



Use Artificial Intelligence in EMR

Vitaly Herasevich, MD, PhD, FCCM

Professor of Anesthesiology and Medicine,

Department of Anesthesiology and Perioperative Medicine, Division of Critical Care

Multidisciplinary Epidemiology and Translational Research in Intensive Care (METRIC)



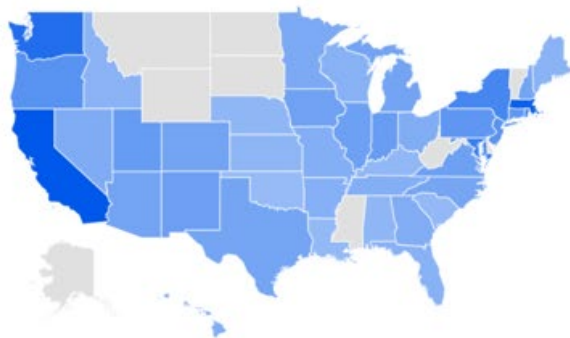
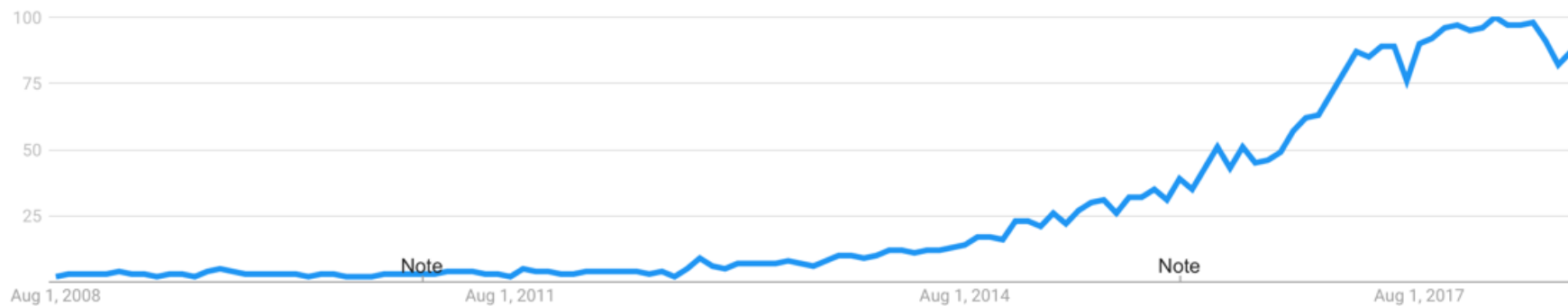
Will AI replace me?
The short answer
is **NO**.



Not yet...

● deep learning
Search term

+ Compare



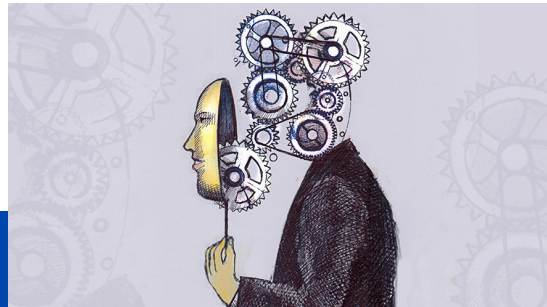
1	California	100	<div></div>
2	Massachusetts	93	<div></div>
3	Washington	81	<div></div>
4	Maryland	67	<div></div>
5	New York	60	<div></div>

Deep learning

- **Deep learning** is a type of **machine learning** that trains a computer to perform human-like tasks.
- Instead of organizing data to run through predefined equations, deep learning sets up basic parameters about the data and **trains the computer to learn on its own** by recognizing patterns using many layers of processing.
- Deep learning is one of the foundations of **artificial intelligence (AI)**, and the current interest in deep learning is due in part to the buzz surrounding AI.

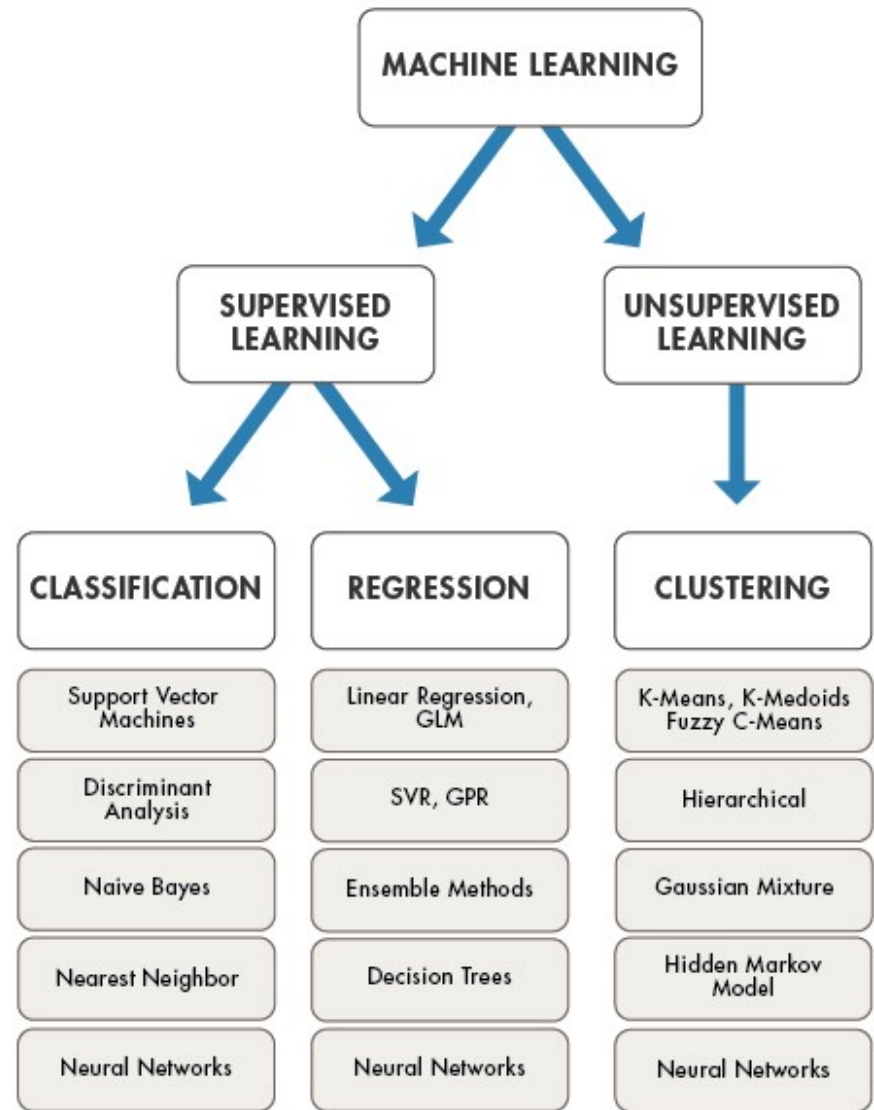
Artificial Intelligence (AI)

