SUPPLEMENTARY MATERIAL

Workshops Process

The *Kickoff* workshop set the stage for the conversation with presentations from that highlight the transformational impact of computing on the fields of meteorology and aerospace, as well as the opportunity and appetite for embracing computational approaches in the field of radiation oncology. Specific highlights included Dr. Kelvin Droegemeier, PhD, MS from the University of Oklahoma and recent Director of The White House Office of Science and Technology Policy (OSTP) in the Executive Office of the President (EOP) messaging on the development of computational approaches to prediction in weather and made the case of how important predictive science is for both fields (1). Dr. Karen Wilcox highlighted the impact of computational engineering in aerospace settings and how it was a critical aspect of predictive science that she felt applied to medical contexts well (2). Finally, Dr. Caroline Chung, a practicing clinician scientist, illustrated the data-enabled opportunities and quantification and decision-support challenges for translation of computing into the field of radiation oncology (3). A panel discussion with speakers and members of the organizing committee discussed the opportunities and challenges to be tackled in the subsequent workshops. In addition, a smaller 2-hour interactive workshop was conducted with students unable to be part of the regular workshop.

The first of the four half day workshops, *Topic Session 1*, focused on biology and was titled "The Biological Machinery for Advancing Radiation Oncology: Mechanisms, Systems, and Simulations." Prior to the start of this and each of the following three Topic Sessions had videos made by the day's discussion leaders setting the stage for the day and introducing their thoughts and approach to the day to the group. Two co-hosts began the session with a call to action outlining the goals of the day and 10 discussion leaders led approximately 100 participants from academia, industry, and government, including patient advocates, through a highly interactive experience to address the topic title. Participants ranged from early career to national leadership in stature and reflected a broad range of backgrounds and perspectives with age, geographic and gender balance being a focus of the process. Teams worked through two breakout sessions with question development and then refinement, with the generation of a document for each topic question that was later presented in a formal session and then given electronic, formal feedback that was recorded and shared on a workshop customized website. While the organizers met to work on optimizing questions and process, the participants were placed into a dynamic collaboration networking space called Collaboration Corner. In this context they initiated discussions on their own. This format was repeated for each of the four topic sessions. The final session summated the questions and topics of focus derived from the workshop overall and are presented in this text.

The Collaborative Corner: Informal Idea Generation and Team Building Area Trends

A parallel process during the series of workshops called the Collaboration Corner (CC) provided a forum where the individual participants could brainstorm, chat, meet new people, and, collaborate on ideas and concepts. In contrast to the more formal question process that was actively managed by the co-hosts, invited

discussion leaders, and the organizers, the CC provided a more organic environment to allow participants to have a place that was more flexible in scope, size, and membership. The currency of the CC took the form of virtual sticky-notes that had links attached to allow for editing the ideas further via Google docs. The CC had the practical and necessary role of progressing discussions among participants while the organizers and other leaders had to convene on the side to integrate or process data to create next steps in question development and theme management.

The CC generated 88 comments and 74 unique collaborative ideas. These were labelled as (1) transformative idea, (2) testable, (3) integrated idea (combined computer science, clinical, and bench biological research), (4) commented upon status, (5) and were incorporated into the workshops.

When these arbitrary "scores" were assigned to the 88 comments and not using strictly robust statistical methods, 22 ideas obtained the most interest (Supplementary Table 2). If one only looked at comments and signups, proxies for collaborative interest, 37 of these ideas garnered the most interest. When integration of computer science, clinical, and basic biologic research was used to evaluate the questions, 18 had reasonable capacity to be called integrated and 9 of these also demonstrated high interest from the group overall.

These ideas could be considered in terms of transformative potential and testable capacity. The numbers of ideas in these categories that seemed to have emerged as "top" scorers were 20 and 15 respectively. The top 12 transformative and testable ideas from the CC were selected to mirror the more formally mentored pathway questions noted above, including the additional criteria that they would reach across disciplines, leverage DOE computational resources, and be broadly useful either for radiation oncology or other fields of science and medicine, producing the following ideas:

1. Insert a chip in/near the tumor that transmits (near-)real-time data on various parameters.
2. Use the genomic and radiomic signature of a patient to predict their future treatment trajectory.
3. Nano-robots accurately delivering radiation to tumors (or for sensing and treatment in general, these nanobots could be wearables).
4. Use natural language processing (NLP) to convert electronic medical records (EMR) and notes to ontology items for analysis.
5. Use ecology and evolutionary principles of resistance to adapt therapy.
6. Use boson sampling through quantum computing with additional processing power provided via the internet of patient things.
7. Work on nanoparticle sensitizers and radiotherapy agents to enhance LINAC therapies and theranostics to tackle diffuse, metastatic disease.
8. Modeling language tools to take a next step toward use of augmented reality tools (e.g. HoloLens) to design, test and run code so that the process becomes more intuitive and accurate for clinicians.
9. Use emerging virtual reality/augmented reality tools to augment radiosurgery/SBRT (training), etc.
10. Explore "all possibilities"- (e.g. Monte Carlo sampling) and possibly use quantum computing for stochastic

modelling of states.

