REDUCING THE CLINICIAN BURDEN WITH ARTIFICIAL INTELLIGENCE.

Enhancing EHR use with AI

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Dr. John W Gachago (NIH)

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What is AI?

“Artificial intelligence constitutes a host of computational methods that produce systems that perform tasks normally requiring human intelligence. These computational methods include, but are not limited to, machine image recognition, natural language processing, and machine learning. However, in health care a more appropriate term is “augmented intelligence” (AI), reflecting the enhanced capabilities of human clinical decision making when coupled with these computational methods and systems.”

Augmented intelligence in health care (AMA Board of Trustees, 2018)
Why should I care?

Machines will not replace physicians but physicians using AI will soon replace those not using it. 

Al-augmented multidisciplinary teams: hype or hope? (Di Ieva, 2019) The Lancet

“Interest in artificial intelligence in healthcare soared in 2019 with investors pouring $4 billion into the sector across 367 deals... That's up from nearly $2.7 billion invested in healthcare AI in 2018 across 264 deals.” “Healthcare led AI investment, topping the $2.2 billion raised by financial and insurance AI.”

Fierce Healthcare coverage of CB Insights Report

AI will be critical in meeting the care needs of a growing, aging population facing projected physician shortages. However, concerted effort is needed to assure this tech advances the quintuple aim. National Academy of Medicine Report on AI (Matheny et al., 2019)
Example of FDA Cleared AI: IDx-DR
Screening retinal images to detect retinopathy

• Diabetic retinopathy is when high blood sugar levels damage blood vessels in retina

• Retinal images are uploaded to a cloud server where IDx-DR software analyzes and tells doctor “more than mild diabetic retinopathy detected; refer to an eye care professional” or “negative for more than mild diabetic retinopathy; rescreen in 12 months”

• Note that this product provides a screening decision without having the clinical also interpret the results, and is therefore usable by healthcare providers not normally involved in eye care.

Source: https://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm604357.htm
Example of FDA Cleared AI: IDx-DR
...continued...

<table>
<thead>
<tr>
<th>Benefit</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>IDx-DR offers the important benefits of potential increased access to diabetic retinopathy screening for people with diabetes in a primary care setting.</td>
<td>No risk of direct harm to the patient</td>
</tr>
<tr>
<td>Earlier detection of Diabetic Retinopathy can help to enable the timely delivery of potentially sight saving interventions.</td>
<td>Risk of false negative mitigated by the slow progression of disease and the recommendation to go for annual eye exams.</td>
</tr>
<tr>
<td></td>
<td>A false positive would lead to referral of the patient to a specialist for further examination.</td>
</tr>
</tbody>
</table>

**Benefits outweigh device risks**

Source: https://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm604357.htm
Why now? What is driving this?

There have been several AI Winters in the past – why is AI warming up again? Why do we think this might be the last Winter?

Two reasons:

1. IoT / Big Data
2. Video games!
Terminology challenges

Agreeing to definitions often takes time, even when people are from the same industry.

• “Narrow AI” vs “General AI” – does the software know a lot about a little, or a lot about a lot?

• “Locked”, “Continuous Learning / Adaptive Systems” – does the system continue to learn over time? If so, does it learn after every single use or in a batched-mode?

Artificial Intelligence practitioners have their own set of terminology that sometimes conflicts with what we think of in medical devices.

• “Validation” for medical devices often refers to meeting user needs; but “validation” in data science is making sure the data is valid (e.g. a negative heart rate is probably not a valid piece of data)

• “Bias” is something that data scientists try to eliminate, but I’ve talked to many caregivers that want algorithms to be biased towards their particular patient demographics.

• “Supervised” vs “Unsupervised” have very different meanings that you’d expect..
“Black Box” Design can lead to challenges

Artificial Intelligence will bring significant improvements to healthcare in many ways

• Improve diagnosis and effectiveness of therapy
• Managing population health
• Managing hospital operations
• Managing manufacturing operations
• Managing post-market activities

But, as with anything else, new benefits come with new risks, new challenges.
Many of the Key Success Factors are things we already know – e.g. Supplier Quality

We traditionally think of supplier quality as only applying to raw materials, sub-assemblies, etc.