- Makes it possible for machines to learn from (human) experience, adjust to new inputs and perform human-like tasks.
- Most AI examples today – from chess-playing computers to self-driving cars – rely heavily on **machine and deep learning**.
- Computers can be trained to accomplish specific tasks by processing large amounts of data and recognizing patterns in the data.



Machine learning vs. data mining

- Machine learning and data mining use the same methods and overlap significantly
- Machine learning** focuses on **prediction**,
- Data mining** focuses on the **discovery** of unknown properties in the data.



Chapter 2

Artificial Intelligence in Medicine (AIM)

The development of expert critiquing systems is part of a growing field involving numerous projects applying artificial intelligence in medicine. This work has been in progress for the past 15 years (Clancey and Shortliffe 1984; Kulikowski 1980; Shortliffe et al. 1979; Szolovits 1982). This chapter gives an overview of these projects. It then discusses the field of AI as a whole. Finally, the chapter discusses how critiquing itself can be performed at different levels of complexity. The critiquing research described in this book focusses on the more complex end of this spectrum.

April
1995

College of Healthcare Information Management Executives

April 1995
\$4.95

healthcare

I N F O R M A T I C S

USING ARTIFICIAL

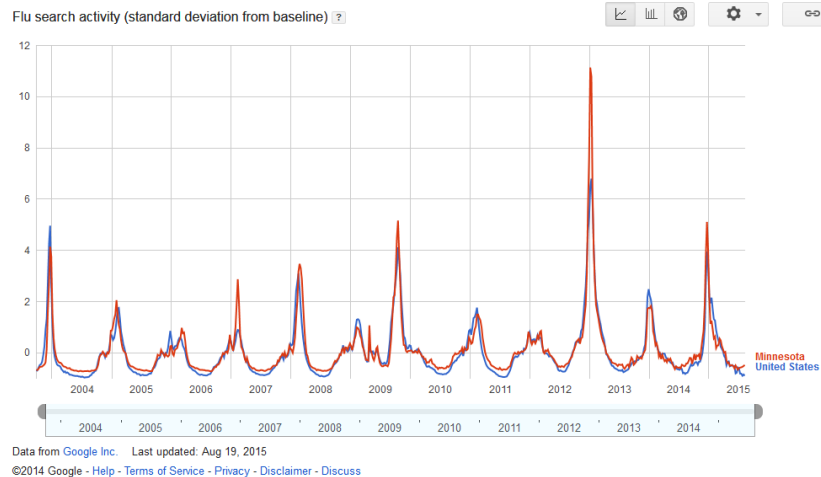
INTELLIGENCE TO PREDICT MYOCARDIAL INFARCTION

Achieving high-quality, cost-efficient patient care with appropriate use of medical services for the potential cardiac patient has been debated as an inpatient resource management issue. With the application of artificial intelligence, or AI, at Florida Hospital, we no longer rely on a physician's judgment alone for the decision to admit a patient for a cardiac workup. Our system esti-

1995

Tracking Disease Outbreaks

- One of the earliest examples was Google Flu Trends, which began offering real-time data to the public in 2008. Based on people's Internet searches for flu-related terms, this tool monitored flu outbreaks worldwide.



BIG DATA

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer,^{1,2*} Ryan Kennedy,^{1,3,4} Gary King,³ Alessandro Vespignani^{5,6,3}

In February 2013, Google Flu Trends (GFT) made headlines but not for a reason that Google executives or the creators of the flu tracking system would have hoped. *Nature* reported that GFT was predicting more than double the proportion of doctor visits for influenza-like illness (ILI) than the Centers for Disease Control and Prevention (CDC), which bases its estimates on surveillance reports from laboratories across the United States (1, 2). This happened despite the fact that GFT was built to predict CDC reports. Given that GFT is often held up as an exemplary use of big data (3, 4), what lessons can we draw from this error?