11. Improve conventional technique – UQ from imaging through treatment to create baseline assessments.
12. Run all possible combinations of sequence/timing/dose/frequency of approved and new treatments to determine the optimal individualized combination at any point in time and track along with all the available feedback/measurement and continued personalized adjustments based on a digital twin.

Group Dynamics Over the Workshops

In the process of the four half days, the entire group became far more productive given increased comfort levels with the technology of the virtual online platform and each other, and the simultaneous exhaustion of their pre-existing ideas leaving them both mechanically and mentally equipped for maximum creativity. In addition to these two trends, the organizing committee performed an intervention between the end of session two and the start of session three to formally request that participants move past the discussions surrounding the issues of data collection and sharing. It was clear that the issues regarding data collection in the environment from which the participants came was something many struggled with, and this made it difficult for some to think about what they would do with the data in hand. Most were able to function well with this constraint making sessions 3 and 4 productive.

References

1. McGovern, A., Rosendahl, D. H., Brown, R. A. & Droegemeier, K. K. Identifying predictive multi-dimensional time series motifs: an application to severe weather prediction. *Data Mining and Knowledge Discovery* **22**, 232-258, doi:10.1007/s10618-010-0193-7 (2011).
2. Kapteyn, M. G. & Willcox, K. E. 3-7 (Springer International Publishing).
3. McGee, K. P. *et al.* Magnetic Resonance Biomarkers in Radiation Oncology. *Med Phys*, doi:10.1002/mp.14884 (2021).

Supplemental Table S1
Full List of questions the participants developed over the workshop series that were brought into the start of the World Café final session.

Initial Rank	Workshop Day (1-4 or merged from several)	Group (n/a if merged)	Question
1	2	3	How to blend ML and mechanistic models for radiation oncology?
2	3	8	How to develop more continuous and dynamic monitoring of patient response with a feedback loop for future therapeutic intervention?
3	3	3	How to associate biomarkers across scales? (Tumor vs Normal, population vs individual, Early biomarkers for late tumor outcomes....)
4	2	11	How to effectively combine multiscale images and physical models to remove bias in models? (How to ensure the data is representative?)
5	3	2	Prioritizing biomarkers (radiomics, genomics...) How do we do this best for a patient and customize into a patient avatar? (supercomputer-defined biomarkers)
6	3	7	How to use advanced computing to guide use of radiation and systemic therapy in clinical practice? (how to select systemic therapy as well as timing, implementation, education, rollout...)
7	1	3	How to overcome uncertainties in modeling and data?
8	3	11	How to develop a measure of "health" that reflects the individuality, complexity, and nuance of an individual patient? (many different normals, learning from patients' lifestyles...)
9	2	8	How to achieve machine-human hybrid approaches? (interpreting data from models, and how to feed human input back into the models)
10	2	5	How can advanced computing help us in the featurization of the data? (where to dig, extracting meaning from data)
11	1	1	What are the patient specific factors that lead to formation of cancer and response to treatment?
12	1	4	How does radiation kill a cell, a neighborhood of cells, a tumor, and a patient and how does heterogeneity affect this process at multiple scales?
13	2	9	How to achieve prediction in real-time for physicians?
14	4	4	How to incorporate patient-level experience into decision weightings/penalties/processes? (subjective inputs and objective measures, patient-centric approaches...)
15	2	7	How might we use advanced computing to connect previously unconnected data?
16	3	1	How to develop tumor monitoring strategies (serial, granular...) during therapy to alter treatment? (how to do these in a non-invasive way)
17	Merged	n/a	Can patient specific computational models be employed (even custom silicon) - my twin infrastructure is not the same as yours's? One digital twin size does not fit all....
18	1	7	How to collect data in a noninvasive fashion that yields standardized data, takes advantage of "latent data" using wearables and other advanced sensing techniques?
19	2	2	How to understand when you can trust the model? (What is the minimum data size?)

