenarios, from a prudent, stratified approach to the abandonment of w_T . As possible examples:

- AI will offer **new insights in LSS** and worldwide cancer data: possible impact on the (current) set of w_T
- The **synergy between AI and MC** will facilitate the use of more personalized phantoms in “dose” calculations
- Some **individual characteristics** may enter into the way ICRP calculates “dose(s)” (making changes to the S-RP)

How AI will change the way we study the LSS

- The **Life Span Study** of the Hiroshima and Nagasaki survivors is the **single most influential human dataset** linking quantified dose of tens of thousands of individuals to long-term health outcomes across decades
- The LSS is the primary source of data for understanding **radiation effects on humans**, and developing **risk factors** and the System for Radiological Protection



How AI will change the way we study the LSS

- Conventional **statistical methods**, while foundational, are often insufficient to address the **increasing complexity** of modern biological and epidemiological questions in radiation health research
- Recently, various studies [09], [21], [22], suggested the use of **AI tools in conducting more complex reviews of the LSS data**: RERF [23] has expanded its analytical toolkit to include mechanistic models, mediation analysis, and methods for multiple outcomes like competing risks and multistate models

How AI will change the way we study the LSS

- **Causal Machine Learning (CML)** has been applied to a review of LSS mortality data [09], [21]
- Unlike standard ML, which focuses on prediction, CML is designed to uncover causal relationships **without imposing rigid parametric dose-response assumptions**
- CML can **process dozens of variables simultaneously** (High-Dimensionality, e.g., smoking, diet, socio-economic status) to better isolate the specific "causal" effect of radiation from "confounding" lifestyle factors

The synergy between AI and MC

There is a great potential in the synergy MC-AI!

- MC is **physically accurate but slow**, especially for **low-probability events** (deep shielding, out-of-field dose, rare interactions) or when you must **run it many times** (optimisation, uncertainty quantification and propagation, patient-specific plans, facility digital twins)
- AI excels in **learning mappings from data** (fast approximation, inference from sparse measurements, pattern extraction, optimization, anomaly detection)

The synergy between AI and MC

Some examples of the MC-AI synergy include:

- Use MC to generate a high-quality training set, then train AI to emulate dose maps, detector response functions, spectra, doses, etc. 
- Train AI on many MC-generated “forward” simulations, so that the model learns to solve the inverse mapping 
- Use AI to reduce variance in MC calculations
- Constrain AI to reduce hallucinations by enforcing MC physics (e.g.: PINNs [24])

Individual response to radiation exposure

Two individuals in the same radiation field: the **same dosimetric readings**, but **two different biological doses** in reality

- Today, we fail to capture this difference in the S-RP
- In most cases, the difference is minimal (and probably smaller than the dosimetry uncertainties)
- However, while recognizing that some individual factors may have a bigger impact than others, the current S-RP is not designed for personalised dose assessments

Individual response to radiation exposure

Elements that could be considered are:

- **Demographics and body size** (sex, age at exposure, population, height, mass, BMI, etc.)
- **Anatomical and morphometric** data (organ volumes and masses, tissue composition, etc.)
- **Physiological function** (ventilation rate, cardiac output, renal function, hydration status, inflammation, etc.)

(continues...)

Individual response to radiation exposure

- **Biokinetics and intake-specific** factors (radionuclide chemical form and solubility class, AMAD, route of intake, wound characteristics, GI absorption fraction, excretion parameters from bioassay: urine volume, creatinine, etc.)
- **Lifestyle and medical modifiers** (smoking, alcohol use, diet, exercise, medications that alter uptake/clearance, comorbidities, etc.)

Individual susceptibility

- It is recognized that **vulnerable subpopulations** and **individual susceptibilities** may be inadequately accounted for in the current protection framework
- As medical uses of radiation continue to increase globally and radiation biology understanding advances, there is an urgent need to move beyond "one-size-fits-all" approaches toward **more individualized radiological protection strategies**
- See the draft ICRP TG111 document, in consultation [07]

How AI will change computational phantoms

It's an exciting time for computational phantoms (CPs)!