The problems we identify are not limited to GFT. Research on whether search or social media can predict x has become commonplace (5–7) and is often put in sharp contrast with traditional methods and hypotheses. Although these studies have shown the value of these data, we are far from a place where they can supplant more traditional

ability and dependencies among data (12). The core challenge is that most big data that have received popular attention are not the output of instruments designed to produce valid and reliable data amenable for science.


Large error
avoidable
of big data



Google Flu Trends 2008-2013

2011

Paging Dr. Watson: AI Jeopardy! Soon To Be Physician's Assistant

By **Jeremy Ford** - Mar 09, 2011  5,032

Is there an AI doctor in the house?

poised to be a sidekick for future physicians. IBM and **Nuance Healthcare** have teamed up with **Columbia University** and the **University of Maryland** to build a medical Watson that's fine-tuned to address the queries of doctors. The goal is

Will you ever be treated by **Dr. Watson**? Not Sherlock Holmes's **right-hand man**, but the AI Jeopardy! champion who's

Don't miss a trend.

Get Hub delivered to your inbox

Enter your email...

 **USA TODAY** | **News**

 **Subscribe**

 **Mobile**



Google USA TODAY

Home

News

Travel

Money

Spor

Tech: Blogs | Products | Gaming | Science & Space

IBM's Watson delving into medicine

By **Jim Fitzgerald**, Associated Press

Posted 5/21/2011 4:28:22 PM |  3

YORKTOWN, N.Y. — Some guy in his pajamas, home sick with bronch

2013

PATIENTS & FAMILY

PREVENTION & SCREENING

DONORS & VOLUNTEERS

FOR PHYSICIANS

RESEARCH

MD Anderson Taps IBM Watson to Power "Moon Shots" Mission

MD Anderson News Release 10/18/13

The University of Texas MD Anderson Cancer Center and IBM today announced that MD Anderson is using the IBM Watson cognitive computing system for its mission to eradicate cancer. Following a year-long collaboration, IBM and

Special Review of
Procurement Procedures Related to the
M.D. Anderson Cancer Center Oncology Expert Advisor Project

2016



Through August 31, 2016, approximately \$62.1 million has been paid to external firms for planning, project management, and development of OEA. More than half of the funding used towards the system came from restricted gifts donated or pledged specifically for this purpose. This total reflects payments to external entities only; it does not include internal resources such as staff time, technology infrastructure, or administrative support. OEA has not been updated to integrate with MD Anderson's new electronic medical records system, and is not in clinical use.



LIFE HACKS NOVEMBER 28, 2016 ISSUE

COOKING WITH CHEF WATSON, I.B.M.'S ARTIFICIAL- INTELLIGENCE APP

Watson makes suggestions that no human would ever make, like adding milk chocolate to a clam linguine or mayonnaise to a Bloody Mary.



2018

THE WALL STREET JOURNAL.

U.S. Edition | August 15, 2018 | Today's Paper | Video

Home World U.S. Politics Economy **Business** Tech Markets Opinion Life & Arts Real Estate WSJ Magazine

Search

BUSINESS

IBM Has a Watson Dilemma

Big Blue promised its AI platform would be a big step forward in treating cancer. But after pouring billions into the project, the diagnosis is gloomy.

By *Daniela Hernandez and Ted Greenwald*

Aug. 11, 2018 12:19 a.m. ET

The *WSJ* claims Watson often “didn’t add much value” or “wasn’t accurate.” This lackluster assessment is blamed on Watson’s inability to keep pace with fast-evolving treatment guidelines, as well as its inability to accurately evaluate reoccurring or rare cancers. Despite the more than \$15 billion IBM has spent on Watson, the *WSJ* reports there is no published research showing Watson improving patient outcomes.

Lukas Wartman, MD, Assistant Professor, McDonnell Genome Institute at the Washington University School of Medicine in St. Louis, told the *WSJ* he rarely uses the Watson system, despite having complimentary access. IBM typically charges \$200 to \$1,000 per patient, plus consulting fees in some cases, for Watson-for-Oncology, the *WSJ* reported.

“The discomfort that I have—and that others have had with using it—has been the sense that you never know how much faith you can put in those results,” Wartman said.

The New York Times



By Adam Liptak

May 1, 2017



When Chief Justice John G. Roberts Jr. visited Rensselaer Polytechnic Institute last month, [he was asked a startling question](#), one with overtones of science fiction.

“Can you foresee a day,” asked [Shirley Ann Jackson](#), president of the college in upstate New York, “when smart machines, driven with artificial intelligences, will assist with courtroom fact-finding or, more controversially even, judicial decision-making?”

The chief justice’s answer was more surprising than the question. “It’s a day that’s here,” he said, “and it’s putting a significant strain on how the judiciary goes about doing things.”



How artificial intelligence can help us make judges less biased

Predicting which judges are likely to be biased could give them the opportunity to consider more carefully

By Angela Chen | @chengela | Jan 17, 2019, 12:07pm EST

The New York Times

In Wisconsin, a Backlash Against Using Data to Foretell Defendants' Futures



The Wisconsin State Capitol. Wisconsin is one of several states to use algorithms in the sentencing process. One defendant, Eric L. Loomis, has appealed his sentence. Scott Bauer/Associated Press

By Mitch Smith

June 22, 2016



CHICAGO — When Eric L. Loomis was sentenced for eluding the police in La Crosse, Wis., the judge told him he presented a “high risk” to the community and handed down a six-year prison term.



