Emerging Telehealth and Artificial Intelligence Policy

MODERATED SESSION

Prevent Blindness
Focus on Eye Health National Summit

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Digital Diagnostics and University of Iowa

Focus on Eye Health Summit:
Our Changing Vision

Emerging Telehealth and Artificial Intelligence Policy

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Prevent Blindness
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Disclosures

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  - Research to Prevent Blindness
- No commercial relationships

NIH U.S. National Library of Medicine

Research to Prevent Blindness

NIH DIRECTOR'S EARLY INDEPENDENCE AWARD

Overview

- An introduction to telehealth
- Different types of telehealth and example cases
- Changes in relation to the COVID-19 Pandemic
- Ongoing challenges
- Opportunities for artificial intelligence

Telehealth – Definitions

- "Telemedicine" coined in the 1970s: "**Healing at a distance**"
- "The delivery of health care services, where **distance is a critical factor**, by all health care professionals using **information and communication technologies** for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers, all in the interests of **advancing the health of individuals and their communities**" (WHO)
- "The use of **electronic information and telecommunications technologies** to support **long-distance** clinical health care, patient and professional health-related education, public health and health administration" (HealthIT.gov)

Telehealth – Key Principles

- Providing clinical support
- Overcome geographical barriers
- Involves use of information and communication technologies
- Goal of improving health outcomes

- “Telehealth” intended to be more broad than “telemedicine” but often used interchangeably

Forms of Telehealth


Image credit: Scripps Health

Synchronous

Phone calls, Video Visits


Image credit: Medscape

Asynchronous

Patient messages, image interpretation, data portals, remote sensing

Diagnosis of an internal carotid artery aneurysm via telehealth

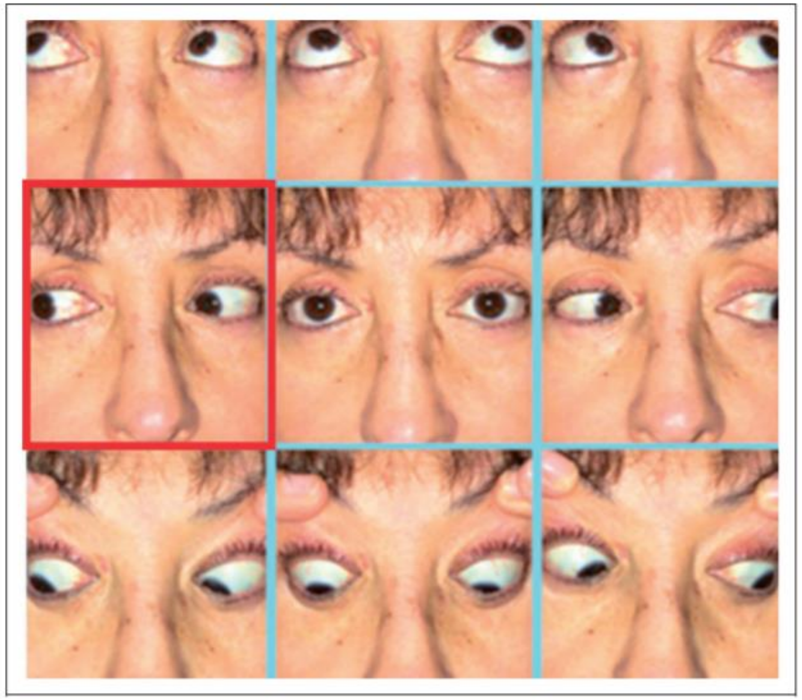

Figure 1. Photographic montage of eye positions for a patient presenting with acute binocular diplopia. The patient had acquired these images at home using a smartphone application (9 Gaze app, See Vision LLC, Richmond, VA, USA). She had a subtle abduction deficit in the right eye (middle image in the left-most column, highlighted in red), which was more noticeable during dynamic examination at the time of the telemedicine video visit.

- 59 yo F called triage line complaining of double vision associated with vertigo and headache
- Underwent video visit evaluation (patient declined in-person evaluation due to COVID-19 pandemic) using Doxy.me
- At home tools to gain ophthalmic data:
  - Snellen visual acuity chart (Safe Eyes America)
  - Extraocular movements (9Gaze app)
  - Dynamic examination also conducted during videoconference

Findings consistent with acute CN6 palsy and referred for emergent neuro-imaging

Diagnosis of an ICA aneurysm via telehealth

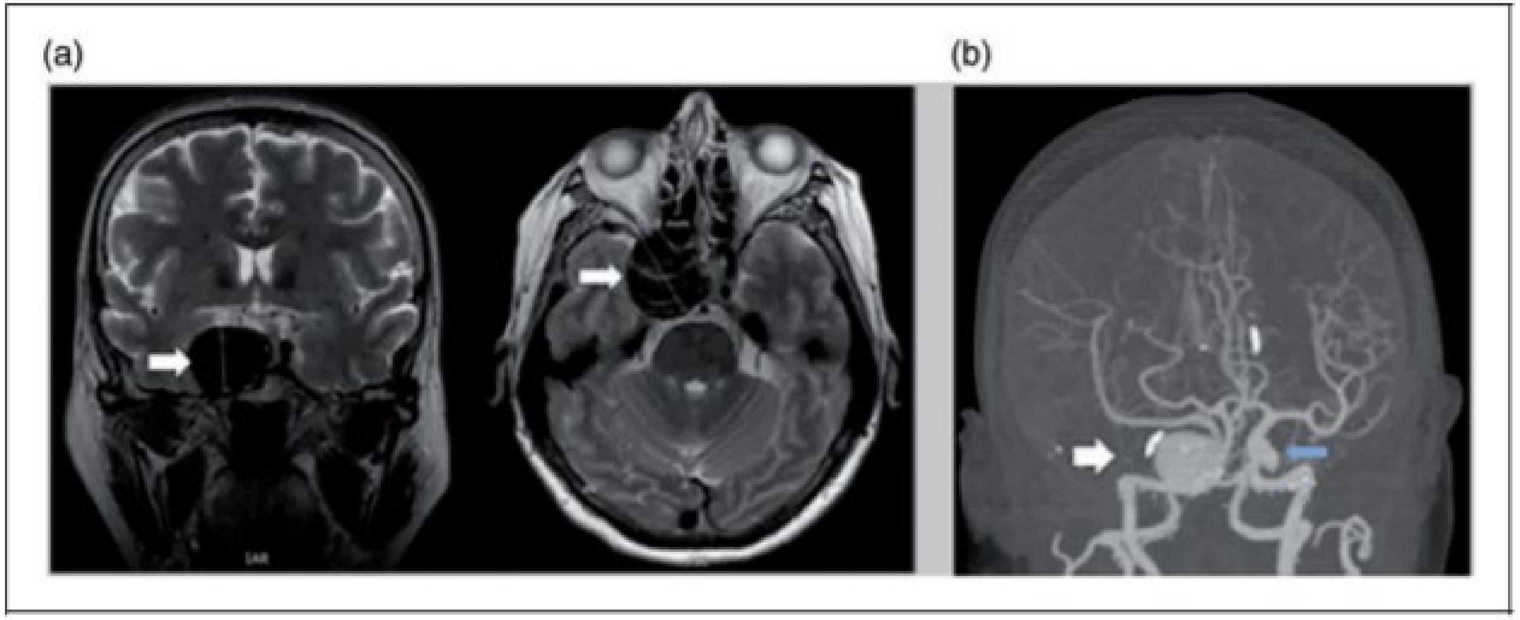

Figure 2. Giant internal carotid artery (ICA) aneurysm visualized on neuroimaging. The white arrows highlight various views of the partially thrombosed giant aneurysm arising from the right cavernous ICA, which measured 3.4 × 3.1 × 2.6 cm, on both magnetic resonance images (a) and computed tomography angiography (b). There was also a 2 mm aneurysm projecting posteriorly from the left ICA terminus (blue arrow in (b)).