- Many groups around the world have been developing highly specialised human phantoms for **specific populations** (e.g.: UF/NCI, korean, chinese, japanese CPs)
- **New reference ICRP CPs** have been developed for adult male and female, for children, for the foetus and the pregnant mother
- From the recent voxel CPs, initially the standard ICRP reference CPs, we are moving to **nurbs/mesh CPs**

A variety of computational phantoms

Age-Dependent Effective Dose

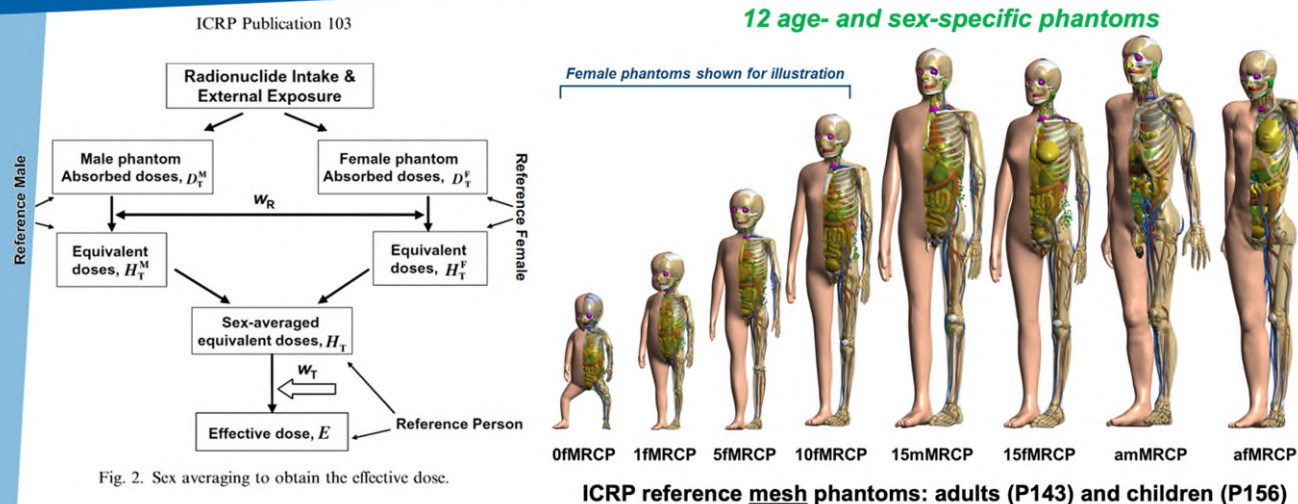


Fig. 2. Sex averaging to obtain the effective dose.



Effective dose to Reference Person (adult, children) at six ages

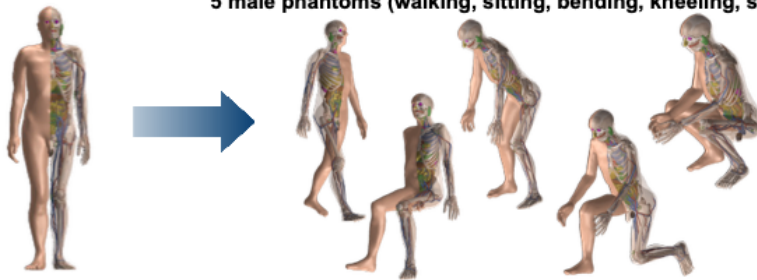
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Courtesy of Prof. Yeon
Soo Yeom, Yonsei
University and ICRP TG128

A variety of computational phantoms

Posture-Dependent Reference Phantoms

5 male phantoms (walking, sitting, bending, kneeling, squatting)



5 female phantoms (walking, sitting, bending, kneeling, squatting)