For Machine Learning, the training data is the “raw material” – bad raw material results in poor quality finished product.
Success Factor: Good Data Handling Practices

One challenge is that AI seems mysterious and magical, and people think we need a whole new way of thinking about it.

I propose that we handle data according to these rules:
• Keep records / retain information on the origin of the sample
• Sourcing, processing, preservation, testing and handling should be done in a safe manner
• Protect against contamination, viruses

Note: these concepts are already captured in IMDRF GRRP WGN47 FINAL:2018 document – when talking about tissue samples !!

My point is that we already know many good practices that simply need to be adapted for AI. We don’t need to re-invent the wheel..

Image source: https://xkcd.com/1838/
New Technology = New Risks

Pedestrian fatalities rose 11% in 2016, ‘distraction’ as a contributing factor.

As we gain new skills, what do we give up?
There are new Hazards that we’ve never had to deal with before...
AI Can Fail in Unexpected Ways

Source: “Artificial Intelligence and Medical Algorithms” Berkman Sahiner, FDA, International Conference on Medical Device Standards and Regulations, March 23, 2018
Real World Example – Afib Prediction

• Hospital developed AI software to identify patients at-risk for Afib.
• Software identified patients and reduced Afib – great!
• But software missed some patients as well – hospital looked into it
• Talked to floor nurse – MIL visited the afternoon of the event
• MIL are apparently a new hazard that have not previously been identified.
• Takeaway – systems don’t capture everything, there will always be extra information that affects the patient but software doesn’t know.
Challenge – we forget items that are second nature to us

• Draft UL standard on fully-autonomous vehicles: what does the vehicle do when approaching a stoplight that just turned yellow?
• Defeating facial recognition software
• Defeating speed limit sign

**Takeaway: we are in an age of “Narrow AI”**

What are the limitations? What can go wrong?

• Will people blindly follow what the system says, even when they are given a choice?
  – Technology doesn’t know everything - consider the 2017 California fires, the LA Times Reported “The Los Angeles Police Department asked drivers to avoid navigation apps, which are steering users onto more open routes — in this case, streets in the neighborhoods that are on fire. “
  
Model Diversification – Refinement & Drift

• Many of us have a long history of working in an environment that is slow to change, and therefore we offer a generic solution to meet common healthcare problems.

• However, with Continuously Learning Systems, the system wants to change. It wants to be customized for a particular customer. A CLS system can learn about a local population and can optimize for that particular hospital.

• But the manufacturer is responsible for configuration management and change control. The manufacturer is responsible for root cause analysis when something goes wrong and the application doesn’t perform as it should.
Model Diversification – Refinement & Drift continued..

• If every hospital is different, how can you compare performance? How do you handle performance claims that change over time?

• DRIFT: Even if you lock a system and don’t allow changes, patient populations DO change over time, and the performance you had 5 years ago might not be the level you are at today. Medical practice also changes over time and that may have an impact to performance.
  • Therefore, having a completely locked system isn’t necessarily the best idea either...
Possible Solution...

• Advanced Broad-Based Analytics is an approach where there is not just a single ML ‘brain’ in the product, but rather the product consists of multiple trained systems (neural net, linear regression, etc.) that acts as a team of consultants.

• Just as your doctor might refer you to a specialist, what if the application itself contained multiple ‘specialists’ that have been trained with different data? What if there is a ‘team’ of algorithms that analyze patient data – one could be the original algorithm, one could be the specialized algorithm for this hospital; they may be sub-specialties (e.g. is pediatric cancer diagnosis specialized to pick up small bits of data that adult cancer doesn’t consider?)