20	4	5	How do we compute all possible trajectories and, once computed, analyze them to inform limitations on prediction and variations? How do we regularize the analysis of the trajectories?
21	Merged	n/a	Can we develop visualization tools and biomarker tensors of normal and tumor tissue that integrate sensor data and radiation dosimetry to define an individual's biologic dose to allow optimal treatment planning and radiation blending (photon/proton/other mixtures with other agents as well)?
22	Merged	n/a	How can advanced computing and biomarker data integration help develop new drugs and treatment methods?
23	2	1	How to achieve data standardization and precision measurement? (Quantitative inputs and outcomes)
24	4	3	How to determine the significant parameters in building an in-silico patient? (how to eliminate factors? how to identify factors? from population predictions to patient predictions)
25	Merged	n/a	Can we go back in time to use debiasing methodologies to re-evaluate previous clinical studies and/or combine disparate studies to answer questions with newfound statistical power? Can we use noise?
26	1	2	How to bridge between pre-clinical and clinical data/findings?
27	4	2	How might we optimally integrate models into patient care frameworks? (Actionability, is there an intervention and can it be made into a go-no-go?)
28	4	6	How to model time-varying risk and right-censored time-to-event data?
29	4	7	How might we define which outcomes (plural) that we want to predict? (patient/healthcare team, prevention/treatment/surveillance)
30	3	4	How to develop physically tumor-embedded devices and integrate biomarkers for patient simulations (i.e., digital twin)
31	3	6	How do we develop robust and reproducible AI models to better identify and predict microscopic disease either before or after treatment?
32	3	5	Knowing when biomarkers are not robust? (Making biomarkers actionable, technical and clinical validation...)
33	3	10	How to better understand timing with specific patients (every 3 months, really, we can't be more tailored than that?)
34	4	1	How to have more fair, less bias, more ethical/humane predictions from our models?
35	4	9	How might we continually learn from the data acquisitions, decisions we make, and mistakes we make? (Currently, we tend to bury our mistakes, or at least not publish them)
36	2	6	How might advanced computing help us to understand the utility of complex models beyond simple models?
37	3	9	How can biomarkers measure tumor, normal tissue, technical, heterogeneity? (which biomarkers at which stage?)
38	4	8	How to utilize quantum computing to define the states and model the trajectories?
39	1	9	How and when and where do we intervene in toxicity? (Tumor Clock)

40	2	10	How might we use advanced computing to learn and explain ontology? (Advanced computing might know things we don't. How to get that understanding out of the "black box?")

Supplementary Table S2
Collaborative Corner Ideas

1. **(Example) — Wouldn't it be great if we could...** figure out how cancer cells behave under various forms of radiation **...by...** exposing them to the Hulk and other radiated superheroes?

Comments:

- *Any work done on the correlation between lesion uptake of radionuclides and temporal dynamic of change in lesion volume?*
- *So, we do have some "clean" clinical situations where our predictions on outcomes are very good, and we can use these to "develop and test" models. For example, conventionally fractionated radiation therapy for small cancers of the larynx cure greater than 90% of patients. Similarly, radiosurgery for brain metastases or small lung nodules provides excellent control. We can estimate the number of tumor cells in these lesions, and we can back-calculate the dose response curve for individual cells. We can then use these estimates in other situations where's the control rate is less good and see if adding some probabilistic components, perhaps including variables related to variations local biological factors, to see if we can accurately model outcomes in these other situations. At the other extreme, there are clearly situations where our control rates are not good and these also provide useful "boundary condition" data can be used to validate or guide our models.to estimate the number of tumor cells, their response rate, etc.*

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2. Wouldn't it be great if we could monitor outcomes for all patients receiving radiation therapy by using EMRs and ML/AI?

Comments:

- *As one who has been doing manual retrospective chart reviews (on hundreds/thousands of charts!) I have to say that it would be nice if EHR's had a "baked in" system whereby one can annotate when/how a cancer patient fails. But it would still be dependent on MD's filling out the chart (which probably wouldn't happen, given "click fatigue.")*
- *I think with enough data (requiring sharing), we may be able to move past formal ontologies and have the model learn these relationship*
- *Radiotherapy has three silos of data; treatment planning, treatment delivery, and clinical information. The first two have structured data but clinical data is unstructured. It would be nice to have clinical workflow templates that can make clinical information structured*
- *Fully agree NCI-DOE funding multi-institutional, professional society collaborative efforts that both develop the ontologies/databases and use them to construct meaningful sources is important. The most effect solutions are grounded incremental steps that actually produce data.*
- *Absolutely! We should be learning from the vast majority of patients treated. Fixing this is key to addressing removing selection bias that creeps in because of which subset of patients for which you can get data. It would mean that we can then include underserved populations, rural populations. patients treated in the range from community clinics to major academic cancer centers.*
- *Making EMRs more accessible and friendly to patients and caregivers will substantially improve EMR data quality.*
- *Do we understand how different types of cells are affected by radiation? That may provide some good insights.*
- *There are some nice works done in this area (no specifically for RT I guess) using natural language processing (NLP) on EHR data; the catch is the each institution will probably need to set up its own system for data annotations; but surely the framework is there and can be taken advantage of.*
  https://scholar.google.com/scholar?hl=en&as_sdt=0%2C22&q=NLP+on+EHR&btnG=
- *Key is universally accepted data dictionary, ontologies, and taxonomies*
- *Adding on the NLP comment, we can have generative machine learning models simulate outcomes based EMR data and existing knowledge on other factors*
- *Since most of the EMR's are built around billing, would there be a way to harness the strength of the largest single payer in the U.S. (Medicare) to require that some of this standardization be built into the EMR and thereby create a dataset that could be used for subsequent analysis?*
- *Yes, it would be great to leverage the different aspects of EMR to "self check" each other. An outcome can be reflected in the EMR in many different ways. How can we best use that to our advantage?*
- *I think it would be great if the NCI spent some effort on developing a standardized data base or form to be used for specific tumor types or organs that would also allow the patient to be followed and updates on response, toxicities, etc., added over time.*
- *Ditto this. The current EHRs are not designed in a manner that makes the collection of discrete information efficient. This is an enormous problem gathering large scale clinical Data*

3. Wouldn't it be great if we could standardize public datasets by having a protocol with common metadata and have ML models more comparable?

Comments:

- *How can we keep radiation oncologists (rare resource) interested and in the loop during increasing competitions?*
- *Would it be useful to identify quality metrics for the public data?*
- *and share information between one doctor and another.*
- *and getting the data in the hands of a crowd of different scientists / enthusiasts from different backgrounds -- and have competitions to pitch a variety of approaches against one another. For example in protein structure prediction there is an annual competition to figure out the structure of a protein -- similarly for each radiation oncology dataset released, there can be a challenge question and a prize.*
- *Involving Apple, Garmin and Fitbit is a necessary, although not sufficient, step.*

4. If we could use the genomic and radiomic signature of a patient to predict their future radiation treatment trajectory?

Comments:

- *And if we could monitor changes to those signatures over time (probably easier with radiomics than genomics) as a signature for prediction.*
- *The index is not based on more than one fraction....in reality it can be modified by rate of treatment, agents/drugs, fraction number, comorbidities, etc. It is not a fixed number. So, we have room for improvement here. Great idea.*
- *The concept of radiation sensitivity index is already present -- could we take this further by having an in-silico model that predicts sensitivity to radiation at multiple scales -- genome scale, pathway scale, cell fate scale, microenvironment scale etc. One can make this modular where each model handles a scale and have an "oncosimulator" convolve or integrate across scales. The modules can be powered by AI or physics-based models or a combination. The question is will such an approach ever be able to capture the biological complexity and hence be predictive -- so the models have to evolve and we need an aggressive strategy to measure our progress and discard bad models and improve the good models*
- *Need to design measurements to directly capture changes we are aware of.*

5. Wouldn't it be great if we could identify and track all abnormalities (e.g. cancer lesions) in an individual over time by computationally assembling and analyzing all longitudinal patient scan data?

Comments:

- *And correlating that advanced imaging data with molecular and biological changes monitored with corresponding serial biopsies/liquid biopsies*
- *Would be great if the reporting and analysis of the serial imaging took into account the radiation or other targeted therapy delivered and dose distribution and reported this out in a standardized way.*
- *Imaging data allied to incidence reports could revolutionize uncertainty quantification*
- *Definitely second the collection and collation of longitudinal imaging data :)*
- *Good observation. Combining information from multiple sources, in a longitudinal way, can drastically cut down uncertainties.*
- *Would be great if we can track the tumor behavior reliably during the radiotherapy course (weeks) in addition to the time scale of several months. Imaging resources are limited though.*

6. Wouldn't it be great if we could use early treatment response dynamics (imaging, PRO, liquid biopsies) to predict individual patient's response for the remainder of the treatment and outcomes

Comments:

- *Timing vs sensitivity is the concern here.*
- *An example is the ADC as imaging biomarker at the beginning of RT course for glioma response. Research like that was conducted in past two decades.*
- *An interesting question related to that is the "timing" of "early" data collection: early enough so that there is room for intervention, and not too early so that RT effect hasn't been manifested yet.*

7. Wouldn't it be great if we could monitor changes to a patient's tumor/tumor microenvironment during the course of treatment by monitoring changes in imaging/radiomics signatures?