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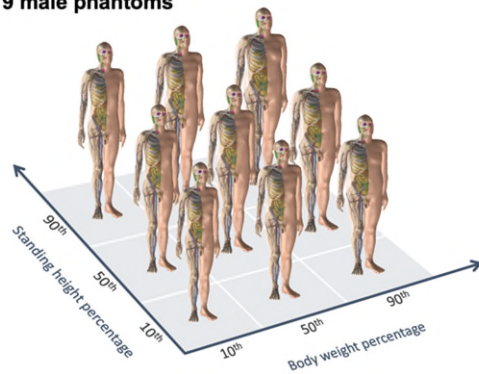
Yeom et al., PMB (2019)

Courtesy of Prof. Yeon
Soo Yeom, Yonsei
University and ICRP TG128

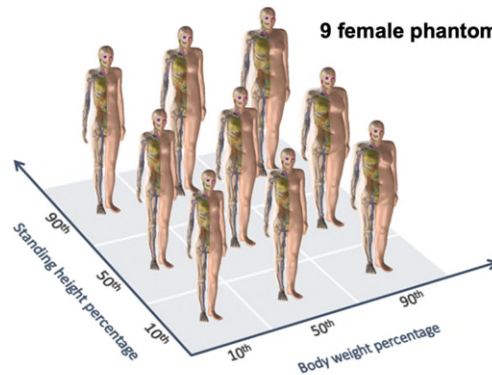
A variety of computational phantoms

Percentile-Dependent Reference Phantoms

9 male phantoms



9 female phantoms



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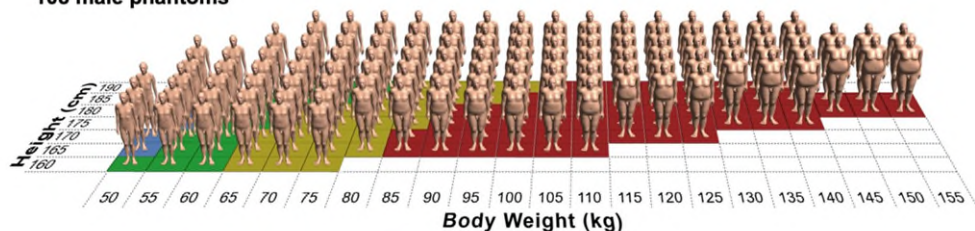
Lee, Yeom et al., PMB (2019) ¹⁷

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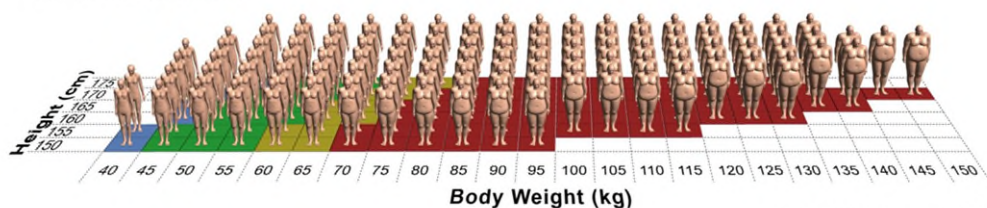
How AI will change computational phantoms

Adult Library (from P145 mesh phantoms)