Diagnosis of an ICA aneurysm via telehealth

Case Report

Journal of Telemedicine and Telecare
0(0) 1–5

DOI: 10.1177/1357633X20985392
journals.sagepub.com/home/jtt
SAGE

Internal carotid artery aneurysm presenting as diplopia via telemedicine during COVID-19

Sally L Baxter[1,2], David E Kuo[1] and Shira L Robbins[1]

Abstract

A patient presented with acute onset of double vision during the start of the COVID-19 pandemic when elective medical care was restricted. Initially declining an in-person evaluation, she was examined using a telehealth video visit, incorporating multiple technological modalities to ascertain ophthalmic examination elements. Her findings prompted emergent neuroimaging, revealing a giant internal carotid artery aneurysm, which was successfully embolized to prevent debilitating and possibly fatal intracranial haemorrhage. This case report illustrates the successful use of telemedicine and remote patient data acquisition to make a life-saving diagnosis.

Keywords

Remote consultation, tele-ophthalmology, telehealth, telemedicine, teleneurology

Date received: 3 December 2020; Date accepted: 12 December 2020

Diabetic Retinopathy Screening Programs

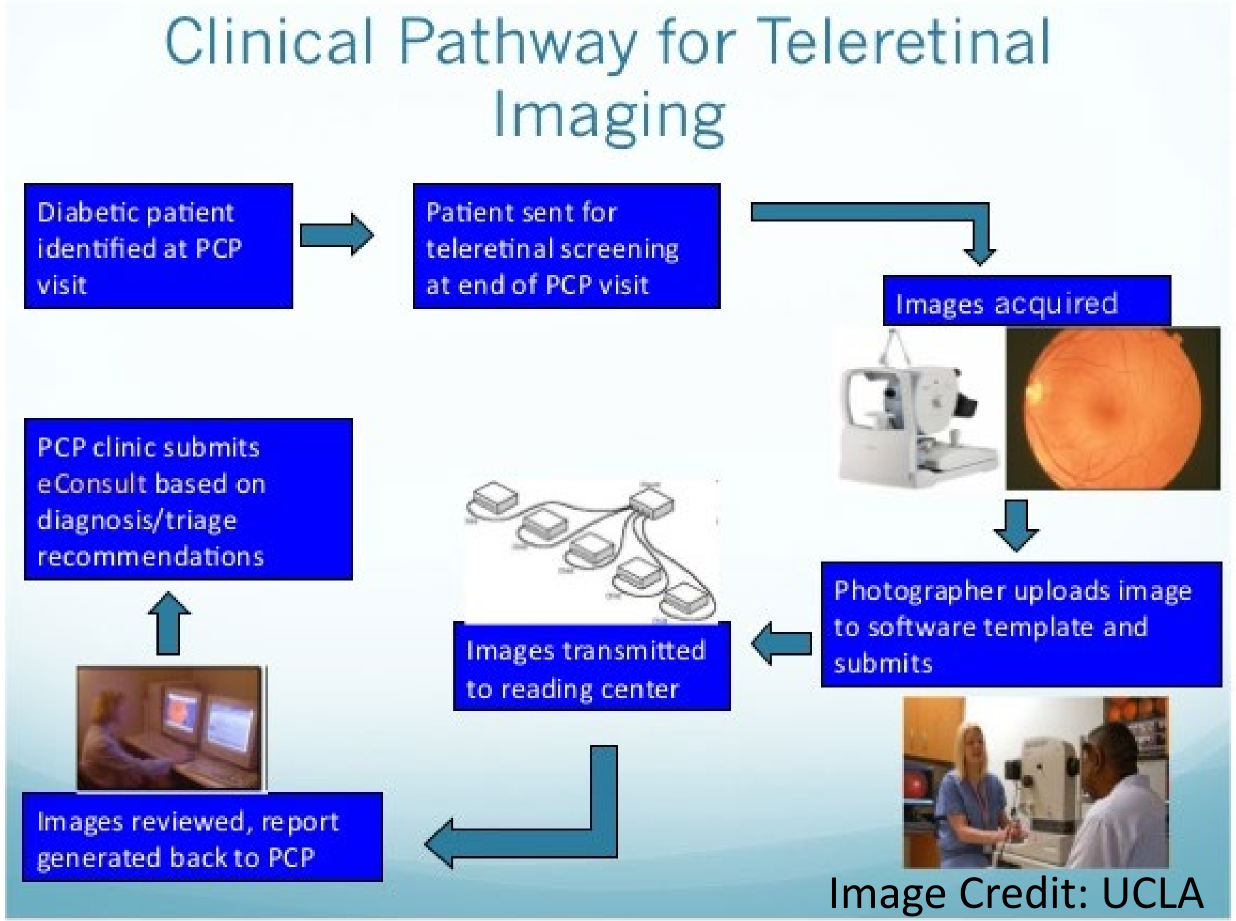

Image Credit: UCLA

Installing cameras at primary care clinics and screening patients at primary care visits to improve access to diabetic retinal exams

Images read and interpretations provided asynchronously (i.e., not in real time)

Diabetic Retinopathy Screening Programs

38-year-old man with Type 2 diabetes and no visual complaints, had never seen ophthalmology before

Imaging at primary care office found to have evidence of diabetic retinopathy

Diabetic Retinopathy Screening Programs

Found to have neovascularization on ultra-wide field retinal imaging upon follow-up visit to ophthalmology

New diagnosis of proliferative diabetic retinopathy thanks to teleretinal program

Diabetic Retinopathy Screening Programs

Afshar et al • UWF Imaging for DR Screening

Figure 1. Photographs showing the mobile ultra-widefield imaging (UWFI) program: (**A**) the University of California, San Francisco, mobile eye service van; (**B**) an Optos Daytona (Optos Plc, Dunfermline, United Kingdom) camera bolted to a custom, adjustable-height table on the van; (**C**) patient being screened with mobile UWFI unit; and (**D**) map of San Francisco including 3 fixed cameras (red tabs) and 7 primary care clinic stops through the city for the mobile eye van screenings (blue tabs).

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Growing Digital Health Environment