• This broad-based approach has the ability to provide increased performance for a particular patient population while still allowing for comparisons to be made across the performance of different algorithms.
AI/ML-SaMD - New Concepts from the FDA

Initial Premarket Assurance of Safety and Effectiveness:

• This framework gives manufacturers the option to submit a “predetermined change control plan” for modifications during the initial premarket review of an AI/ML-based SaMD:

SaMD Pre-Specifications (SPS):

based on the retraining and model update strategy, and the associated methodology;

Algorithm Change Protocol (ACP):

being used to implement those changes in a controlled manner that manages risks to patients;
AI/ML-SaMD - Modifications to SPS and ACP

Approach for modifications after initial review with an established SPS and ACP:

...manufacturers are expected to evaluate the modifications based on risk to patients as outlined in the software modifications guidance:
SPS and ACP Templates – in progress!

The Medical Device Innovation Consortium (www.mdic.org) has been involved in previous FDA initiatives, such as the Case for Quality.

MDIC is close to publishing a whitepaper on this topic, including advice for SPS and ACP. Although the scope is limited to IVDs, it is written so that it can apply to a wide variety of regulated software.
The FDA published an Action Plan earlier this year, and the agency highlighted the following intended actions and goals (emphasis added):

- Develop an **update to the proposed regulatory framework** presented in the AI/ML-based SaMD discussion paper, including through the issuance of a Draft Guidance on the Predetermined Change Control Plan.

- Strengthen FDA’s encouragement of the harmonized development of Good Machine Learning Practice (GMLP) through **additional FDA participation in collaborative communities and consensus standards** development efforts.

- Support a patient-centered approach by continuing to host discussions on the role of transparency to users of AI/ML-based devices. Building upon the October 2020 Patient Engagement Advisory Committee (PEAC) Meeting focused on **patient trust** in AI/ML technologies, **hold a public workshop** on medical device labeling to support transparency to users of AI/ML-based devices.

- Support **regulatory science efforts** on the development of methodology for the evaluation and improvement of machine learning algorithms, including for the identification and elimination of bias, and on the robustness and resilience of these algorithms to withstand changing clinical inputs and conditions.

- Advance **real-world performance pilots** in coordination with **stakeholders** and **other FDA programs**, to provide additional clarity on what a real-world evidence generation program could look like for AI/ML-based SaMD.
Good Machine Learning Practice Principles

The FDA, Health Canada, and MHRA recently published a draft set of GMLP Guiding Principles (comments due in February)

Standards Overview

There has been very little published as a standard, and therefore not much that I can say “you must follow this standard!” Instead, there are several projects that are in their early stages.

- ISO/IEC JTC1, SC42, developing horizontal standards for all industries. Many simultaneous projects and even more are being created. **Not likely that these horizontal standards would be required for medical devices, but they may contain ideas that we like and would carry to healthcare.**

- ISO/IEC TC215 (health software standards like 62304, 82304, 80001-x series, +200 more standards) has a report with some recommendations, and has created a Task Force to maintain a current landscape, collect use cases, etc. **TF5 does not write standards.**

- IEEE also developing a number of AI standards, but only a few are specific to healthcare.

- CTA is developing general AI standards as well as healthcare-specific AI standards.

- AAMI & BSI have also started an AI standards committee.
TC215 Ad Hoc Group on Application of AI to Health Informatics

An Ad Hoc group was formed inside of ISO/TC 215 to prepare a report regarding AI’s impact to Health Informatics. Tasks included:

- Conduct a landscape survey of the topic with respect to health informatics
- Identify key considerations for TC 215
- Provide a set of recommendations for future work

Final report had ~ 30 recommendations, including the development of standards / TR for:

- Definitions
- Software lifecycle for AI solutions
- Evaluating performance and validity of AI health applications
- Explainability disclosures
- Security & privacy considerations
- Development of checklist of things to consider when developing or updating standards
- Consider educational projects
- Collaborate w/other organizations

Since many recommendations are ongoing (not one-time), a Task Force was formed to provide ongoing assistance (e.g. liaisons to other groups, keeping track of other related standards projects, etc.)
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Enhancing EHR use with AI

Dr. John W Gachago

January 17th 2021
United States EHR ecosystem – 2020 Contracts per major EHR, KLAS EHR Hospital Market Share 2021

RCB – RCB Findings on EHR Use, Report of HL7-RCB Group on EHRs, 21st Century Cures Act, RCB Summary Position

Understanding AI, Relationship between AI/ML/DL, Illustration of application of AI/ML to EHRs.