108 male phantoms



104 female phantoms



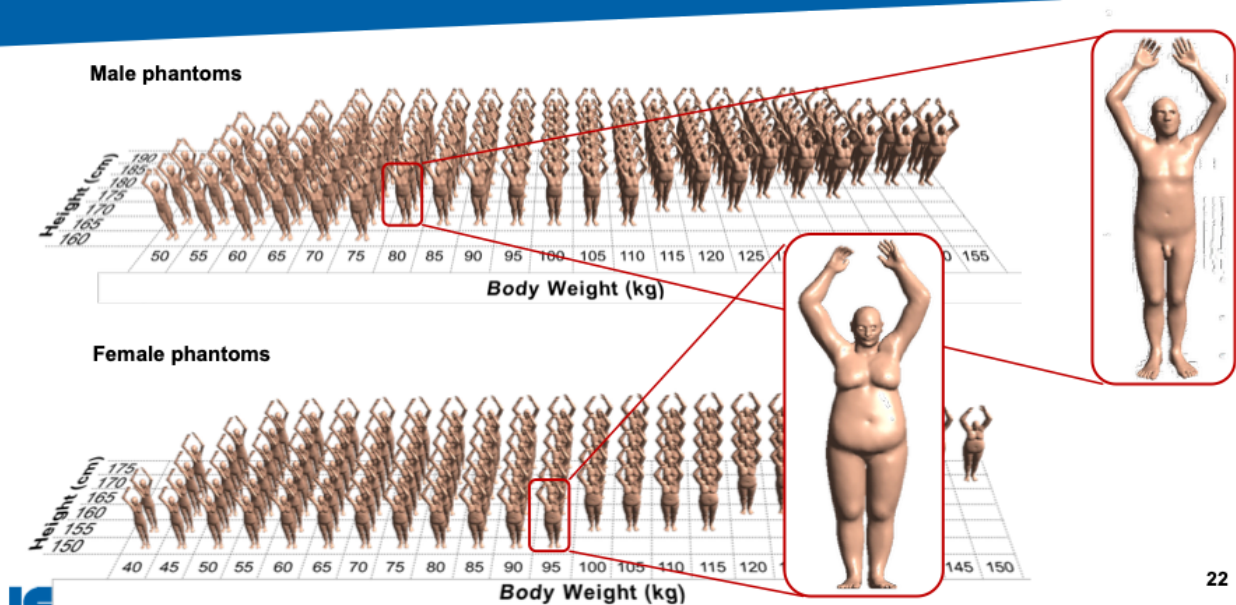
ICRP

21
Choi, Yeom et al., PMB (2020)

Courtesy of Prof. Yeon
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A variety of computational phantoms

Adult Library (Raised Arms)



22

Courtesy of Prof. Yeon
Soo Yeom, Yonsei
University and ICRP TG128

What are CPs used for?

- As “**metrology artifacts**”, they are used as a standardized “body” to define dose coefficients
- CPs are a digital representation of anatomy + tissue composition, and are used to compute quantities like organ absorbed dose, equivalent dose, and effective dose via transport codes (MCNP, Geant4, FLUKA, PHITS, etc.) and assumptions
- This is how ICRP obtains external and internal dose coefficients [15], [16], [17], used in RP practice by most of us

What are CPs used for?

- As an “**inference engine**”, CPs are used to turn measurements $\rightarrow$ organ doses $\rightarrow$ (E?) $\rightarrow$ an “expression” of risk [19]
- Traditionally, in the medical field, CPs have been used to calculate doses from well characterized radiation radiation fields and exposure
- More recently, Monte Carlo methods are extensively used (with limitations due to speed and computational power)

How AI will change computational phantoms

- AI models can be used as a **surrogate dose engine** (MC replacement or accelerator)
- AI models can be **trained on MC “truth”** (from various anatomies and irradiation conditions), to predict organ doses, effective dose, dose maps, etc. much faster than running full MC each time
- This is already possible (and done) in the medical field [18], and is studied as real-time dose estimation for complex non-medical fields

How AI will change computational phantoms

- This use of CPs, though, also introduces **new issues**
- Dose conversion coefficients represent a smart way to directly obtain equivalent, committed and effective dose from Reference CPs without running complex simulations
- Today, with a large enough catalog of CPs differentiated by sex, stature, BMI, etc., and a deep learning network able to quickly probe them, **the need for conversion coefficients could even subside!**

How AI will change computational phantoms

- However, **the meaning of those CP-computed doses needs to be better understood**, especially for radiation protection
- In a future in which different CPs co-exist, and inevitably produce different dose results, which one is to be accepted?
- **If a “national” CP produces a higher dose than the ICRP reference CP, which one should be used?**
- The answer is clear today, but what about the future?

