Healthcare challenges in the 21st Century ...and potential solutions

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We believe in "Convergence Sciences"





Medical Errors & Hospital-Acquired Infections kill up to 440,000 Americans each year

That's more than two jumbo jets full of passengers crashing every day

MEDICAL ERRORS NATION'S THIRD BIGGEST KILLER IN 2013



Source: Martin Makary, Michael Daniel study at Johns Hopkins University School of Medicine





The problem of Big Data – The doctor (and administrator) is drowning



J Clin Oncol 2010;28:4268; JMI 2012 Friedman, Rigby; BMJ Clinical Evidence



Evidence based medicine

- Less then 3% of the patients
- Highly biased population
- Randomized trials rarely done for new technologies



Effectiveness of 3000 treatments as reported in randomised controlled trials selected by Clinical Evidence. This does **not** indicate how oftentreatments are used in healthcare settings or their effectiveness in individual patients.



The grey tsunami

Our Aging Population



The Silver or Grey *Tsunami* is a metaphor used to describe population aging

Example: Elderly patient with rectal cancer - having no evidence can have dramatic consequences



Rutten et al. Lancet Oncology 2008; 9: 494

HEALTH CARE COSTS: WE'RE NUMBER ONE!

Not only does the U.S. have the highest per-capita health costs in the world, but they've been going up faster than in other rich countries for the past three decades - yet we haven't gotten more or better care for our money.



The potential solutions?

The Fifth Revolution Cognitive

Big Data creates more knowledge









Why? The 5 P's of Precision Medicine

- « P » for Personalized
- « P » for Preventive
- « P » for Predictive
- « P » for Participative
- « P » for Pragmatic*

*New: Value-based healthcare get paid based on outcomes that matter to patients.

The NEW ENGLAND JOURNAL of MEDICINE

REVIEW ARTICLE

FRONTIERS IN MEDICINE

Machine Learning in Medicine

Alvin Rajkomar, M.D., Jeffrey Dean, Ph.D., and Isaac Kohane, M.D., Ph.D.

N ENGLJ MED 380;14 NEJM.ORG APRIL 4, 2019

When we have large amount of data we need A.I.

ARTIFICIAL INTELLIGENCE

A program that can sense, reason, act, and adapt

MACHINE LEARNING

Algorithms whose performance improve as they are exposed to more data over time

DEEP Learning

Subset of machine learning in which multilayered neural networks learn from vast amounts of data

Deist, Lambin et al. Med Phys Jul;45(7):3449-3459.2018

Glass box transparent and understandable >< the black box Deep Leaning like



BY TOM LIMONCELLI

Automation **Should Be** Like Iron Man, **Not Ultron**

Courtesy of Joe Deasy http://queue.acm.org/detail.cfm?id=2841313



Iron Man's exoskeleton takes the abilities that Tony Stark has and *accentuates them*. By having his exoskeleton do this for him, he can focus on *other things*. Of course, if he disagrees or wants to do something the program wasn't coded to do, he can *override* the trajectory.



Ultron, on the other hand, was intended to be *fully autonomous*. It did everything and was, basically, so complex that when it had to *be debugged* the only choice was (spoiler alert!) to destroy it.

Proposal: Use the 97%: Rapid Learning Health Care or "Big data in health care"

Clinical trials, comparative

[..] rapid learning [..] where we can **learn from each patient** to guide practice, is [..] crucial to guide rational health policy and to contain costs [..].

Lancet Oncol 2011;12:933

effectiveness research, molecular and biologic data Information-rich. patient-focused data Evaluation of outcomes Patien Transformation of subsequent care Data deliverv aggregation, evidence generation

Examples:

- 1. Radiotherapy CAT (www.eurocat.info)
- 2. ASCO's CancerLinQ
- 3. www.predictcancer.org

Lambin et al. Nat. Rev Clin Oncol 2012, Adv. Drug Dev 2016



Rapid Learning Health Care ("Big Data")

Low data quality

High data quantity

Reality

Unassigned patients
 "Clinical grade" QA/Protocol
 Ad hoc biobanking/translational research

Relton C et al. BMJ. 2010; Burbach et al. Trials 2015; Lambin et al. Acta Oncol 2015

Tension:

Big Data-based solidarity >< Privacy of individuals

Courtesy of David Townend

The technologies helping protecting privacy:

- 1. distributed learning of federated databases,
 - 2. synthetic data and
 - 3. blockchain-like solutions

Privacy preserving distributed learning



www.eurocat.info; Lambin et al. Radiother Oncol 2013, Deist et al 2017



Edmond de Belamy is a generative adversarial network portrait painting constructed in 2018 by Paris-based artscollective *Obvious, sold* for \$432,500 at Christies. Precision medicine will only progress if the collection and integration of *multimodal* data
qualitative and quantitative - across time, and health status can be facilitated in a responsible manner.