Image Credit: iCare

Image Credit: Reviewed.com

Image Credit: University of Michigan

The Impact of COVID-19 on Telehealth

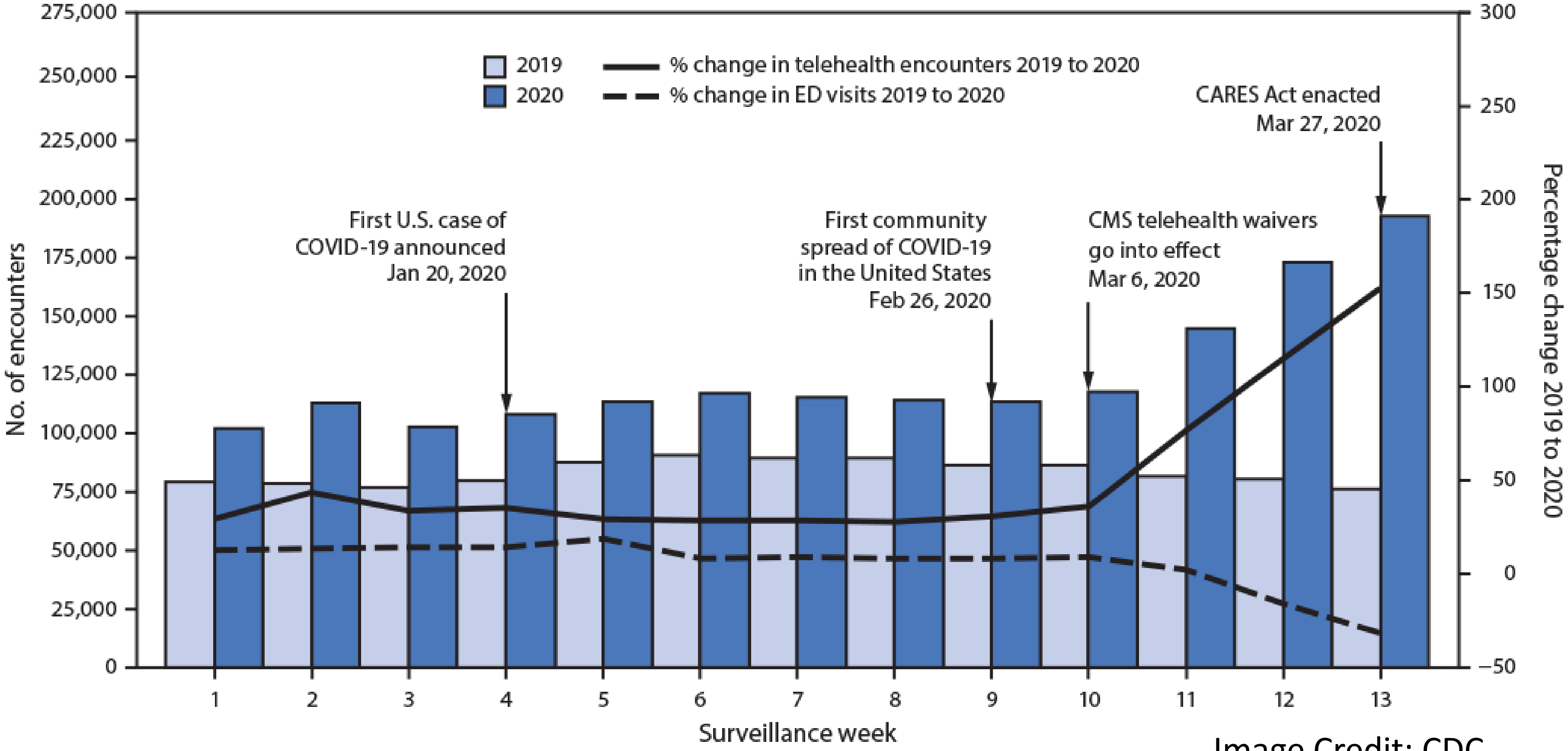

Image Credit: CDC

The Impact of COVID-19 on Telehealth

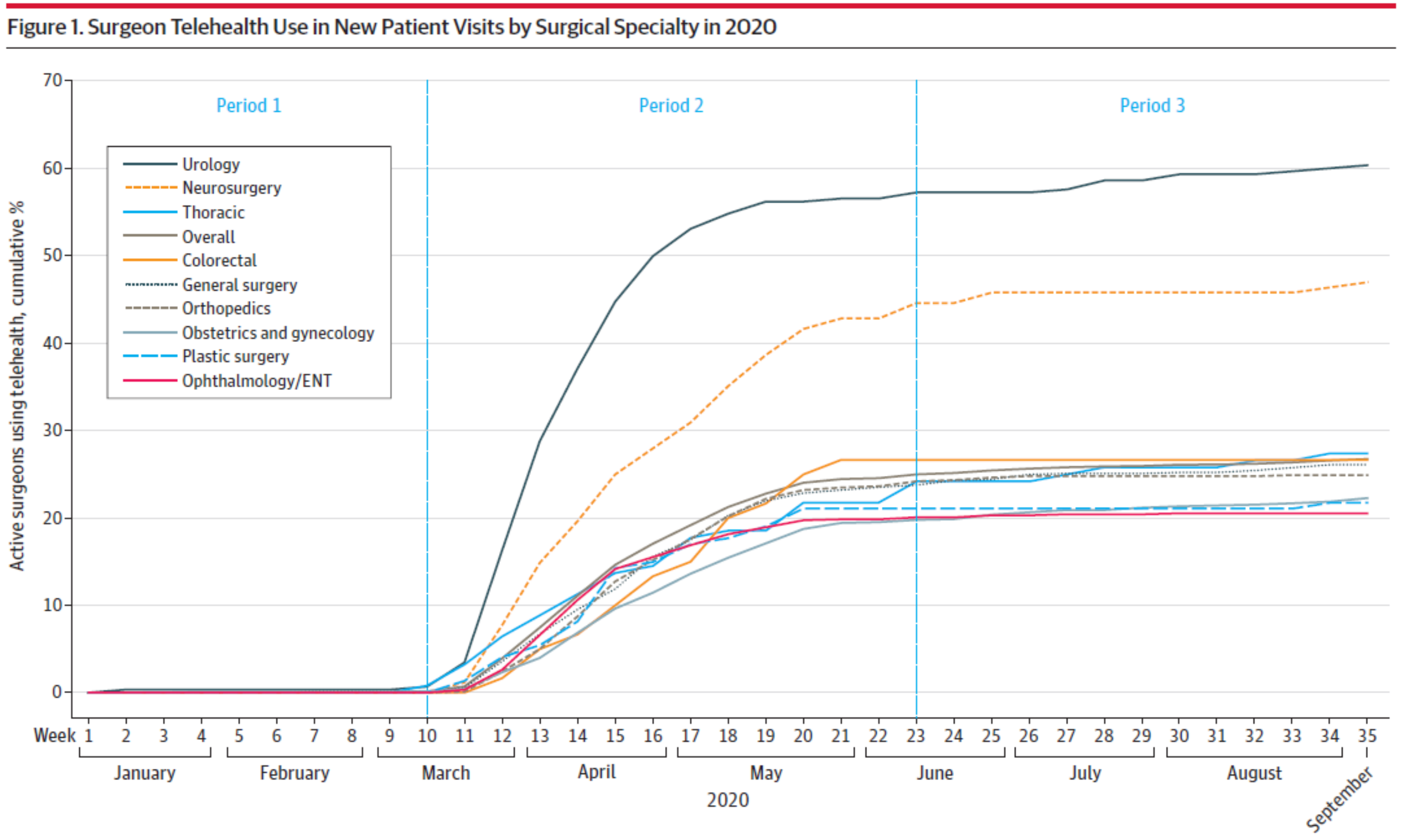

Image Credit: JAMA Surgery

The Impact of COVID-19 on Telehealth

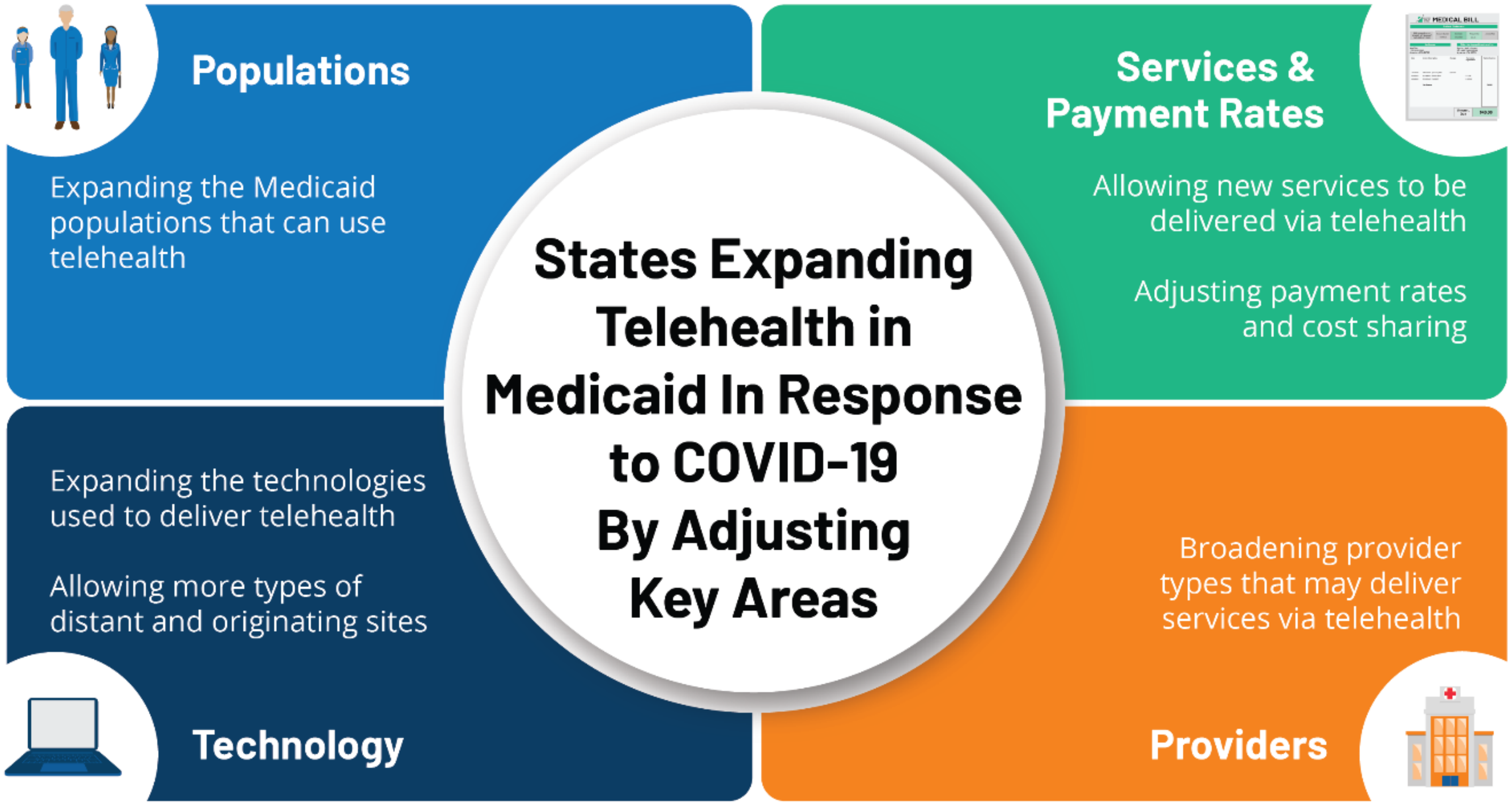

Image Credit: Kaiser Family Foundation

Ongoing Challenges

- Evolving policies as the pandemic restrictions are easing – how will access and reimbursement be affected?
- Digital Divide

Disparities in broadband access → Disparities in access to technology → Disparities in education and digital literacy

Ongoing Challenges

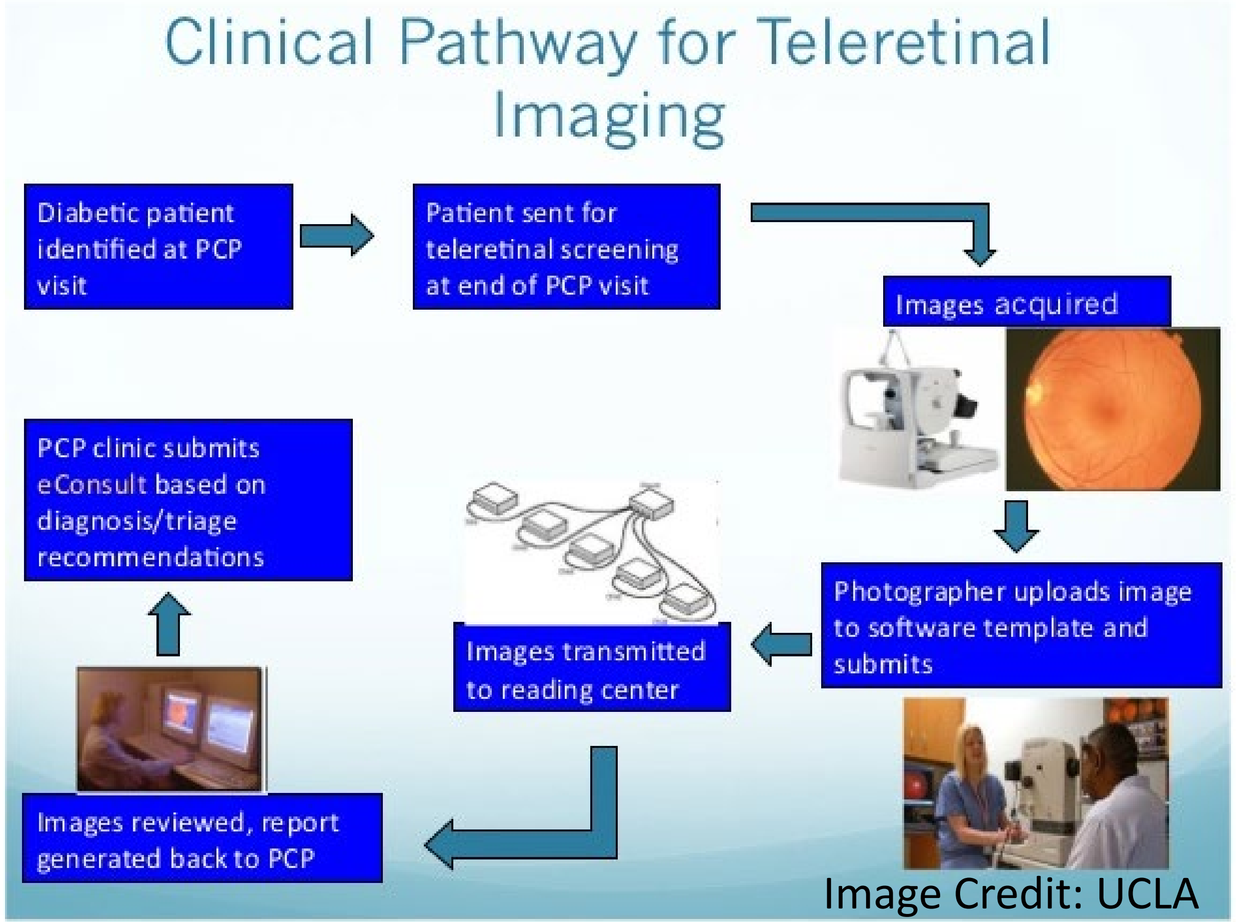

Image Credit: UCLA

- Time delays
- Possible communication gaps
- Loss to follow-up

Other industries have undergone digital transformation…

Analog → Digital

"Dumb Digital"→ Continuously Improved Digital

Slide courtesy of Aaron Neinstein, MD

Opportunities for Artificial Intelligence

- Ability to scale
- Managing large volume of data from both traditional clinical encounters and telehealth encounters