Increasing computational complexity

- Full dose calculations are already very complex in the current System
- Adding in the calculation individual factors as population, age at exposure, sex, target organs, etc. would add layers of complexity and rapidly transform the effective dose computation into a **highly intricate, multi-dimensional problem**

Increasing computational complexity

- The implications on the overall System for Radiological Protection and **practical benefits for occupational and public exposure** related to “small” exposures should be **closely monitored**
- Check out the ongoing work of ICRP Task Group 128 [06]

AI is already changing personal dosimetry

AI models are already being applied to **traditional personal dosimetry**, mainly as AI excels in identifying patterns and clusters [25], [26]:

- Improvements in the workflow and expanded information extracted from TLDs [27], [28]
- Automation of cytodocimetry with a automated scoring by using CNNs [12], [11], [13], [14] for population triage during a radiological emergency
- Radon dosimetry with CR39 [29]

AI will change the RP practice

- The current RP system in the practice is based on Operational Quantities defined through the use of the Reference Person and Reference Computational Phantoms
- There is tension between the current “static” system, and a real-time dosimetry system which will allow to become *predictive*, not only *retrospective*
- AI will bring new quantities in the operational dosimetry practice, person-adjustable and updated in real-time

How AI will enable predictive dosimetry

- The combined use of MC and AI models will enable a future dosimetry defined by **real-time, predictive, and autonomous systems**
- But this will bring a shift in perspective, from “*Dosimetric Historians*” (we report the dose after it happens) to “*Dosimetric Futurists*” (predicting and acting before radiation is even delivered!)
- Can we trust the algorithm as much as we trust the ionization chamber 😊 ?

How AI will change regulatory compliance

- Demonstration of regulatory compliance is performed, for workers and the public:
- ...calculating protection quantities H and E in advance, *a priori*
- ...measuring the operational quantity H_p and assessing $E(50)$ after the exposure, *a posteriori*
- All calculations are based on the “Reference Person” model, using computational phantoms

How AI will change regulatory compliance

- In the current demonstration of regulatory compliance, there is no direct connection to the actual characteristics of individuals!
- In a world of AI dosimetry, personalised phantoms and individualised parameters, **we need to rethink what compliance means, and how to demonstrate it**
- Ethical values will play a major role in this shift

How AI will change cytodosimetry

- AI excels in recognizing patterns in images ()
- The golden standard in cytodosimetry, DCA analysis, always had cell scoring as its bottleneck
- Automated scoring by using CNNs have been proposed [12] and demonstrated [11], [13], [14] for population triage during a radiological emergency

How AI will change cytodosimetry

- A hybrid, semi-automatic framework [11], coupling a deep-learning-based dicentric classifier with expert review reached 99.8% specificity, 98.7% accuracy, and 0.977 area under the curve (AUC), among 2000 metaphase images analyzed
- This (relatively straightforward!) application would allow to free tens of expert scorers to more important functions during a radiation emergency

The practice of dosimetry and the RPE

The RPE's role will also shift:

- from being mainly a post-hoc dose interpreter and compliance checker, to managing forecasts and actions
- from static workplace assessments to dynamic digital models
- from “one-number doses” to uncertainty-aware decisions
- AI model governance becomes core RPE work

Will AI make intercomparisons obsolete?

How should EURADOS adjust, to keep the pace?

- Intercomparisons with AI systems?
- Shared training datasets?
- Reference AI models?
- New WG mandates?

AI will amplify EURADOS' role

EURADOS

What AI will never replace

AI is a powerful tool, and will help in estimating dose(s) and risk, but protection goes beyond mere computation.