Comments:

- *These are all superb ideas! I was originally coming at this from the other direction: i.e. that maybe we can interpret changes in the longitudinal signatures/measurements that we already have available and see how they correlate with changes in the tumor/tumor microenvironment, but I like the idea of directly measuring changes as well.*
- *This is a great idea....take it big...in every cell in real time with models to test things like what kind of radiation for this patient is best...or mix....protons, electrons, photon, radioisotopes.....etc. Go big. Imaging we have a quantum computer than can keep track of 10^25 cells at the same time....each described by a simple model made up of 10^6 PDEs.....as an example..*
- *Wouldn't implantable dosimeters be great?*
- *At LLNL, bioengineers have developed implantable probes for pH and oxygen sensing. Adding other sensing modalities should be possible in the future*
- *How can we leverage on-treatment imaging or procedures in a systematic way that clinicians can easily incorporate into treatment decisions?*
- *Your comment would relate well with idea on Card 10, as well.*
- *A reference to the Myeloma work mentioned: https://clincancerres.aacrjournals.org/content/clincanres/early/2020/12/22/1078-0432.CCR-20-2839.full.pdf*
- *Adding the other data types would add a lot of power to the predictions.*

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8. Wouldn't it be great if we could remove human bias from e.g. skin scoring of wound healing from cutaneous radiation injury, to determine benefits of treatments over time?

Comments:

- *In the case of wound healing, it would be interesting to be able to assess how macrophage profiles at the wound site correlate to clinician assigned scores, assess the extent to which these quantitative and qualitative metrics of healing really diverge, and account for that uncertainty in our models.*
- *This is where animal models may be useful. Apart from human evaluation, one might consider a long list of biochemical and other "observer neutral" measurements.*
- *This may be viable with modern machine learning methods: there are now some techniques coming up that are useful for estimating the bias accounting for them in different parts of the data and protocol*
- *If we use human evaluation as gold-standard, how would we know that ML is doing the right thing?*

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9. Wouldn't it be great if we could model tumor growth by building interpretable mechanistic models whose parameters can be predicted from imaging/genomics using machine learning?

Comments:

- *This idea resonates with me -- interpretability is key as initially we will do poorly on prediction -- but over time we can improve -- i am thinking a combination of AI powered and physics powered models here*
- *Yes, mechanistic models are very nice. Will need a concerted effort to calibrate with longitudinal data. The question that excites me is what data to collect, when, and how often*
- *Wouldn't it be great if we could just machine learning to *propose* mechanistic models for tumor growth?*
- *I agree - optimal experimental design is an interesting (and important) question.*
- *Great question. I guess many mechanistic parameters may not need to be patient specific. Some likely are. Let's find out which are which*
- *Can we simplify the calibration part by learning parameters from "similar" patients using machine learning?*
- *Exactly, I am particularly interested in how we can use machine learning to advance our understanding of underlying biophysical mechanisms within mechanistic models, particularly to determine which biological factors are most relevant to treatment response, and how can we adapt our treatment approaches on a patient-specific basis*

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10. Wouldn't it be great if we could insert a chip in/near the tumor that transmits (near-)real-time data on various parameters?

Comments:

- *This could also be combined with in vitro models for testing predictions?*
- *Other potentially informative features: metabolism, temperature, vasculature density .*
- *Will be interesting to think about what factors would be highest priority for this near-continuous monitoring - things like pH, oxygenation, etc. come to mind.*
- *Wouldn't it be great if we could monitor tumor response/biomarker expression by utilizing nanoparticles as "chip" for near-real time data?*

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11. Wouldn't it be great if we can use AI/DL to understand complex mechanisms of cell/tumor response that can then be targeted for treatment.

Comments:

- *Good idea! I have a few work along this direction. Very interesting!*

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12. Wouldn't it be great if we could tell patients what more they could do for themselves (e.g. exercise - but what kind? at what time? how much?, what specific foods?, addressing emotional and physical aspects) to work with us to improve their outcomes -- supported by data and ongoing feedback to them -- it would be so empowering and motivating

Comments:

- *Continuous monitoring with feedback (incentives) will be indeed impactful. In our ATOM-HP projects, we found that younger cancer patients who played Pokemon Go had a better activity signature than older patients. We should also be aware of the alarm-fatigue while thinking about the design of incentives.*
- *NIH has the active data collection happening in combining some these physical aspects in https://allofus.nih.gov/*
- *This is a great business idea. How do we develop a viable business plan. there are plenty of patient engagement platforms and apps from which to choose, but how do we build a large enough patient community to make this self-sustaining.*
- *I think we already can do some of this, but it would be better if patients (and clinicians too!) actually listened and acted upon that advice!*
- *They may be more likely to listen and feel motivated if there is an ongoing feedback mechanism (e.g. serious gamification approaches?)*
- *Ver important indeed! I guess this requires integrating physicians' notes into analysis, using streamlined approaches such as Natural Language Programming (NLP).*

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13. Wouldn't it be great if we could test treatments (individual and combination) in vitro before administering them in vivo so we could determine optimal dose for specific patients rather than treating everyone as the "average" patient?