- Enhanced predictive models and risk stratification
- Autonomous AI can provide point-of-care results without waiting for clinician input
- AI can also facilitate synchronous telehealth interactions (e.g. chatbots)
- Opportunities to streamline/automate workflows

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Our Changing Vision

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Our Changing Vision

Implications in the adoption of AI during the COVID-19 pandemic

Michael D. Abramoff, MD, PhD

The Watzke Professor of Ophthalmology and Visual Sciences
University of Iowa
Founder and Executive Chairman, Digital Diagnostics
Fellow, ARVO

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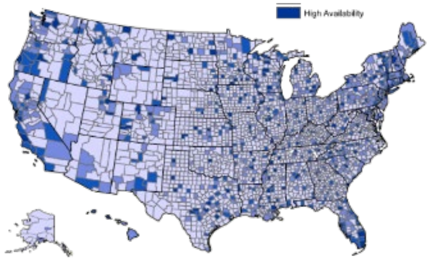
Choosing Autonomous AI

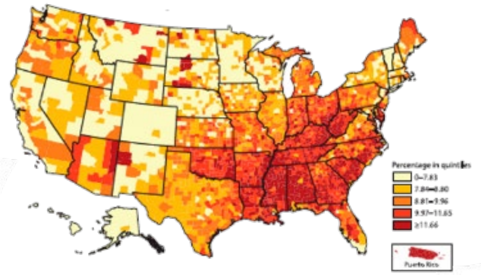
Reduce physician burned and improve patient outcomes

Autonomous AI	Assistive AI
Medical decision made by the AI	Medical decision made by the clinican
No human oversight	Clinician needed
Point of Care	Time to review
Primary care	Specialty care
Liability with AI creator	Liability for clinician

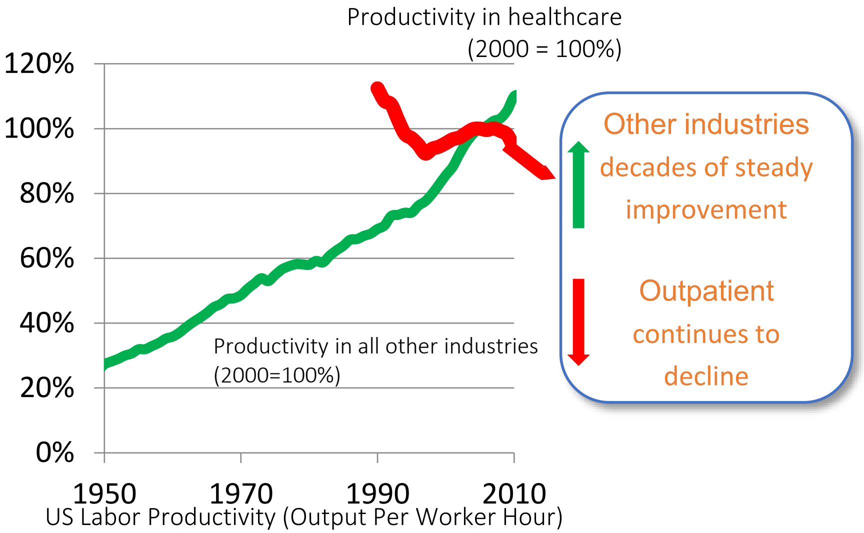
Healthcare problems to be solved by Autonomous AI