Courtesy of Michel Dumontier

The solution = a virtual machine

Multifactorial Decision Support Systems



Lambin et al. Nature Rev. Clin. Oncol. 2013



Prediction by RadOnc's? Two years survival of NSCLC



Non Small Cell Lung Cancer 2 year survival 30 patients 8 MDs *Retrospective AUC: 0.57 (AUC 0.5 = random)*

Cary Oberije et al. Radiother Oncol 2014

1

Prospective trial (n=154): Models (blue) always significantly better then Rad Onc (red) & TNM



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Decision Support System



Protons versus photons

Proton therapy Decision Support System



Cheng Q, Roelofs E, Lambin P et al. Radiother Oncol 2016

Proton Decision Support for H&N cancer



Reduction of complications with protons

Cheng Q, Roelofs E, Lambin P et al. Radiother Oncol 2016

Proton Decision Support for H&N cancer



Markov model cost-effectiveness Lung cancer



Cheng Q, Roelofs E, Lambin P et al. Radiother Oncol 2016

Proton Decision Support for H&N cancer



There are still unknown variables



Cancers are Heterogeneous (RCC)



- PD-L1 alone is not an optimal biomarker
 - Additional biomarkers are needed....

Cell

Heterogeneous Tumor-Immune Microenvironments among Differentially Growing Metastases in an Ovarian Cancer Patient

Graphical Abstract



Authors

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In Brief

Distinct tumor immune microenvironments co-exist within a single individual and may help to explain the heterogeneous fates of metastatic lesions often observed post-therapy.

The Radiomics hypothesis



Humans are apes There is only so much information we can hold at the same time Quantitative Image Analysis Will disrupt current interpretative, subjective imaging

Lambin et al. EJC, 2012;; Lambin et al. Nat Rev Clin Oncol 2017

Future of Radiomics: combine information towards "Holomics", "Panomics" or "Totalomics"

Defining the biological basis of radiomic phenotypes in lung cancer

Patrick Grossmann^{1,2}, Olya Stringfield³, Nehme El-Hachem⁴, Marilyn M Bui⁵, Emmanuel Rios Velazquez¹, Chintan Parmar^{1,6}, Ralph TH Leijenaar⁶, Benjamin Haibe-Kains^{7,8}, Philippe Lambin⁶, Robert J Gillies³, Hugo JWL Aerts^{1,2,9*}

Combining different data types resulted in increased prognostic performances.

¹⁸F-fluorodeoxyglucose positron-emission tomography (FDG-PET)-Radiomics of metastatic lymph nodes and primary tumor in non-small cell lung cancer (NSCLC) – A prospective externally validated study

Sara Carvalho¹, Ralph T. H. Leijenaar¹, Esther G. C. Troost^{1,2,3,4}, Janna E. van Timmeren¹, Cary Oberije¹, Wouter van Elmpt¹, Lioe-Fee de Geus-Oei^{5,6,7}, Johan Bussink⁸, Philippe Lambin¹*

Combining imaging information based on FDG-PET-Radiomics features from tumors and LNs is desirable to achieve a higher prognostic discriminative power for NSCLC.







About the 4th « P»: Participatory

"The good physician treats the disease;

the great physician treats the patient who has the disease".



Dr. William Osler, the father of modern medicine

Lambin P et al. Adv Drug Deliv Rev. 2017

...Nothing about me without me...

Valerie Billingham, Through the patients eyes. Salzburg seminar sessions 356, 1998.

Healthcare in a land called People Power: nothing about me without me.

Tom Delbanco, MD, Donald M. Berwick, MD, Jo Ivey Boufford, MD, Edgman-Levitan, PA, 4, Gunter Ollenschager MD, Diane Plamping, PhD, and Richard G. Rockefeller, MD.

2001 Health Expectations, 4, pp. 144-150.

SDM: The current evidence

Cochrane database of systematic reviews 2017, issue 4. Art. No. C0001431

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| www.cochran | |

Increase in:

- Participants' knowledge (52 studies; N=13.316; ++++)
- Accuracy risk of perceptions (17 studies; N=5.096; +++)
- Congruency between informed values and care choices (10 studies; N=4.626; ++)

Decrease in:

- **Decisional conflict** (27 studies; N=5.707; +++)
- Indecision about personal values (23 studies; N=5.068; +++)
- Proportion of passive people in decision making (16 studies; N=3.180; ++)



Denis et al. JNCI 2017

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| Lump under skin | 0 | 0 | 0 | 0 | D | 0 | D | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | D | 0 | 0 | 0 | 0 | ۵ | 0 | 0 |
| Voice changing | 0 | 0 | | 0 | 6 | | | | 0 | 0 | 0 | 0 | 0 | | | 0 | 0 | 0 | p | 0 | 0 | D | | 0 | 0 | 0 | ø | 0 | σ |
| Blood in sputum | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | D | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Objective response after induction chemotherapy: Maintenance



Progression: → Docetaxel



Progression: → Nivolumab





Denis et al. JNCI 2017



The Exposome, adapted from NIH



What's next?

The patient managing its own data = Patient Electronic Health Record





Conclusions

- Healthcare challenges in the 21st Century
 - Too much information
 - Aging of the population "the silver tsunami"
 - Lack of evidence of treatment efficacy
 - Tension solidarity >< privacy
 - Increase costs
 - Request for more participative medicine
- There is evidence level 1 in favor of Shared Decision making (« Participatory Medicine »)







The clinicians who do not use A.I., will be replaced by the clinician who does.

Confor your attention

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"The D-Lab team"

visit: www.thedlab.info

"The M-Lab team"

website under construction











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