AI in Healthcare: Impact, Applications, Challenges, Keys to Success with AI

RCB with AI: Improving Medical Documentation, AI-EHR evidence base, Cardiology/Ophthalmology Evidence

Limitations to the application of AI to EHRs.

The AI Conundrum in healthcare.

Impact of EHR vendors incorporating Add-On technology to RCB

Illustration of leveraging AI for more equitable care

Conclusion, Thank you/Questions
CONTRACTS PER EHR SYSTEM IN 2020

Epic: 1,713
Cerner: 1,354
Meditech: 901
CPSI: 503

Allscripts: 271
Medhost: 179
Azalea Health: 26

KLAS named Epic its 2021 Best in KLAS Overall Software Suite, the 11th year in a row.

More small standalone hospitals switched to Cerner than any other EHR company.

Nineteen such hospitals inked contracts with Cerner, while Meditech landed nine. CPSI, Epic and Azalea Health landed seven, four and two, respectively.

CPSI lost 22 hospital contracts, 20 of which were competitive — that is, those hospitals switched from CPSI to other EHR companies because of a new contract.

Remaining two CPSI losses were from EHR standardization of single hospitals within larger health systems.

Cerner suffered the most contract losses with 59 — 51 of which were competitive, with the remaining eight coming from health system standardization.

Epic lost only three hospital contracts in 2020, due to standardization efforts stemming from mergers and acquisitions.

Patient data is more easily accessible, but entry and retrieval of that data is less than optimal and not designed to accommodate the HCPs workflow.

HCPs often have to use templates and copy and paste functionality which can result in overly wordy notes that are repetitive and disorganized.

Breakdown in how care is delivered and the way it is noted in the EHR causes HCPs to perceive the EHRs as inefficient and disruptive.

Progress being made with interoperability, but it still remains rather elusive across all EHR systems.

Lack of coordinated data governance and trust relationships amongst HSOs, high cost of HIE interfaces or HIE membership, challenges with accurately mapping the correct record to the correct patient, a variety in state privacy rules and in HSO interpretation of HIPPA, and inadequate technical standards for communication.

Tools such and Drug allergy and drug-drug interaction (DDI) are amongst the most appreciated features because of their ability to minimize the incidence of adverse drug events (ADEs but DDI feature are considered interruptive because of low value alerts which are responsible for alert fatigue (between 50-90% of the time DDI alerts tend to be overridden for valid clinical reasons).

(Krenn & Schlossman, 2017)
The introduction of the EHR has been associated with:

- 192 clicks per encounter with other HCPs registering significantly more.

- Multitasking which has an impact on eye contact, the ability to process non-verbal cues, active engagement, and various other elements of HCP-patient engagement.

- HCPs spending 37% of their patient exam time on and 49% of their total work time on EHRs and desk work.

- Studies have related decreased patient satisfaction to increased HCP screen time.
ADDITIONAL CHALLENGES – 21st CENTURY CURES ACT

New reporting requirements

Need to manage multiple terminologies/standards and code sets

Transmission and receipt of clinical data/incoming data curation

Enhancing usability as value-based care becomes the norm

New data transparency requirements giving patients access to their records

Requirement to consider SDOH

Pressure to improve outcomes, and documentation requirements.