Healthcare Cost - Access

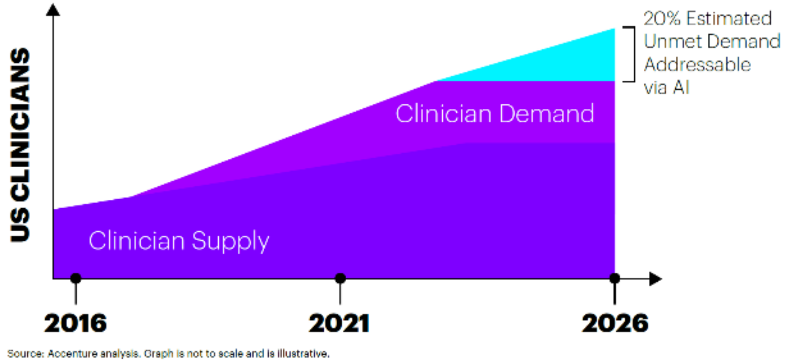




Healthcare Cost - Productivity



Healthcare demand - workforce gap



US Bureau Labor Statistics, 2010
Lam et al, The effect of electronic health records adoption on patient visit volume at an academic ophthalmology department BM Health Serv Res, 2016
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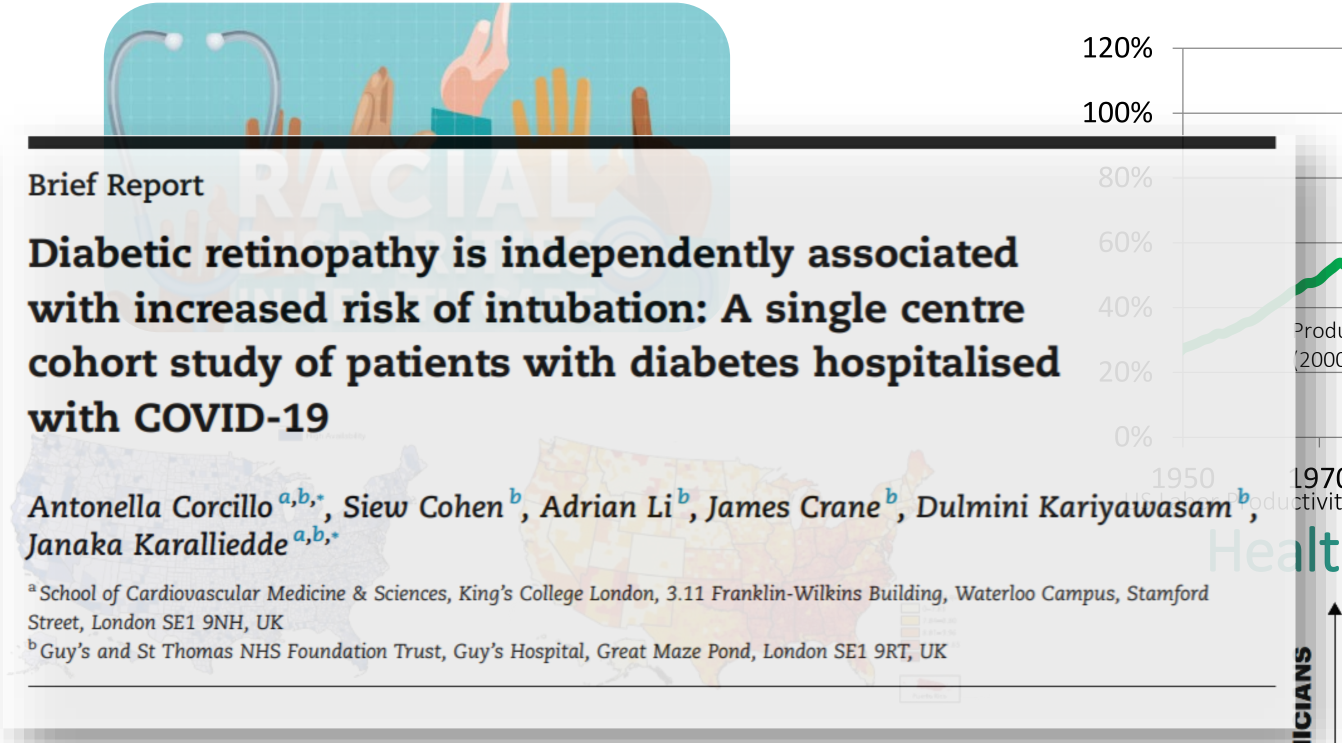
https://www.cdc.gov/diabetes/pdfs/library/diabetesreportcard2017-508.pdf

Healthcare problems to be solved by Autonomous AI

Healthcare Cost - Access



Brief Report

Diabetic retinopathy is independently associated with increased risk of intubation: A single centre cohort study of patients with diabetes hospitalised with COVID-19

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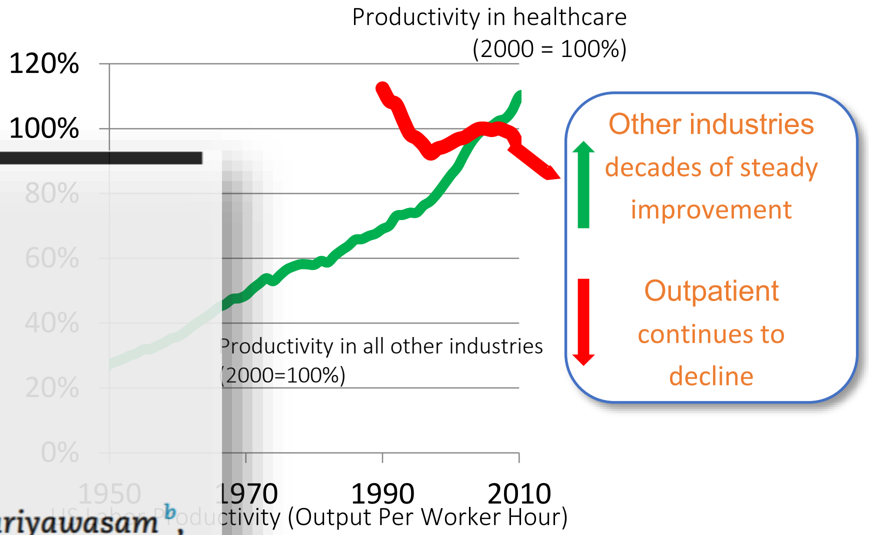
[b] Guy's and St Thomas NHS Foundation Trust, Guy's Hospital, Great Maze Pond, London SE1 9RT, UK

Healthcare Cost - Productivity



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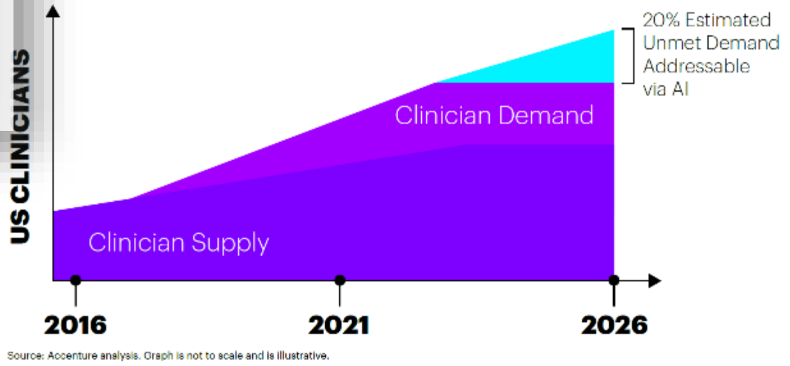