Comments:

- *Maybe easier to get real-time information/feedback in-vitro too, compared to in vivo.*
- *Totally agree with preclinical testing. An ex vivo system that truly replicates human physiology such as 3D organ on chip testing would be best.*
- *Love it! Also, agreed on the average patient thing. It is crucial for these models to incorporate estimates for a variety of patients/patient types (i.e. random effect).*

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14. Wouldn't it be great to run all possible combinations of sequence/timing/dose/frequency of approved and new treatments to determine the optimal individualized combination at any point in time and track along with all available feedback/measurement and continued personalized adjustments based on a digital twin?

Comments:

- *See some work along these lines in pharma/medical oncology, likely incentivized by financial considerations. How can we pull this off in radiation oncology if the result is going to be less revenue? Need a policy fix to put all oncology treatments on the same cost-benefit scale.*
- *I am a big proponent of a digital twin as a goal.*
- *Digital twin is crucial!*
- *YES!*
- *Multi-scale, multi-dimensional (spatial and temporal is key!) personalized digital twin that incorporates multi-modal treatment*
- *What about an entire population of 'twins' so we can characterize the uncertainty in our predictions?*
- *Me too! Also to this point: such searches can potentially be done in a more individualized way and efficiently using recent machine learning tools*
- *The cool thing about a digital twin is that an entire population of twins is same as one single twin multi-tasking on different processors doing different things! So yes, a population of twins should help.*
- *Agreed. Excited to know more about digital twins for oncology*
- *Digital Twin with predictive AI capabilities.*

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15. Wouldn't it be great if we could capture physician's experience into predictive modeling and design a fully transparent and interpretable machine learning/deep learning models to predict patients' response

Comments:

- *Even better...rather than replace an MD (how this sounds) make the big DOE machine be able to augment a physician in real time based on her approach to optimize her path in the process of helping patients via visual aids, decision making support, data interpretation and review… etc. Not a right path finder but an all-paths guide.*
- *This is useful. Am interested to discuss more*

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16. Wouldn't it be great if the radiation photos/screen shots could be posted into the patient's My Chart with the Radiologist's comments in their original entry and then in layman's common English. Note: a patient often does not talk or see his/her radiologist. In the patient's consult with the doctor, the more generalist doctor often does not let the patient see the doctor's EPIC screen and the doctor does not give the details of the findings.

Comments:

- *GREAT idea to expand patients' understanding!*

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17. Wouldn't it be great if we could solve the data access problem by having a national database accessible by research institutions?

Comments:

- *https://datacommons.cancer.gov/*
- *There are examples of that at NASA Ames for Life Sciences research on the International Space Station (ISS): tissue sharing and gene sharing. The GeneLab Data System (GLDS) is an open access database containing fully coordinated and curated 'omics' (genomics, transcriptomics, proteomics, metabolomics) data, detailed metadata and radiation dosimetry for a variety of model organisms. https://genelab.nasa.gov/about*

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18. Wouldn't it be great if we could create an open source, non-vendor based, solution for gathering wearables data so that we don't have to implicitly support commercialization of health data in order to research in this area.

Comments:

- *It is great to have a benchmark dataset, with meta data information such as patient descriptions, data collection environment, to enable ML/DL-based augmentation (e.g., using generative models).*

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19. How to use ML when you know certain factors and how certain things work, but not all?

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20. Use the computational power of patients' tablet/iPhone/etc while they are in the clinic for biological simulation

Comments:

- *In the right direction. Couple the power of the mobile device in the patient's hands with the large scale and advanced computing resources. How would we develop a high-fidelity predictive model for the patient that is accessible from the patient's own device? How can the patient's mobile device be part of a learning system?*

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21. Wouldn't it be great if we could use the processing power of patient and caregiver smart phones and tablets to power cellular-level agent simulation models?

Comments:

- *Similar comment to #20. Think bigger in terms of compute.*

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22. How to keep track of multiple features (dosage, toxicity, ...) using ML?