(Lareau, 2022)
“The context in which EHRs exist including the processes and regulations that drive EHR use substantially increase the difficulty of realizing the goals for which they were originally intended”.
UNDERSTANDING ARTIFICIAL INTELLIGENCE (AI)

The ability of computer systems to perform cognitive tasks that we typically associate with the human mind.
THE RELATIONSHIP BETWEEN AI/ML/DL

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<tr>
<td>Machine Learning</td>
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<tr>
<td>Deep Learning</td>
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Deep Learning
The subset of machine learning composed of algorithms that permit software to train itself to perform tasks, like speech and image recognition, by exposing multilayered neural networks to vast amounts of data.

Machine Learning
A subset of AI that includes abstruse statistical techniques that enable machines to improve at tasks with experience. The category includes deep learning.

Deep Learning
Any technique that enables computers to mimic human intelligence, using logic, if-then rules, decision trees, and machine learning (including deep learning).

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<th>Machine Learning Examples</th>
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<tbody>
<tr>
<td>IBM Deep Blue Chess Program</td>
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<td>Electronic Game Characters (Sims)</td>
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<tr>
<td>IBM Watson</td>
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<tr>
<td>Google Search Algorithm</td>
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<td>Amazon Recommendations</td>
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<td>Email SPAM filter</td>
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<tr>
<td>AlphaGo</td>
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<tr>
<td>Natural Speech Recognition</td>
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<tr>
<td>Waymo Level 4 Automated Driving System</td>
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</table>
THE MOST COMMON MACHINE LEARNING ALGORITHMS
USED TO TRAIN ENTERPRISE AI MODELS.

Machine learning models cheat sheet

**Supervised learning**
- Data scientists provide input, output and feedback to build model (as the definition)
- **EXAMPLE ALGORITHMS:**
  - Linear regressions
  - Sales forecasting
  - Risk assessment
  - Support vector machines
  - Image classification
  - Financial performance comparison
  - Decision tree
  - Predictive analytics
  - Pricing

**Unsupervised learning**
- Use deep learning to arrive at conclusions and patterns through unlabeled training data.
- **EXAMPLE ALGORITHMS:**
  - Apriori
  - Sales functions
  - Word associations
  - Searcher
  - K-means clustering
  - Performance monitoring
  - Searcher intent

**Semi-supervised learning**
- Builds a model through a mix of labeled and unlabeled data, a set of categories, suggestions and example labels.
- **EXAMPLE ALGORITHMS:**
  - Generative adversarial networks
  - Audio and video manipulation
  - Data creation
  - Self-trained Naïve Bayes classifier
  - Natural language processing

**Reinforcement learning**
- Self-interpreting but based on system of rewards and punishments learned through trial and error, seeking maximum reward.
- **EXAMPLE ALGORITHMS:**
  - Q-learning
  - Policy creation
  - Consumption reduction

(Kelley, 2021)
APPLICATION OF AI/ML TO EHRs

(Lin, Chen, & Chiang, 2020)
12 WAYS AI IS EXPECTED TO IMPACT HEALTHCARE

- Unification of mind and machine through brain interfaces.
- Development of next generation radiology tools.
- Expanding care to underserved or LMIC regions.
- Reducing burdens of EHR use.
- Minimizing risks associated with antibiotic resistance.
- Creating more precise analytics for pathology.
- Bringing intelligence to medical devices and machines.
- Advancing the use of immunotherapy for cancer therapy.
- Turning the EHR into a more reliable risk predictor.
- Monitoring health through wearables and personal devices.
- Converting selfies into diagnostic tools.
- Revolutionizing clinical decision making at the bedside.
## AI Applications in Healthcare