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U.S. Centers for Disease Control level distribution of diagnosed diabetes among US adults aged 20 or older, 2013.
https://www.cdc.gov/diabetes/pdfs/library/diabetesreportcard2017-508.pdf

Diabetes health inequities & disparities in access

Affects groups differentially, resulting in large differences in:

- Diabetes incidence and prevalence
- Diabetic retinopathy incidence
- Compliance w/ eye exams
- Visual loss from diabetic retinopathy

Trifecta of vulnerability:
- **Higher risk for getting diabetes**
- **Worse diabetic retinopathy**
- **Under-served when they get it**

Examples:

- In Black Americans, diabetes prevalence 20.4% (95% CI, 18.8%-22.1%), almost twice of that of white Americans
- Diabetes prevalence U.S. Hisps 22.1% (95% CI, 19.6%-24.7%)
- Black Americans 2.5x risk of developing DR at equal A1C levels
- Compliance among the Black American population to have diabetic eye exams is less than all other groups

Shift from referral-based to instantaneous POC A1C testing increases compliance from <50% to 95% in people with diabetes [1,2,3]

Cheng YJ, Kanaya AM, Araneta MRG, Saydah SH, Kahn HS, Gregg EW, et al. Prevalence of Diabetes by Race and Ethnicity in the United States, 2011-2016. JAMA. 2019;322(24):2389-98.
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Harris EL, Sherman SH, Georgopoulos A. Black-white differences in risk of developing retinopathy among individuals with type 2 diabetes. Diabetes Care. 1999;22(5):779-83.
West SK, Klein R, Rodriguez J, et al. Diabetes and diabetic retinopathy in a Mexican-American population: Proyecto VER. Diabetes Care. 2001;24:1204–1209.
Nsiah-Kumi P, Ortmeier SR, Brown AE. Disparities in diabetic retinopathy screening and disease for racial and ethnic minority populations--a literature review. J Natl Med Assoc. 2009;101(5):430-7.

Diabetes health inequities & disparities in access

Affects groups different

- Diabetes incidence and p
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f vulnerability:
risk for getting diabetes
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served when they get it

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Shift from ref … testing
increases c … with

WHO: Biased AI health tech could disadvantage poorer countries

BY ASHLEIGH FURLONG | 06/28/2021 08:59 AM EDT

LONDON — Artificial intelligence poses great possibilities in streamlining health care, but with these products developed mostly by using data from wealthy nations, their deployment in low- and middle-income countries raises concerns of bias and inequitable provision of health care, according to new guidance from the World Health Organization.

The guidance, published Monday , on AI in health care follows two years of consultation by a panel of experts appointed by the WHO, and finds that AI holds great promise in improving patient care, providing more accurate diagnoses and increasing access to health care in settings where the provision of these services is limited.

However, the WHO cautions that in these same settings, AI systems may not work as well. That's due to contextual bias, which is a result of AI systems being designed using data from individuals in high-income countries. "Algorithms may not recommend safe, appropriate or cost-effective treatments for low-income or low-resource settings or for countries that have resources but in which segments of the population still have poor health outcomes," states the guidance.

The guidance also warns of differing liability regimes for AI, with liability rules sometimes being the "only line of defence against errors made by machine-learning technologies." Some low- and middle-income countries may not have the regulatory capacity to assess these new products, with the guidance warning that individuals harmed by these AI systems may also face little recourse to justice.

The guidance sets out six principles to prevent situations such as these, including ensuring inclusiveness and equity, as well as promoting human well-being, safety and the public interest.

Cheng YJ, Kanaya AM, Araneta MRG, Saydah SH, Kahn HS, Gregg EW, et al. Prevalence of Diabetes
Beckles GL, Chou C. Disparities in the Prevalence of Diagnosed Diabetes — United States, 1999–20
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Furlong, Ashleigh, Biased AI health tech could disadvantage poorer countries, World Health Organ

Clinical requirements for Autonomous AI

- Make medical decision without human oversight
  - Autonomous AI
  - Creator assumes liability
  - Easy-to-understand diagnostic output
- Minimal changes to clinic/lab workflow
  - Make diagnosis within minutes
  - Minimal footprint to fit clinic space, power outlet only requirement
  - High diagnosability
- Use existing staff
  - Operable by existing staff (high school diploma)
  - Robotic camera with assistive AI
- Automatic claims, billing and care gap closure
  - Real time, immediate claims and ICD-10 generation
  - Aligned w Standards of Care and Preferred Practice Patterns

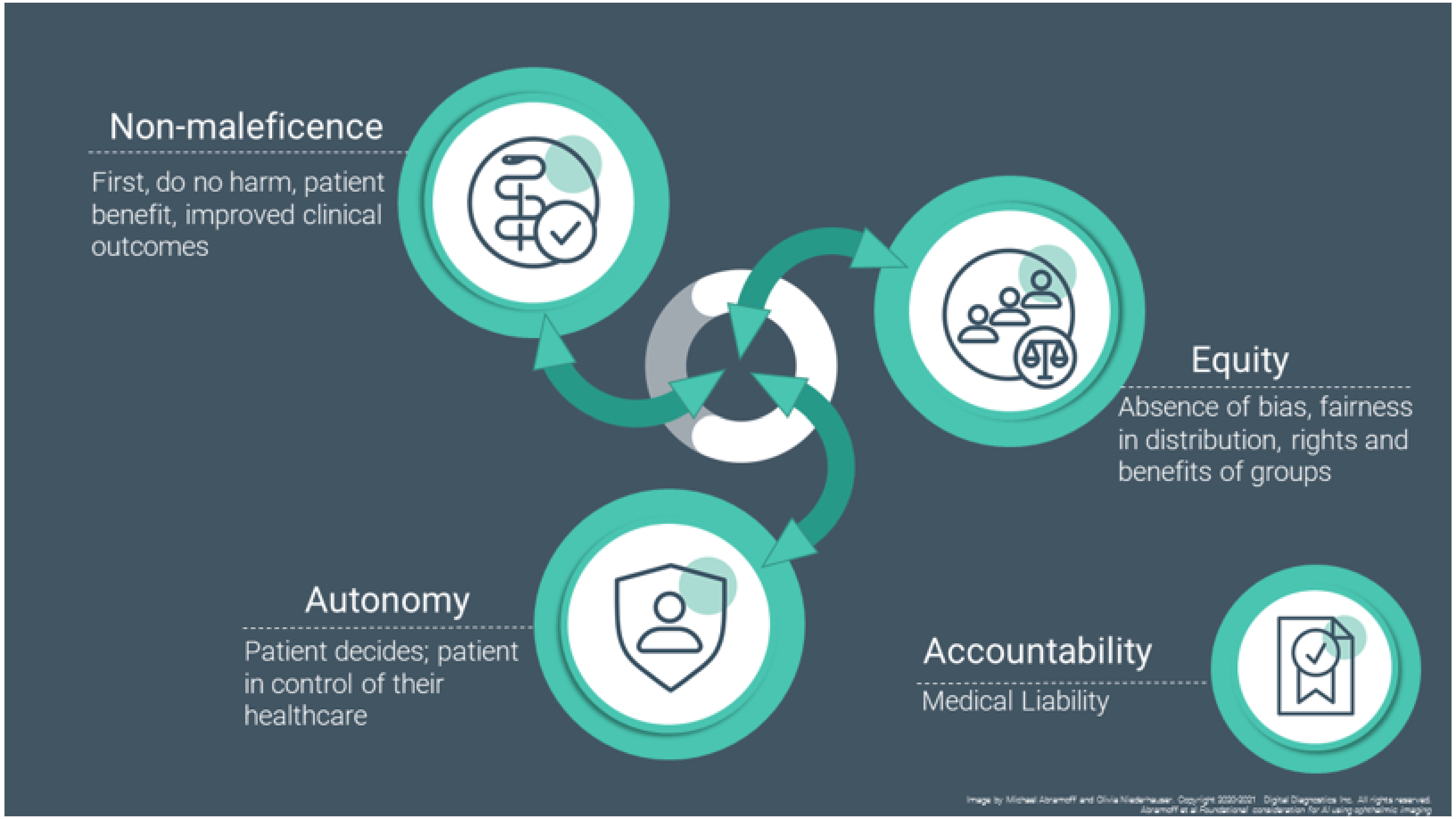
Ethical framework for Autonomous AI requirements

Ethical principles

- Non-maleficence
- Autonomy
- Justice

Legal principle

- Accountability



1. Abramoff MD, Tobey D, Char DS. Lessons Learned About Autonomous AI: Finding a Safe, Efficacious, and Ethical Path Through the Development Process. Am J Ophthalmol. 2020;214(1):134-42.
2. Char DS, Abràmoff MD, Feudtner C. Identifying Ethical Considerations for Machine Learning Healthcare Applications. The American Journal of Bioethics. 2020;20(11):7-17.