AI cannot replace the essential human elements:

- Radiological judgement
- Ethical decisions
- Regulatory responsibility
- Interpretation of uncertainty, ambiguity, and the limits of data

Explainability is no more optional

Explainability is a requirement for metrological and regulatory acceptance, not an add-on

- Physics-informed ML
- Constraint-based learning
- Uncertainty propagation through NNs

Explainable AI is fundamental for trust, accountability, and adoption in radiological protection

What ICRP is doing on “AI and RP”

- In 2023, ICRP established (in addition to the Working Party on AI in medicine, already existing since some time) a **Working Party on “AI in Radiological Protection”**, with representatives from all ICRP Committees, and external Experts
- (A Working Party is an optional initial step before forming a Task Group, to assess whether Recommendations are needed in a specific area (or not!))

What ICRP is doing on “AI and RP”

- The mandate of the C4 WP is to explore the **impact** and **implications** that the adoption of AI tools may have on the System for Radiological Protection
- The WP has so far compiled a wide list of scientific references, published a survey on the use of AI in RP, drafted an ICRP policy on acceptable use of AI (within ICRP), and held discussions on various applications of AI in RP

What ICRP is doing on “AI and RP”

Link to the presentation on
the C4 “WP on AI” given
during the 2025 ICRP
Symposium in Abu Dhabi
(including survey results!)



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Disclaimer on the use of AI in this work

Various AI tools -including ChatGPT 5.2, Gemini 3, Copilot powered by GPT5, NotebookLM, AlphaXiv- have been used in preparing this presentation (versions available in early 2026).

All sources and information have been independently researched and verified by the Author.

The content of the slides has been written by the Author, who assumes full responsibility for the material presented.

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The content of this presentation represents the opinion of the Author.

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- the Federal Authority for Nuclear Regulation (FANR),
- the International Commission on Radiological Protection (ICRP),
- the European Radiation Dosimetry Group (EURADOS).

References

[01] Vinita Chauhan, Olivier Armant, Karine Audouze, Imène Garali, Miroslava Cuperlovic-Culf & Yi Wang (03 Feb 2026): Foundations for AI-assisted Adverse Outcome Pathways (AOPs) in radiation research, International Journal of Radiation Biology, DOI: 10.1080/09553002.2026.2618532

[02] Yunan Gao, Haiyang Li, Han Gao, Zhen Chen, Yidi Wang, Wei Tang, Zhanpeng Li, Xiang Li, Long Chen, Congchong Yan, Liang Sun, THE APPLICATION OF NEURAL NETWORK TECHNOLOGY BASED ON MEA-BP ALGORITHM IN THE PREDICTION OF MICRODOSIMETRIC QUALITIES, Radiation Protection Dosimetry, Volume 198, Issue 7, April 2022, Pages 405–413, <https://doi.org/10.1093/rpd/ncac062>

[03] Missiaggia, Marta, Enrico Pierobon, Chiara La Tessa, and Francesco G. Cordoni. “An Exploratory Study of Machine Learning Techniques Applied to Therapeutic Energies Particle Tracking in Microdosimetry Using the Novel Hybrid Detector for Microdosimetry (HDM).” Physics in Medicine & Biology 67, no. 18 (2022): 185002. <https://doi.org/10.1088/1361-6560/ac8af3>

[04] Missiaggia, M., Pierobon, E., Castelluzzo, M., Perinelli, A., Cordoni, F., Centis Vignali, M., Borghi, G., Bellinzona, E. V., Scifoni, E., Tommasino, F., Monaco, V., Ricci, L., Boscardin, M., & La Tessa, C. (2021). A Novel Hybrid Microdosimeter for Radiation Field Characterization Based on the Tissue Equivalent Proportional Counter Detector and Low Gain Avalanche Detectors Tracker: A Feasibility Study. Frontiers in Physics, 8, 578444.