### AI Potential in Healthcare

<table>
<thead>
<tr>
<th>For HSOs and Administrators</th>
<th>For Patients and HCPs</th>
</tr>
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<tbody>
<tr>
<td>AI-powered RN avatars that engage with patients and prevent hospital readmissions.</td>
<td>Autodetection of diabetic nephropathy.</td>
</tr>
<tr>
<td>Clinical protocol automation.</td>
<td>Measurement of Stroke volume (SV) i.e. the volume of blood ejected by the left ventricle each time it contracts.</td>
</tr>
<tr>
<td>Lessening physician burnout</td>
<td>Algorithms that uncover details in fetal brain MRIs thereby facilitating surgery to fix structures and reverse certain types of autism.</td>
</tr>
<tr>
<td>AI powered chatbots that can answer commonly asked HCP questions.</td>
<td>Curtailing infectious diseases spreading while accommodating limited resources and population factors.</td>
</tr>
<tr>
<td>Improved identification of suspicious or positive cases for early review which in turn helps prioritize radiologists work.</td>
<td>Auto calculation of bone age, plate growth changes, and detection of pulmonary nodules followed by a notification to radiology.</td>
</tr>
<tr>
<td>Improvement in the workflow associated with administrative tasks.</td>
<td>Chest CT review that results in determination of patient longevity or surgical outcomes.</td>
</tr>
<tr>
<td>Air quality-based predictions for busy vs less busy ER activity.</td>
<td>Medical error and drug-drug interaction detection across a variety of medications.</td>
</tr>
<tr>
<td>Fraud detection and elimination.</td>
<td>Mental disorder diagnosis prior to episodes occurring.</td>
</tr>
<tr>
<td>Patient scheduling efficiencies.</td>
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<tr>
<td>Cybersecurity reinforcement.</td>
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</table>
CHALLENGES ASSOCIATED WITH AI IN HEALTHCARE

- Ethics
- The Hammer and nail theory
- Adoption
- Regulations
- Hype and Misinformation
KEYS TO SUCCESS WITH AI IN HEALTHCARE

- HSOs starting to explore AI immediately by incorporating executives and managers from different levels and geographies in experimenting, rapid learning and application of new insights to the subsequent experiments.

- Consciously being aware of where AI is being used to ensure AI is not abused especially in situations where critical employee or patient data has ethical, legal and trust implications.

- Designing and implementing training and recruitment strategies for employees that are willing and capable via soft skills such as collaboration to work with machines.

- Recognizing where the disruptive technology should be incorporated into the workflow.

- Avoiding the temptation to overpromise on its benefits.

- Emphasizing AIs ability to support accurate diagnosis and minimize errors.
REducing the BurDen of EHR Use

Save time by creating more intuitive interfaces and automating routine processes.

NLP (already happening but can be improved)

Possibility of video recording a clinical encounter (use AI to index video from clinical cam for future info)

Virtual at bedside for clinicians to use with embedded AI for order entry

Processing routine requests form HCP inbox e.g. refills and results notifications.

Prioritizing tasks that require HCP attention vs those that do not.

More reliable risk prediction

Algo-bias elimination
6 WAYS AI CAN IMPROVE MEDICAL DOCUMENTATION

- Data Extraction
- Diagnostic Algorithms
- Decision Support
- Documentation and Data Entry
- Simplify communication processes between RCM teams and HCPs
- Accelerate the process of looking up medical records
**AI-EHR: EVIDENCE BASE**

**CARDIOLOGY**

- Early detection of heart failure
- Predict the onset of Congestive Heart Failure (CHF)
- Enhance risk assessment in patients suspected to suffer from coronary artery disease (CAD)

**OPHTALMOLOGY**

- Predict the complication of cataract surgery risk
- Enhance diagnosis of glaucoma and age-related macular degeneration (AMD)
- Perform a risk assessment of diabetic retinopathy (DR)