AUGUST 17, 2012

1.1 COMPAS History and Development

COMPAS was first developed in 1998 and has been revised over the years as new information in the criminal justice field has emerged toward best practice use and intervention. The updated normative data were sampled from over 30,000 COMPAS assessments conducted between January 2004 and November 2005 at prison, parole, jail and probation sites across the United States. The latest revision used the same groups, but in actual proportion to the number of offenders found in each group in the criminal justice system for many

Self Driving cars.

2016

< Tweet



Elon Musk ✓
@elonmusk

In ~2 years, summon should work anywhere connected by land & not blocked by borders, eg you're in LA and the car is in NY

2:11 PM · 1/10/16 · [Twitter for iPhone](#)

4,596 Retweets 7,340 Likes



2010

IEEE
SPECTRUM

il Reports ▾

Blogs ▾

Multimedia ▾

The Magazine ▾

Automaton | Robotics | Robotics Software

21 Sep 2010 | 12:35 GMT

Autonomous Vehicle Driving from Italy to China

A 13,000 kilometer, three-month test drive -- with no driver

By [Erico Guizzo](#)



 **VSLAB..IT**
Extend Your Vision



ELSEVIER

Contents lists available at ScienceDirect

Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aim

Thirty years of artificial intelligence in medicine (AIME) conferences: A review of research themes

Niels Peek^{a,*}, Carlo Combi^b, Roque Marin^c, Riccardo Bellazzi^d

ARTICLE INFO

Article history:

Received 28 January 2015

Received in revised form 17 July 2015

Accepted 17 July 2015

ABSTRACT

Background: Over the past 30 years, the international conference on Artificial Intelligence in Medicine (AIME) has been organized at different venues across Europe every 2 years, establishing a forum for scientific exchange and creating an active research community. The Artificial Intelligence in Medicine journal has published theme issues with extended versions of selected AIME papers since 1998.

Table 3

Frequency of occurrence of the twelve main research themes over the years (both short and long papers). Theme assignment was not exclusive: Many papers addressed multiple research themes. Some papers addressed relatively rare research themes that are not listed in the table.

Research theme	1985	1987	1989	1991	1993	1995	1997	1999	2001	2003	2005	2007	2009	2011	2013	Total	%
Knowledge engineering	8	16	21	15	40	22	11	14	11	5	5	9	1	4	4	186	25
Ontologies and terminologies	0	0	0	0	5	5	4	2	5	8	11	8	8	11	13	80	11
Natural language processing	0	1	1	0	0	1	4	5	4	5	7	8	9	6	8	59	8
Guidelines and protocols	0	0	0	0	4	1	5	5	3	10	16	8	4	9	5	70	10
Temporal information management	0	1	2	0	2	4	3	7	7	7	11	8	5	6	5	68	9
Case based reasoning	0	1	0	0	2	3	2	3	1	3	2	0	2	0	0	19	3
Planning and scheduling	0	0	0	0	0	0	3	1	3	1	1	4	4	2	1	20	3
Distributed and cooperative systems	0	0	0	2	2	2	3	3	4	1	4	7	2	0	2	32	4
Uncertainty management	0	4	3	3	4	4	8	2	11	7	4	8	5	3	6	72	10
Machine learning, data mining	0	1	3	2	11	11	15	14	18	12	23	26	25	11	17	189	26
Image and signal processing	0	0	2	1	6	2	9	4	5	2	6	8	10	4	3	62	8
Bioinformatics	0	0	0	0	0	0	0	0	2	2	4	2	5	3	4	22	3
Total accepted papers	15	26	36	26	60	60	58	50	63	52	70	66	62	45	45	734	

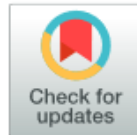
Why AI has become more popular today?

**Increase data
volumes and
storage**



**Improvements in
computing power**





Journal of Clinical Epidemiology 110 (2019) 12–22

**Journal of
Clinical
Epidemiology**

REVIEW

A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models

Evangelia Christodoulou^a, Jie Ma^b, Gary S. Collins^{b,c}, Ewout W. Steyerberg^d, Jan Y. Verbakel^{a,e,f}, Ben Van Calster^{a,d,*}

^aDepartment of Development & Regeneration, KU Leuven, Herestraat 49 box 805, Leuven, 3000 Belgium

^bCentre for Statistics in Medicine, Nuffield Department of Orthopaedics, Rheumatology and Musculoskeletal Sciences, Botnar Research Centre, University of Oxford, Windmill Road, Oxford, OX3 7LD UK

AI Limitation #1

The principle limitation of AI is that it learns from the data.

- There is no other way in which knowledge can be incorporated.
- That means any inaccuracies in the data will be reflected in the results.
- And any additional layers of prediction or analysis have to be added separately.

AI Limitation #2

Today's AI systems are trained to do a clearly defined task.

- The system that plays poker cannot play solitaire or chess.
- The system that detects fraud cannot drive a car or give you legal advice.
- In fact, an AI system that detects health care fraud cannot accurately detect tax fraud or warranty claims fraud.

The imagined AI technologies that you see in movies and TV are (STILL) science fiction.