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23. Collaboration: Create a predictive model for tumor sensitivity using pathology and radiology data?

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24. Wouldn't it be great if we could model physical damage to cellular components at cellular scale by using computational simulation to test radiobiological effects in silico across "virtual cell lines"?

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25. Wouldn't it be great if we could identify what data elements are biased in our datasets by learning what data

to prospectively collect to build cleaner data sets and better models

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26. Would it be great if we have a solution package for imaging quality as input to AI?

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27. Individual and I discussed integrating some machine learning models into a multi-layer neural network to build time-dependent patient representation models

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28. Work on nanoparticle sensitizers and radiotherapy agents to enhance LINAC therapies, theranostics to tackle diffuse metastatic disease

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29. Wouldn't it be great if we can seamlessly combine data driven ML models with physics-based models either at the same scale or at multiple scales?

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30. Wouldn't it be great if we had a set of standardizations and platforms that enabled us to collaboratively develop models, so our focus could be more on the analysis and less on how do we combine data from other institutions?

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32. Wouldn't it be great if we could aid treatment decisions by integrating multiple data types to assess the tumor "state" at different time points?

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33. Somebody could collect and clean our Data?

Comments:

- *Exactly. That should be basis for collaboration, especially international collaboration.*

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34. Wouldn't it be great if we had standardized segmentation that met requirements for large-scale use without human expert curation by leveraging simulation-based approaches (e.g. transfer learning or synthetic data)?

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35. Wouldn't it be great if someone developed a way for EHR systems to feed anonymized data structured more for research than for insurance and lawyers into a shareable repository?

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38. Wouldn't it be great if somebody was developing education and outreach programs to collaborate across disciplines, funding agencies, and with patient and patient families?

Comments:

- *Would also be interested and can think of others too*
- *Agree with this terrific idea. I am ready to volunteer. Maybe we should crowdsource the idea and build a volunteer army from among radonc professionals.*

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40. Wouldn't it be great if we would have the data analysis pipeline that is tunable to the problem at hand?

Comments:

- *As this applies to the new approaches for modeling radiation using computational models.*

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41. Improve reproducibility of publication results.

Comments:

- *As this applies to the new approaches for modeling radiation using computational models.*
- *Yes!! Especially moving from "minimal reporting" (like https://academic.oup.com/jamia/article/27/12/2011/5864179) to "machine readable reporting"!!!*

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43. How to improve data quality by coupling human and machine evaluations (say, of tissues under treatment, or progress of disease)?

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44. Wouldn't it be great to be able to tell, in real time, what is going on with the tumor we are treating at the molecular level?

45. Someone could computerize the process of observing changes in wounds overtime to remove human bias

46. What would you like someone else to do for you -- I would like someone else to make data and knowledge available to me on scales that I don't focus on in my models. A consortium where I can constantly bump into folks that have the same end goal but work on complementary methods, scales etc.

47. Wouldn't it be great if we can have a massive dataset with curated data, well stratified to represent different populations and following a standardized taxonomy?

Comments:

- *We don't need to enforce but use advances in computing technology to 'enforce continued collection [and automated curation] with rigor.*
- *Great idea, Dani. But no one here so we can discuss offline.*
- *Wouldn't it be great if we could enforce continued collection with this rigor indefinitely?*

49. Utilize a database that is somewhat limited like pediatric oncology where most children were on trials and imaging and path date exists to try out some modeling ideas.

Comments:

- *I am on the research arm of a COG clinical 3 trial generating images and lots of genomics (GWAS/Transcripts/DNA repair capacity in peripheral blood, tumor and surrounding normal tissue). Might be a good model?*

50. Xyz, Pdq, and I discussed that we would want (1) more automation in physics workflow (2) automated knowledge of where to dose escalate/de-escalate (3) dept. data managers to collate different data streams and clean to make research-ready

51. We like mechanistic models that include kinetics to understand cell-cell and TME for better benchmarking of radiation treatment. We would also like better control for metastatic disease and ways to include targeted radiotherapies to advance radiation oncology treatments.

52. Wouldn't it be great if models (digital twins) at different scales and for different mechanisms could seamlessly interact and inform each other to describe each patient's predicted outcome.

53. Wouldn't be great to have nano-robots accurately delivering radiation to tumors?

54. Wouldn't it be great if we can use ecology and evolutionary principles of resistance to adapt therapy away from Max Tolerable Dose to Maximize Biological Efficacy.