*(Lin, Chen, & Chiang, 2020)*
## THE OPHTHALMOLOGY EVIDENCE BASE FOR RCB

<table>
<thead>
<tr>
<th>Goal</th>
<th>Disease State</th>
<th>Algorithm Type</th>
<th>AI/ML Technique</th>
<th>Outcome</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disease Detection</td>
<td>Myopia</td>
<td>Supervised machine learning</td>
<td>Random forest</td>
<td>95% CI for predicting onset of high myopia. 3 years onset prediction (AUC: 94%–98.5%), 5 years (85.6%–90.1%), 8 years (80.1%–83.7%)</td>
<td>Machine learning with EHR data can accurately predict myopia onset (Lin et al).</td>
</tr>
<tr>
<td>Enhance Surgical Outcome</td>
<td>Cataracts</td>
<td>Supervised machine learning, Deep learning</td>
<td>SVM-RM MLNN-EM</td>
<td>Both SVM-RM and MLNN-EM achieved significantly better results than the Barrett Universal II formula in the ±0.50 DPE category</td>
<td>SVM-RM and MLNN-EM with HER data can be used to improve clinical IOL calculations and improve cataract surgery refractive outcomes (Sranka et al)</td>
</tr>
</tbody>
</table>
### THE OPHTHALMOLOGY EVIDENCE BASE FOR RCB

<table>
<thead>
<tr>
<th>Improve Diagnostic Accuracy</th>
<th>AMD</th>
<th>Deep learning</th>
<th>Convolutional neural networks</th>
<th>For each patient, AUC (97.45%), accuracy (93.54%), sensitivity (92.64%), and specificity (93.69%)</th>
<th>Linked OCT images to EMR data can improve the accuracy of a deep learning model when used to distinguish AMD from normal OCT images (Lee at al).</th>
</tr>
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<tbody>
<tr>
<td>(....and Identify risk factors)</td>
<td>Glaucoma, intrinsic optic nerve disease, optic nerve edema, orbital inflammation, and thyroid eye disease</td>
<td>Supervised machine learning</td>
<td>Random forest</td>
<td>AUC of classifiers: glaucoma (88%), intrinsic optic neuritis (76%), optic nerve edema (78%), orbital inflammation (77%), thyroid eye disease (85%)</td>
<td>EMR phenotype (from pyPheWAS) can improve the predictive performance of a random forest classifier with imaging biomarkers (Chaganti et al)</td>
</tr>
</tbody>
</table>

<p>| AMD | Supervised machine learning | Logistic regression, decision trees, SVM, random forests, and AdaBoost | AUC of random forest, logistic regression, and AdaBoost (92%); SVM, decision trees (90%) | Machine learning algorithms using clinical EHR data can be used to improve diagnostic accuracy of AMD (Fraccaro et al) |</p>
<table>
<thead>
<tr>
<th>Risk Assessment</th>
<th>Open-angle glaucoma</th>
<th>Supervised machine learning</th>
<th>Logistic regression, random forests, ANNs</th>
<th>AUC of logistic model (67%), random forest (65%), ANNs (65%)</th>
<th>Existing systemic data in the EHR can identify POAG patients at risk of progression to surgical intervention</th>
</tr>
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<tbody>
<tr>
<td>DR</td>
<td>Supervised machine learning</td>
<td>FRF, DRSA</td>
<td>Performance of FRF: Accuracy (80.29%), sensitivity (80.67%), specificity (80.18%) Performance of DRSA: Accuracy (77.32%), sensitivity (76.89%), specificity (77.43%) of DRSA</td>
<td>Ensemble classifiers (RFR and DRSA) can be applied for diabetic retinopathy risk assessment. The 2-step aggregation procedure is recommender. (Saleh et al)</td>
<td></td>
</tr>
<tr>
<td>DR</td>
<td>Supervised machine learning</td>
<td>Ridge, elastic net, and LASSO</td>
<td>In external validation, LASSO predicted DR: AUC (82%), accuracy (75.2%), sensitivity (72.1%), and specificity (76%)</td>
<td>LASSO with EHR data can be used to predict DR risk among diabetic patients. (Yoo and Park)</td>
<td></td>
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</tbody>
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LIMITATIONS TO THE APPLICATION OF AI TO EHRs

Limited interoperability

HCP participation still necessary

Accuracy limitations

(Bailey, 2021)
THE AI CONUNDRUM

As EHR vendors integrating add-on technologies a certain level of innovation is developing to provide usability enhancements for HCPs.