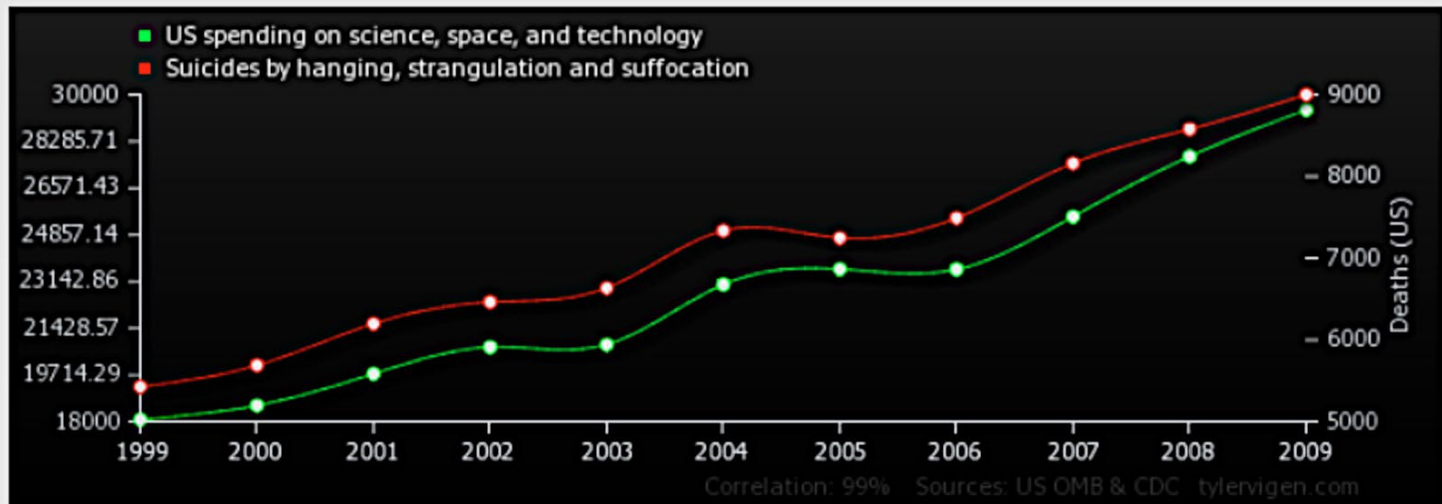
AI Limitation #3 (EMR data)

Problem: EMR data has pre-test probability

- EMR data has characteristics that decrease the practicality of most predictive models.
- It is Pretest Probability which is the probability of a patient having a target disorder before a diagnostic test result is known.
- Data is present in the EMR when clinicians cause it to be there as they suspect a specific health problem. For example, a diagnostic troponin test is ordered because a physician suspects myocardial infarction.

Problem: Data mining does not infer causality

US spending on science, space, and technology
correlates with
Suicides by hanging, strangulation and suffocation



	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
US spending on science, space, and technology Millions of todays dollars (US OMB)	18,079	18,594	19,753	20,734	20,831	23,029	23,597	23,584	25,525	27,731
Suicides by hanging, strangulation and suffocation Deaths (US) (CDC)	5,427	5,688	6,198	6,462	6,635	7,336	7,248	7,491	8,161	8,578

Correlation: 0.992082

3 waves of AI in medicine

First 1990-2005

- Risk calculators
- Doesn't learn new rules
- Doesn't deal with unknown

Second 2010-2018

- Pattern recognition
- Statistical learning or “machine learning”

Third 2018 -

- Inquisitory artificial intelligence
- Automatization

Artificial intelligence 2.0

Time spent on patient care

- In ED physicians spent **44% of their time**, on average, **performing data entry**.

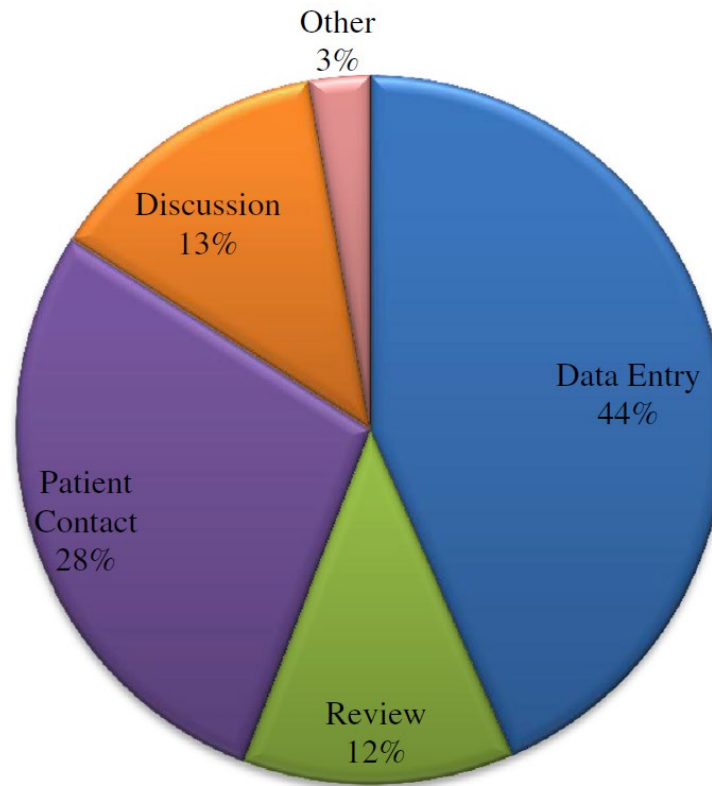


Fig. Emergency department practitioner time allocation.

- Much of what physicians do (checkups, testing, diagnosis, prescription, behavior modification, etc.) can be done better by sensors, passive and active data collection, and analytics.
- But, doctors aren't supposed to just measure.
- They're supposed to consume all that data, consider it in context of the latest medical findings and the patient's history, and figure out if something's wrong.