[05] Missiaggia, M. On the radiation quality characterization in radiation therapy: from linear energy transfer to experimental microdosimetry. Eur. Phys. J. Plus 139, 625 (2024). <https://doi.org/10.1140/epjp/s13360-024-05318-5>

References

[06] ICRP, 2003. Relative Biological Effectiveness (RBE), Quality Factor (Q), and Radiation Weighting Factor (w_R). **ICRP Publication 92**. Ann. ICRP 33 (4)

[07] International Commission on Radiological Protection. “Factors Governing the Individual Response of Humans to Ionising Radiation.” Public Consultation (draft document), posted January 30, 2026. Accessed February 13, 2026. <https://icrp.org/consultation.asp?id=81B70B2F-A66E-4C4D-B6DB-880B8DDAD8AC>

[08] International Commission on Radiological Protection. “Task Group 128: Individualisation and Stratification in Radiological Protection: Implications and Areas of Application” Accessed February 13, 2026. https://icrp.org/icrp_group.asp?id=204

[09] Igor Shuryak, Zhenqiu Liu, Eric Wang, Robert L. Ullrich, David J. Brenner: “Causal Machine Learning Analysis of Radiation-Induced Leukemia and Solid Tumor Incidence in Japanese Atomic Bomb Survivors” medRxiv 2024.04.30.24306639; doi: <https://doi.org/10.1101/2024.04.30.24306639> (pre-print)

[10] Grant, E. J., Brenner, A., Sugiyama, H., Sakata, R., Sadakane, A., Utada, M., Cahoon, E. K., Milder, C. M., Soda M., Cullings, H. M., Preston, D. L., Mabuchi, K. and Ozasa, K. Solid Cancer Incidence among the Life Span Study of Atomic Bomb Survivors: 1958–2009. Radiat. Res. 187, 513–537 (2017)

[11] Wang, Ping, Yingyi Peng, Zhifang Liu, Gang Li, and Na Zhao. “AI-Assisted Chromosome Aberration Analysis for Rapid Biological Dose Estimation of Ionizing Radiation.” Radiation Research, published online February 3, 2026. <https://doi.org/10.1667/RADE-25-00227.1>

References

[12] Seungsoo Jang, Sung-Gyun Shin, Min-Jae Lee, Sangsoo Han, Chan-Ho Choi, Sungkyum Kim, Woo-Sung Cho, Song-Hyun Kim, Yeong-Rok Kang, Wolsoon Jo, Sookyung Jeong, and Sujung Oh "Feasibility Study on Automatic Interpretation of Radiation Dose Using Deep Learning Technique for Dicentric Chromosome Assay," Radiation Research 195(2), 163-172, (14 December 2020). <https://doi.org/10.1667/RADE-20-00167.1>

[13] Jang, S., Lee, J., Kim, S. H., Han, S., Shin, S. G., Lee, S., ... Lee, C. G. (2024). Radiation dose estimation with multiple artificial neural networks in dicentric chromosome assay. International Journal of Radiation Biology, 100(6), 865–874. <https://doi.org/10.1080/09553002.2024.2338531>

[14] Ryan TL, Escalona MB, Smith TL, Albanese J, Iddins CJ, Balajee AS. Optimization and validation of automated dicentric chromosome analysis for radiological/nuclear triage applications. Mutat Res Genet Toxicol Environ Mutagen. 2019 Nov;847:503087. doi: 10.1016/j.mrgentox.2019.50308. Epub 2019 Sep 23. PMID: 31699339

[15] ICRP, 2010. Conversion Coefficients for Radiological Protection Quantities for External Radiation Exposures. ICRP Publication 116, Ann. ICRP 40(2-5), <https://icrp.org/publication.asp?id=ICRP%20Publication%20116>

[16] ICRP, 2015. Occupational Intakes of Radionuclides: Part 1. ICRP Publication 130. Ann. ICRP 44(2), <https://icrp.org/publication.asp?id=ICRP%20Publication%20130>