Mitigating bias through AI design

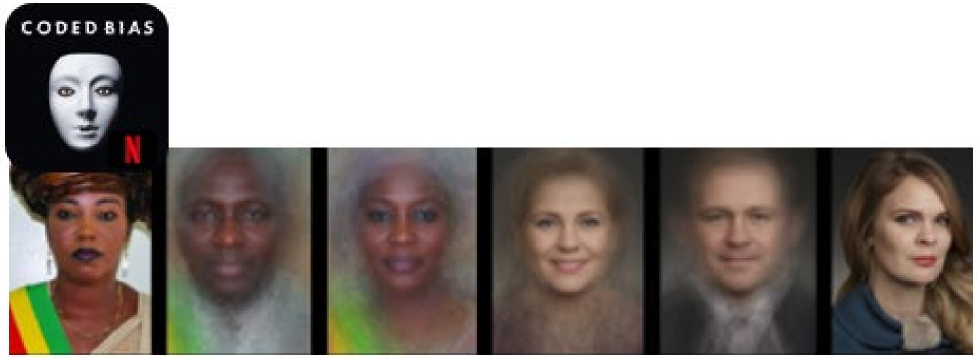
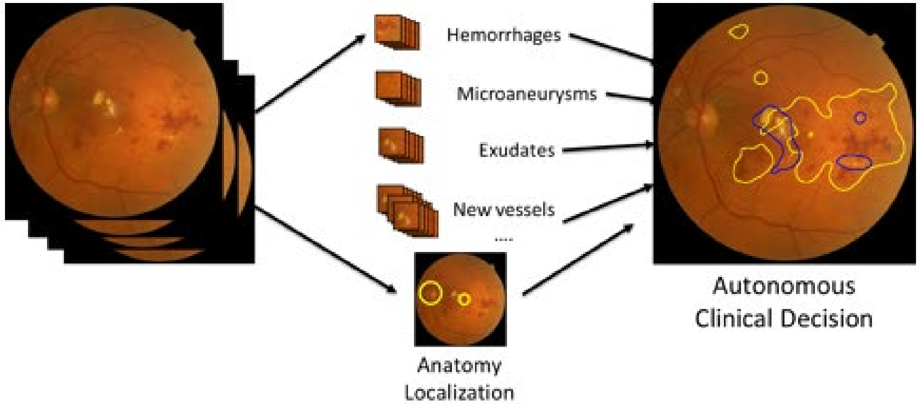
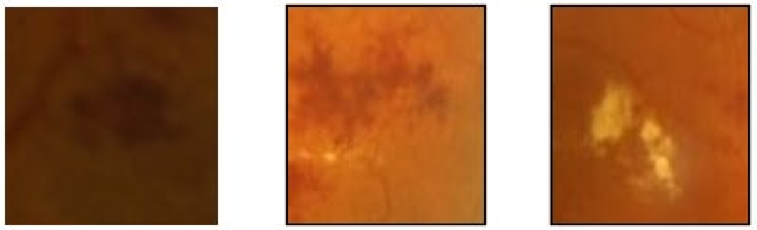


Image based training of convolutional neural networks

High risk of (racial) bias



Detector based design – lesion specific
Racially invariant detectors



Low to zero risk of (racial) bias

1. https://www.netflix.com/title/81328723
2. https://dam-prod.media.mit.edu/x/2018/02/06/Gender%20Shades%20Intersectional%20Accuracy%20Disparities.pdf (figure 1)
3. Hansen MB, Abramoff MD, Folk JC, Mathenge W, Bastawrous A, Peto T. Results of Automated Retinal Image Analysis for Detection of 4. Diabetic Retinopathy from the Nakuru Study, Kenya. PLoS One. 2015;10(10):e0139148. doi:10.1371/journal.pone.0139148]
4. Abramoff MD, Alward WL, Greenlee EC, et al. Automated segmentation of the optic disc from stereo color photographs using physiologically plausible features. Invest Ophthalmol Vis Sci. 2007;48(4):1665-73
5. Abramoff et al. Lessons Learned About Autonomous AI: Finding a Safe, Efficacious, and Ethical Path Through the Development Process. Am J Ophthalmol. 2020;214(1):134-42.
6. Char, Abràmoff, Feudtner. Identifying Ethical Considerations for Machine Learning Healthcare Applications. The American Journal of Bioethics. 2020;20(11):7-17.
7. American Diabetes Association. 11. Microvascular Complications and Foot Care: Standards of Medical Care in Diabetes − 2020. Diabetes Care; 43(Supplement 1): S135-S151, 2020.
8. https://www.ncqa.org/wp-content/uploads/2020/07/20200701_Summary_Table_of_Measures_Product_Lines_and_Changes.pdf
9. https://www.ama-assn.org/practice-management/digital/ophthalmologist-doing-health-care-ai-right-way

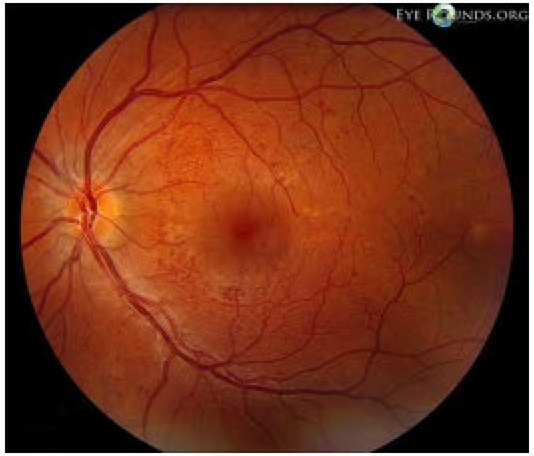
Validation against clinical outcome

- Evidence based markers for diabetic retinopathy
  - Studies from 70s and 80s and today
  - Highly reproducible and consistent over decades
  - Used today for FDA drug trials: ETDRS, DRS and DRCR
  - Cannot be created again ethically
- Clinicians not validated against this standard
  - Low diagnostic accuracy and diagnostic drift
  - Lack of consistency

ALL DR management and treatment based on this reference standard

Rigorous Validation of AI Against Prognostic Standard

	FDA Superiority Endpoint	IDx-DR(n=819)	Remote Reading Network / Telemedicine	Board Certified Ophthalmologist in Clinic
Sensitivity	85%	87%[1] (81% - 91%)	72% (65%-79%)[6]	33%[2]-34[3]%
Specificity	82%	90%[1] (88% - 93%)	97% (95%-99%)[6]	99%[2]-100[3]%
Repeatability		99%	<80%[6]	60%[4]
Reproducibility		99%[5]		83%[4]
Equity: No significant effects for sex, race, ethnicity, HbA1C, lens status, or site			All other AI, remote readers, and clinician studies do not use surrogate outcome as the standard, and only compare to unvalidated clinicians (who may or may not correspond to outcome markers)	



Surrogate outcome:

Stereo imaging: ETDRS level 43

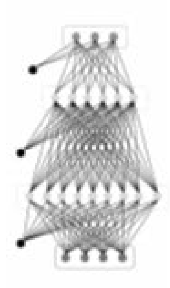
- 1-year risk of early PDR 26.3%
- 1-year risk of high-risk PDR: 8.1%

OCT: DRCR level no ci-DME

- No benefit from treatment

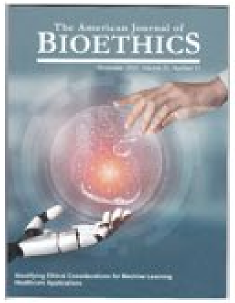
Creation of a new industry:
Autonomous AI in Healthcare

'Diagnostic AI Algorithm'



300+ papers
(2008)

Foundation in Ethics



Ethical Foundations
(2020)

Clinical trial design / Regulatory Approval

FDA

First FDA de novo clearance
(2018)

Second FDA clearance with 510k
(2020)

Standards of Care

American Diabetes Association.