Vinod Khosla,
*co-founder of Sun Microsystems,
founder of Khosla Ventures*

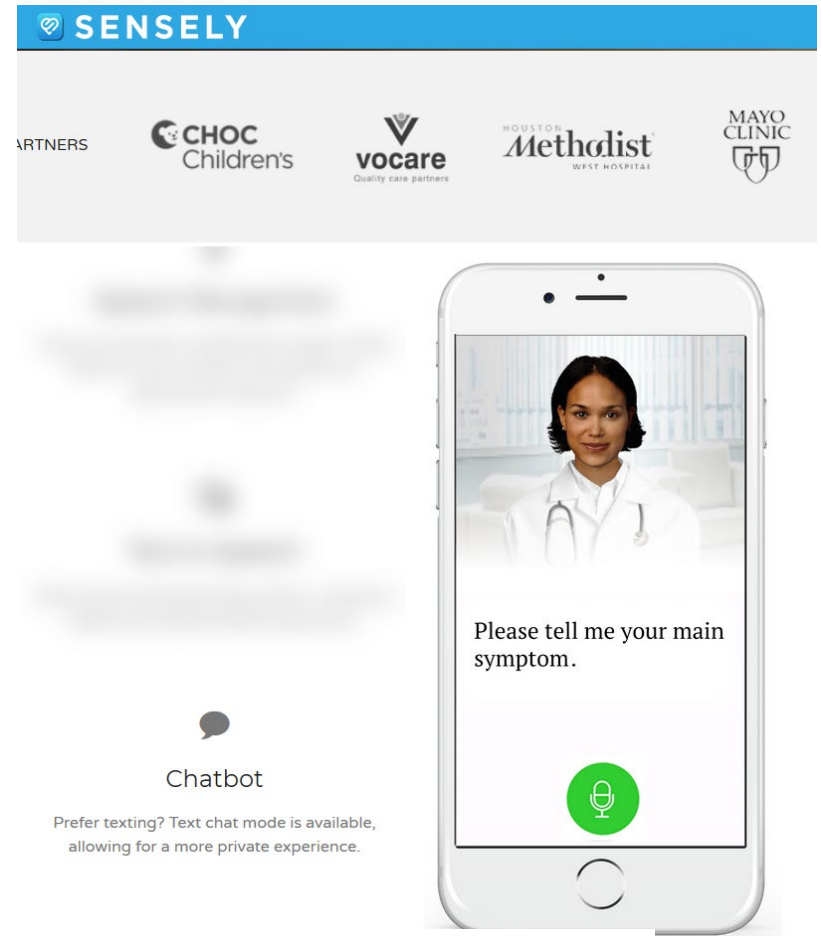
AI's First Foray Into Health Care

Doctors are a conservative bunch—for good reason—and slow to adopt new technologies. But in some areas of health care, medical professionals are beginning to see artificially intelligent systems as reliable and helpful. Here are a few early steps toward AI medicine.

ROBOTIC SURGERY Currently used only for routine steps in simple procedures like laser eye surgery and hair transplants.	IMAGE ANALYSIS Experts are just beginning to use automated systems to help them examine X-rays, retina scans, and other images.	GENETIC ANALYSIS With genome scans becoming a routine part of medicine, AI tools that quickly draw insights from the data are becoming necessary.	PATHOLOGY Experimental systems have proved adept at analyzing biopsy samples, but aren't yet approved for clinical use.
CLINICAL-DECISION SUPPORT Hospitals are introducing tools for applications like predicting septic shock, but they haven't yet proved their value.	VIRTUAL NURSING Rudimentary systems can check on patients between office visits and provide automatic alerts to physicians.	MEDICAL ADMINISTRATION Companies are rushing to offer AI-enabled tools that can increase efficiency in tasks like billing and insurance claims.	MENTAL HEALTH Researchers are exploring such applications as monitoring depression by mining mobile phone and social media data.

Chatbots

- The majority of current and emerging use cases appear to focus on checking patient symptoms. Specifically, natural language processing is used to help diagnose a user based on the symptoms he or she provides.