AI can bolster the accuracy of EHR documentation integration allowing HCPs to focus more on healthcare.

Recent KPMG survey: for AI to be beneficial, HSOs must prioritize AI education for providers.

Same survey: only 67% of healthcare insiders said their employees support AI adoption, and 47% said that their HSOs offered AI training.

Major concern: AI can exacerbate bias and worsen healthcare equity particularly when AI models are trained on data from very narrow segments of the population, are insufficiently transparent and when developed by teams that are limited in diversity.

(Khan, Bates, & Kovacheva, 2021).
IMPACT OF EHR VENDORS INCLUDING ADD-ON TECHNOLOGIES

View clinical problems, related medications, lab orders and results, therapies and procedures, patient history including SDOH, physical exam findings, and co-morbidities for any problem in one unified place with a single click.

Quickly determine what clinical quality measures, including eCQMs apply to particular patients, whether they have been met or not and if necessary, prompt the HCP to take appropriate action and especially so while the patient is before them physically or virtually.

Identify whether any diagnoses qualify for risk adjustment using the hierarchical condition codes (HCCs) and if the documentation meets federal requirements for management, evaluation, assessment, and treatment of each diagnosis for Medicare Advantage (MA) patients.

(Khan, Bates, & Kovacheva, 2021).
ILLUSTRATION OF INTEGRATING AI CAN INTO CARE DELIVERY FOR PREGNANT PATIENTS AT RISK OF POST-PARTUM HEMORRHAGE TO DELIVER MORE EQUITABLE CARE.

(Khan, Bates, & Kovacheva, 2021).
AI IS A CRITICAL KEY TO RCB

AI IS NOT GOING AWAY – IT IS HERE TO STAY

THE CHALLENGE OF AN AGING POPULATION, GROWING PATIENT VOLUMES, FREQUENT MEDICAL ERRORS, AND OVER 60% OF THE POPULATION HAVE SINGLE CHRONIC ISSUES VERSUS 40% THAT HAVE MULTIPLE CHRONIC ISSUES.

SHORTAGE OF HCPS IN THE WAKE OF CHANGING PAYMENT MODELS, PRESENT HCPS EXPRESS CONTINUED FRUSTRATION WITH INCREASING DATA DEMANDS AND DATA OVERLOAD, DISORGANIZED DATA, BURNOUT CONCERNS AND INADEQUATE TIME WITH PATIENTS.

THE EFFICACY OF THE APPROACH TO THIS IS DIRECTLY PROPORTIONAL TO THE LEVEL OF BENEFIT THAT AI AND MACHINE LEARNING DELIVER TO DIAGNOSIS AND CLINICAL DECISION SUPPORT.

AI IS DISRUPTIVE TO CARE DELIVERY

THE IMPLEMENTATION AND ADOPTION OF AI DEMANDS MANAGEMENT OF CULTURAL CHANGE AND EFFECTIVE IMPLEMENTATION.

THANK YOU / QUESTIONS
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Wrapping Up...
Observations about AI

As you get involved in AI, there are some things that you notice that you would not have originally anticipated.

After a long day of getting nowhere in developing a standard for medical device interoperability, I commented “before we can get machines to talk to each other, we need to be better at getting people to talk to each other.”

This started me thinking about some of the ironies embedded in technology and in AI.
Lessons Learned from 1980s pop culture

During a human factors study, a common question that I would ask is “What has changed in the past 10 years?” and a nurse replied “I entered this field to take care of patients, but I spend all my time taking care of technology!”

This was 15 years ago. I assume that things have not improved..

This was noted (by another industry) a long time ago -- in the 1980s, the band Styx recorded the song “Mr. Roboto”; the lyrics include:

- The problem is plain to see
- Too much technology
- Machines to save our lives
- Machines de-humanize

Challenge: can we work together and use technology to re-humanize healthcare?
Questions?

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