Standards of Medical Care in Diabetes
(2020)

Reimbursement

AMA CMS
AMERICAN ACADEMY OF OPHTHALMOLOGY

First ever CPT Code 92229
(2019)

Coverage
$55.66
(2020)

Data transparency and traceability

USPTO
11,004,565

Affect patient outcomes/ Address health disparities

Preventing blindness and visual loss

Resolving health disparities and closing care gaps

Case Study: Improving access in New Orleans

Pre-implementation

- Largely Black population
- Hardly any eye care providers
- 805+ patients w care gaps for diabetic eye exam
- > 4-month appointment wait time

9 months post IDx-DR

- Eliminated care gaps for 805+ patients
- <u>Same day appointments if eye exam needed</u>


npr WBEZ91.5
Shots
How Can We Be Sure Artificial Intelligence Is Safe For Medical Use?

LCMC Health

25% had a potentially blinding disease

Case Study: Reducing COVID backlog in Iowa

APR	MAY	JUNE	JULY
100 patients not tested	70 patients tested	30 patients tested	Backlog cleared
Diabetic eye exams halted due to lack of access	IDx-DR added to address eyecare back log/eliminate extra visits		Routine use of IDx-DR

17% had a potentially blinding disease

"With IDx-DR we stayed on top of closing care gaps even during a pandemic. Access to diabetic eye exam is not a problem anymore because of the highly scalable capacity."

Michelle Havinga (Director Population Health & ACO Ops UIHC)

University of Iowa Hospitals & Clinics
University of Iowa Health Care

References

Slide 3&4:

1. US Bureau Labor Statistics, 2010
   Lam et al, The effect of electronic health records adoption on patient visit volume at an academic ophthalmology department BM Health Serv Res, 2016
2. Redd et al, Electronic health record impact on productivity and efficiency in an academic pediatric ophthalmology practice, JAAPOS 2014
3. Fong DS, Aiello L, Gardner TW, et al. Diabetic retinopathy. Diabetes Care. 2003;26(1):226-229.
4. Centers for Disease Control and Prevention. Diabetes Report Card 2012. Atlanta, GA: U.S. Department of Health and Human Services;2012
5. U.S. Centers for Disease Control level distribution of diagnosed diabetes among US adults aged 20 or older, 2013. https://www.cdc.gov/diabetes/pdfs/library/diabetesreportcard2017-508.pdf

Slide 5:

1. Cheng YJ, Kanaya AM, Araneta MRG, Saydah SH, Kahn HS, Gregg EW, et al. Prevalence of Diabetes by Race and Ethnicity in the United States, 2011-2016. JAMA. 2019;322(24):2389-98.
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4. West SK, Klein R, Rodriguez J, et al. Diabetes and diabetic retinopathy in a Mexican-American population: Proyecto VER. Diabetes Care. 2001;24:1204–1209.
   Nsiah-Kumi P, Ortmeier SR, Brown AE. Disparities in diabetic retinopathy screening and disease for racial and ethnic minority populations--a literature review. J Natl Med Assoc. 2009;101(5):430-7.

Slide 6:

Furlong, Ashleigh, Biased AI health tech could disadvantage poorer countries, World Health Organization

Slide 7:

1. Abramoff MD, Tobey D, Char DS. Lessons Learned About Autonomous AI: Finding a Safe, Efficacious, and Ethical Path Through the Development Process. Am J Ophthalmol. 2020;214(1):134-42.
2. Char DS, Abràmoff MD, Feudtner C. Identifying Ethical Considerations for Machine Learning Healthcare Applications. The American Journal of Bioethics. 2020;20(11):7-17.

Slide 8:

1.https://www.netflix.com/title/81328723
2.https://dam-prod.media.mit.edu/x/2018/02/06/Gender%20Shades%20Intersectional%20Accuracy%20Disparities.pdf (figure 1)
3.Hansen MB, Abramoff MD, Folk JC, Mathenge W, Bastawrous A, Peto T. Results of Automated Retinal Image Analysis for Detection of 4. Diabetic Retinopathy from the Nakuru Study, Kenya. PLoS One. 2015;10(10):e0139148. doi:10.1371/journal.pone.0139148]
4.Abramoff MD, Alward WL, Greenlee EC, et al. Automated segmentation of the optic disc from stereo color photographs using physiologically plausible features. Invest Ophthalmol Vis Sci. 2007;48(4):1665-73
5.Abramoff et al. Lessons Learned About Autonomous AI: Finding a Safe, Efficacious, and Ethical Path Through the Development Process. Am J Ophthalmol. 2020;214(1):134-42.
6.Char, Abràmoff, Feudtner. Identifying Ethical Considerations for Machine Learning Healthcare Applications. The American Journal of Bioethics. 2020;20(11):7-17.
7.American Diabetes Association. 11. Microvascular Complications and Foot Care: Standards of Medical Care in Diabetes − 2020. Diabetes Care; 43(Supplement 1): S135-S151, 2020.
8.https://www.ncqa.org/wp-content/uploads/2020/07/20200701_Summary_Table_of_Measures_Product_Lines_and_Changes.pdf
9.https://www.ama-assn.org/practice-management/digital/ophthalmologist-doing-health-care-ai-right-way

Slide 9:

1. ETDRS report number 9. Ophthalmology 98, 766-785 (1991).
2. ETDRS report number 10. Ophthalmology 98, 786-806 (1991).
3. ETDRS report number 12. Ophthalmology 98, 823-833 (1991).
4. DCCT Progression of retinopathy with intensive versus conventional treatment in the Diabetes Control and Complications Trial. Ophthalmology 102, 647-661 (1995).
5. DCCT The relationship of glycemic exposure (HbA1c) to the risk of development and progression of retinopathy in the diabetes control and complications trial. Diabetes 44, 968-983 (1995).
6. Browning et al., Optical coherence tomography measurements and analysis methods in optical coherence tomography studies of diabetic macular edema. Ophthalmology 115, 1366-1371, 1371 e1361 (2008).
7. DRCR, Three-year follow-up of a randomized trial comparing focal/grid photocoagulation and intravitreal triamcinolone for diabetic macular edema. Arch Ophthalmol 127, 245-251 (2009).
8. Glassman et al., Comparison of optical coherence tomography in diabetic macular edema, with and without reading center manual grading from a clinical trials perspective. Invest Ophthalmol Vis Sci 50, 560-566 (2009). Abràmoff MD, Lavin PT, Birch M, Shah N, Folk JC. Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. Nature Digit Med 2018;1:39off
9. Pugh JA, Jacobson JM, Van Heuven WA, et al. Screening for diabetic retinopathy. The wide-angle retinal camera. Diabetes Care. 1993;16(6):889-895.
10. Lin DY, Blumenkranz MS, Brothers RJ, Grosvenor DM. The sensitivity and specificity of single-field nonmydriatic monochromatic digital fundus photography with remote image interpretation for diabetic retinopathy screening: a comparison with ophthalmoscopy and standardized mydriatic color photography. AmJOphthalmol. 2002;134(2):204-213. Liu et al, 2018
11. Lynch et al, IOVS, 2018
12. Abramoff et al, Improved Automated Detection of Diabetic Retinopathy Through Integration of Deep Learning, IOVS, 2016. Compared to 3 retina specialists.
13. Folk et al, Macula Society. Accuracy of the diabetic eye exam by ophthalmologists, as well as telemedicine by retina specialists and reading center, against a validated outcome standard.

Slide 11:

1. www.npr.org/sections/health-shots/2019/04/14/711775543/how-can-we-be-sure-artificial-intelligence-is-safe-for-medical-use

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