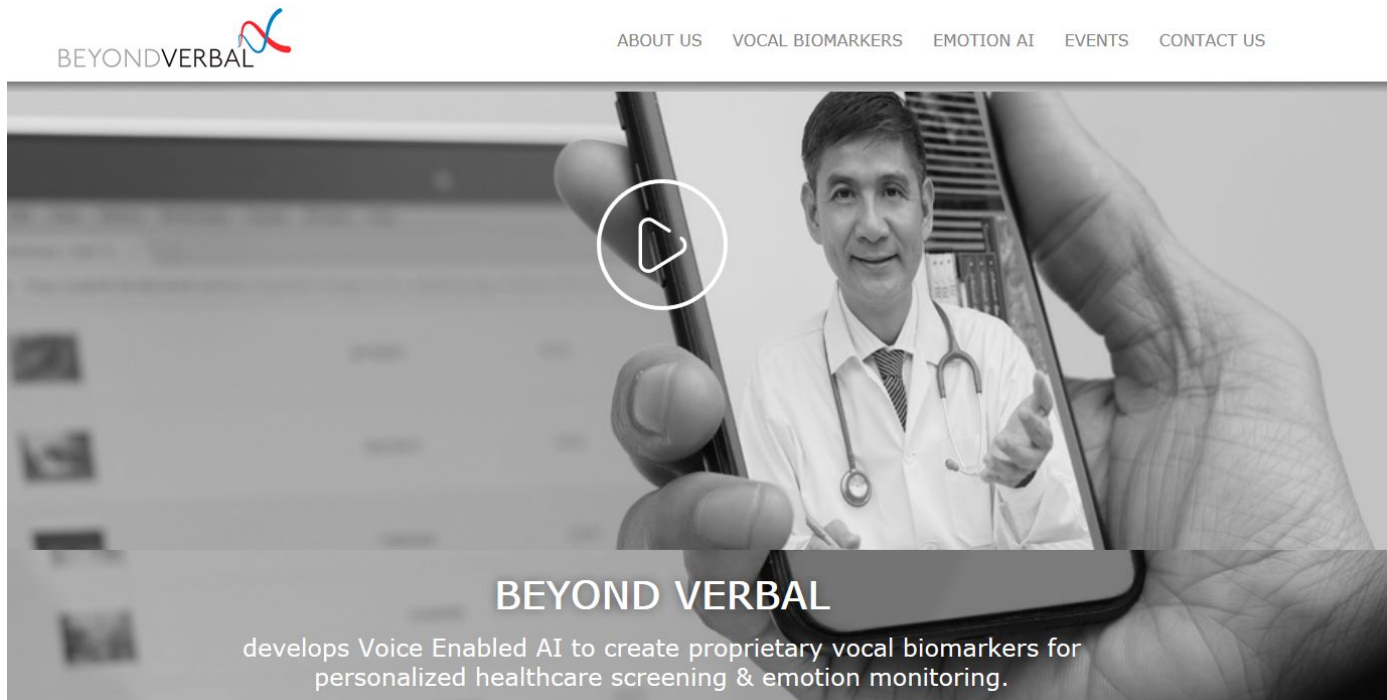


Mayo Clinic, Sensely collaborate on patient assessment solution

Written by Jessica Kim Cohen | May 15, 2017 | [Print](#) | [Email](#)

Rochester, Minn.-based Mayo Clinic [joined forces](#) with Sensely to support the health IT company's virtual medical assistant app.

Voice recognition



Detecting Coronary Artery Disease (CAD) by the voice – through joint research with the Mayo clinic.

Maor, E., Sara, J.D., Orbelo, D.M., Lerman, L.O., Levanon, Y., and Lerman, A. Voice signal characteristics are independently associated with coronary artery disease. Mayo Clin Proc. 2018;93: 840–847a

A Survey on Computer Vision for Assistive Medical Diagnosis From Faces

Jérôme Thevenot^{ID}, Miguel Bordallo López^{ID}, and Abdenour Hadid^{ID}

Abstract—Automatic medical diagnosis is an emerging center of interest in computer vision as it provides unobtrusive objective information on a patient's condition. The face, as a mirror of health status, can reveal symptomatic in-

for building artificial systems that can perceive and understand their environment, similarly to humans who perceive the great majority of information about their environment through sight.

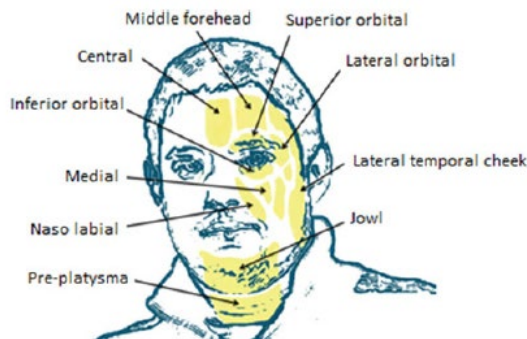


Fig. 1. The superficial fat compartments of the face.

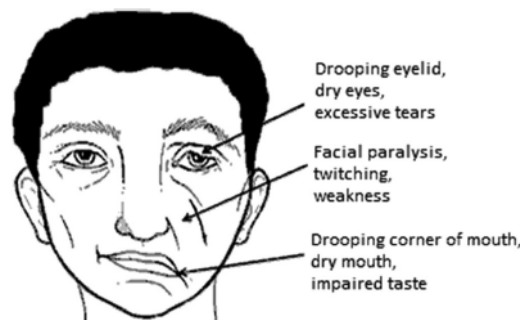


Fig. 2. An example of Bell's palsy.