55. Personalization with diverse data

58. The bridge. What data and modelling is relevant?

61. Wouldn't it be great to use NLP bots to convert EMR, notes to ontology items for analysis?
Comments:
- *When you say Ontology, do you mean Knowledge Graphs?*

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62. How can topological and geometric aspects of data help in ML -based analysis?

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63. A major breakthrough will happen when we can do boson sampling through quantum computing, with additional processing power supplied by the internet of patient things.

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64. Wouldn't it be great if we could use next-generation natural language processing tools to analyze transcripts from hundreds of tumor board discussions to look for patterns and problems with our intuition and decision making?

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65. Digital twin for cancer therapy and clinical outcome prediction powered by multiscale models and use patient sourced data at multiple scale to challenge the digital twin

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66. Wouldn't it be great if we had longitudinal data to apply ML to quantify the temporal dynamics of oncological phenomena?

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67. Wouldn't it be great to build patient-specific simulation models that incorporated both physics and biology of the individual and be able to model multiple scales from sub-cellular to whole-body?
Comments:
- *I would love to see this as "Wouldn't it be great to build a space of patient-specific simulation models that incorporated both physics and biology of the individual and be able to model multiple scales from sub-cellular to whole-body?"*

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68. Reverse liquid biopsy during treatment to assess treatment response while on treatment based on cell death or whatever.

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69. Wouldn't it be great if we had a clear definition of the biological target for radiotherapy?
Comments:
- *I agree it's not clearly defined, but we tend to make the assumption it's all about DNA damage. That could be starting point for comparison of early and late effects. Does that make sense?*

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70. Can we do a science (cancer, radiology) sensitive feature selection for ML methods?

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71. Wouldn't it be great if human-in-the-loop could be integrated in ML/AI? Wouldn't it be great if we had digital twins?

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72. Wouldn't it be great if we could use emerging virtual reality / augmented reality tools to augment radiosurgery/SBRT (training), etc.?
Comments:
- *great idea. I am ready to collaborate on this.*
- *I'd love to too, but this was definitely a "Heisenberg Compensator" type of idea from me - would love to discuss what it would take for this to happen though.*

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73. Wouldn't it be great if modeling language tools took a next step toward use of augmented reality tools (e.g. HoloLens) to design, test and run code so that the process became more intuitive, accurate and intuitive for clinicians.

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76. Wouldn't it be great if AI decision framework tools could have better hooks to clinical data as it evolves to continuously refine and sanity check

78. Wouldn't it be great if we could divide all data standardization issues into two categories: (a) those for which there are multiple standards, such as EHR and imaging data, and (b) those for which no one knows enough to define the standards yet, such as quantum computing. Then, for all of the (a) group, figure out what minimum set of participants would be both necessary and sufficient to establish useful standards. Finally, figure out how to lock them in a room, and for how long, until they reach agreement?

79. Any work done on the correlation between lesion uptake of radionuclides and temporal dynamic of change in lesion volume?

81. Wouldn't it be great if we could leverage AI/ML on radiomics/proteomics data collected during treatment to understand the tumor recurrence (say, its likelihood, loco-reginal or distant, etc.) and design optimal post-therapy follow-up screenings accordingly?

82. Could we use AI to rapidly identify early biomarkers of radiation toxicity, while predicting late effects of treatment?

83. Wouldn't it be great if we could remove human bias from e.g., skin scoring of wound healing from cutaneous radiation injury, to determine benefits of treatments over time?
And modify treatment mid-course.

Comments:

- *OMG! what I would give for an objective wound or tissue edema/fibrosis metric RN!!*

84. Wouldn't it be great if we had access to common compute libraries (e.g. Markov decision processes, reinforcement learning) built for handling time-varying or right censored data so we could easily compare prediction accuracy using a reproducible code "library of models" for different types of multi-omics (e.g. immune values, radiomics, serum biomarkers, CTCs, cfDNA) data "streams" across multiple institutes?

85. Wouldn't it be great to capture the relevant context at the time of observation/measurement to enable calibration of that particular observation across patients/clinical provider/institution across time for clinical application into models or direct clinical application?

86. Wouldn't it be great if we could routinely/regularly capture responders vs non-responders and use the available data to train new AI/ML models?

87. Wouldn't it be great if we could use advanced computing and AI to help develop a "response index" or a predictive measure of response that takes into account all variables, not just in the data, but in subjective inputs as well (e.g. clinician/patient preferences)?

88. Wouldn't it be great to communicate the complexity of personalized treatment (ideally computational and data-driven) clearly enough to patients to ensure we can have informed discussions that include the patient's personal priorities and goals in our care decisions?

Comments:

- *great idea. ties in with patient engagement, and informed consent.*