References

- [17] ICRP, 2024. Dose Coefficients for Intakes of Radionuclides by Members of the Public: Part 1. **ICRP Publication 158**. Ann. ICRP 53(4-5), <https://icrp.org/publication.asp?id=ICRP%20Publication%20158>
- [18] Berris, Theocharis, Marios Myronakis, John Stratakis, Kostas Perisinakis, Apostolos Karantanas, and John Damilakis. "Is Deep Learning-Enabled Real-Time Personalized CT Dosimetry Feasible Using Only Patient Images as Input?" *Physica Medica* 122 (June 2024): 103381. <https://doi.org/10.1016/j.ejmp.2024.103381>.
- [19] ICRP, 2021. Use of dose quantities in radiological protection. **ICRP Publication 147**. Ann. ICRP 50(1), <https://icrp.org/publication.asp?id=ICRP%20Publication%20147>
- [20] ICRP, 2022. Radiation detriment calculation methodology. **ICRP Publication 152**. Ann. ICRP 51(3), <https://icrp.org/publication.asp?id=ICRP%20Publication%20152>
- [21] Igor Shuryak, Zhenqiu Liu, Eric Wang, Xiao Wu, Robert L. Ullrich, Alina V. Brenner, Munechika Misumi, David J. Brenner Causal Machine Learning Analysis of All-Cause Mortality in Japanese Atomic-Bomb Survivors medRxiv 2025.09.03.25335009; doi: <https://doi.org/10.1101/2025.09.03.25335009> (pre-print)
- [22] Zhenqiu Liu, Igor Shuryak, Dose-Response after Low-dose Ionizing Radiation: Evidence from Life Span Study with Data-driven Deep Neural Network Model, medRxiv 2024.04.09.24305578, doi: <https://doi.org/10.1101/2024.04.09.24305578>

References

- [23] Cologne J, Misumi M, Lindner H, Liu Z, Sposto R. Recent evolution of risk analyses in atomic bomb survivor studies: new methods and applications. *Carcinogenesis*. 2025 Sep 4;46(3):bgaf043. doi: 10.1093/carcin/bgaf043. PMID: 41144259; PMCID: PMC12558145
- [24] Mishra, Siddhartha, and Roberto Molinaro. "Physics Informed Neural Networks for Simulating Radiative Transfer." *Journal of Quantitative Spectroscopy and Radiative Transfer* 270 (August 2021): 107705. <https://doi.org/10.1016/j.jqsrt.2021.107705>
- [25] Russakovsky, O., Deng, J., Su, H. et al. ImageNet Large Scale Visual Recognition Challenge. *Int J Comput Vis* 115, 211–252 (2015). <https://doi.org/10.1007/s11263-015-0816-y>
- [26] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks." In *Advances in Neural Information Processing Systems* 25 (NIPS 2012), edited by F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger. Red Hook, NY: Curran Associates, 2012
- [27] Mentzel, F., E. Derugin, H. Jansen, K. Kröninger, O. Nackenhorst, J. Walbersloh, and J. Weingarten. "No More Glowing in the Dark: How Deep Learning Improves Exposure Date Estimation in Thermoluminescence Dosimetry." *Journal of Radiological Protection* 41, no. 4 (November 15, 2021). <https://doi.org/10.1088/1361-6498/ac20ae>

References

[28] Amit, Gal, Roy Vagerman, and Oran Revayev. “TLDetect’: AI-Based Application for Detection and Correction of Anomalous TLD Glow Curves.” Sensors 24, no. 21 (2024): 6904. <https://doi.org/10.3390/s24216904>

[29] Panthanuwong, Pannathad, and Rawiwan Kritsananuwat. “Development of Machine Learning Based Computer Software for Alpha Track counting on CR-39 Using YOLOv8 Instance Segmentation Model.” Radiation Environment and Medicine 13, no. 2 (2024): 96–. https://doi.org/10.51083/radiatenvironmed.13.2_96