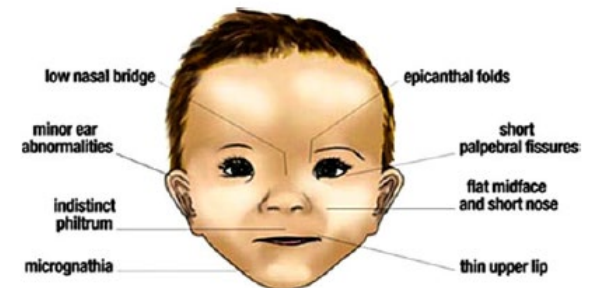
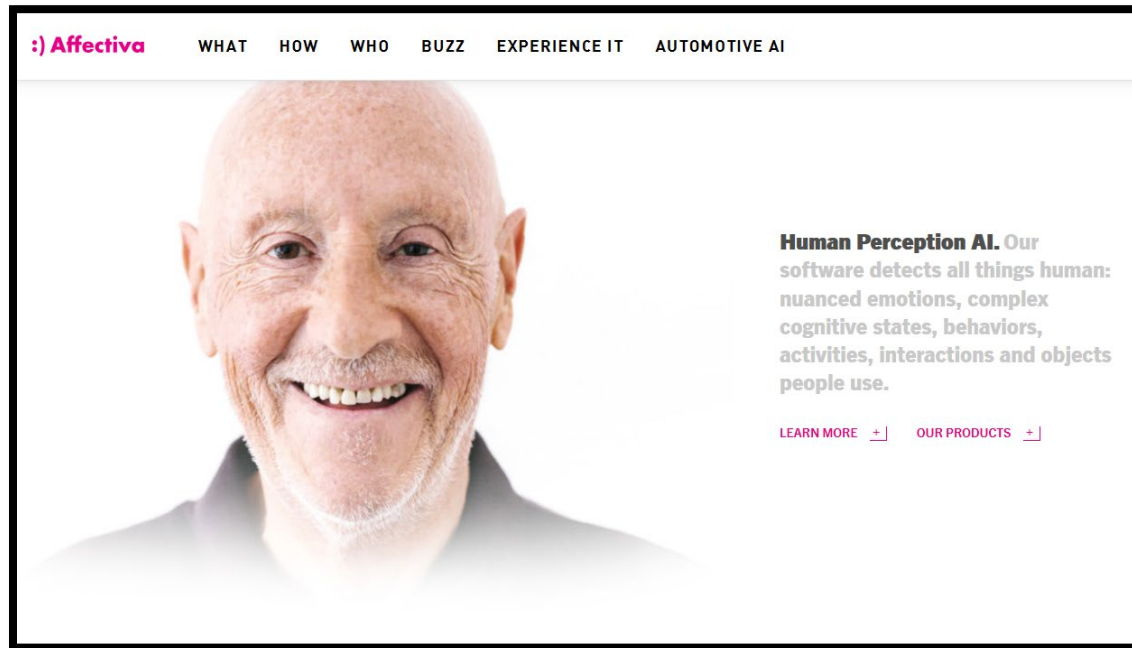


Fig. 3. Facial characteristics associated with fetal alcohol syndrome [132].

Emotion recognition

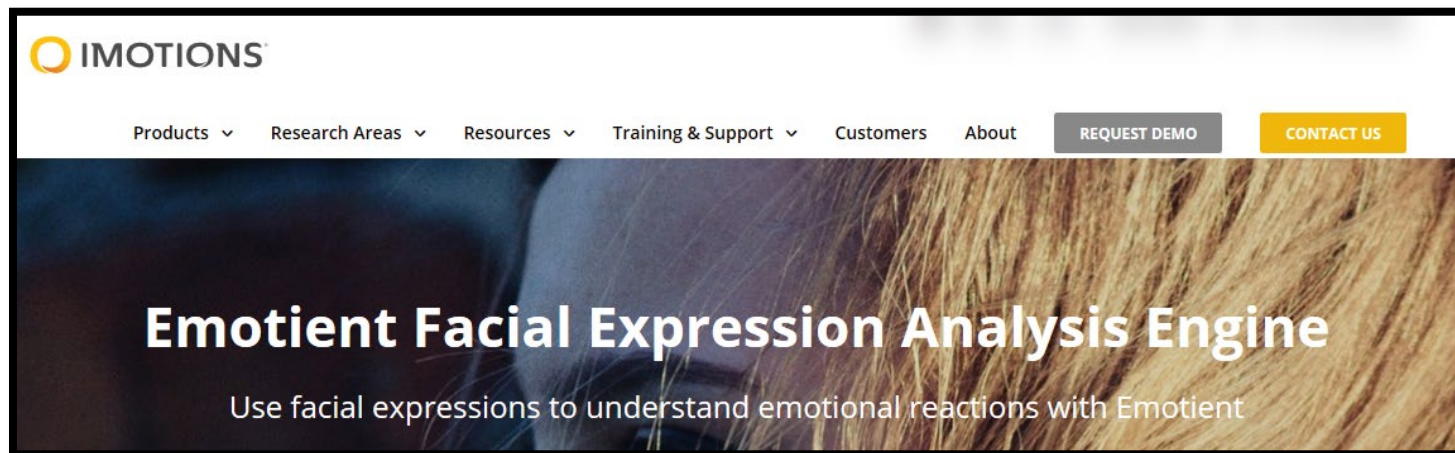


The image shows the header section of the Affective AI website. It features a navigation bar with the Affective logo (a pink smiley face followed by the word 'Affective') and links for WHAT, HOW, WHO, BUZZ, EXPERIENCE IT, and AUTOMOTIVE AI. Below the navigation bar is a large portrait of an elderly man with a white beard, smiling. To the right of the portrait, there is a text block that reads: 'Human Perception AI. Our software detects all things human: nuanced emotions, complex cognitive states, behaviors, activities, interactions and objects people use.' Below this text are two links: 'LEARN MORE' and 'OUR PRODUCTS', both with small pink plus icons.

:) **Affective** WHAT HOW WHO BUZZ EXPERIENCE IT AUTOMOTIVE AI

Human Perception AI. Our software detects all things human: nuanced emotions, complex cognitive states, behaviors, activities, interactions and objects people use.

[LEARN MORE](#) [OUR PRODUCTS](#)



The image shows the header section of the IMOTIONS website. It features a navigation bar with the IMOTIONS logo (a yellow circle followed by the word 'IMOTIONS') and links for Products, Research Areas, Resources, Training & Support, Customers, and About. There are also two buttons: 'REQUEST DEMO' and 'CONTACT US'. Below the navigation bar is a large banner image showing a close-up of a person's face with a focus on the hair. Overlaid on the banner is the text: 'Emotient Facial Expression Analysis Engine' and 'Use facial expressions to understand emotional reactions with Emotient'.

IMOTIONS

Products Research Areas Resources Training & Support Customers About [REQUEST DEMO](#) [CONTACT US](#)

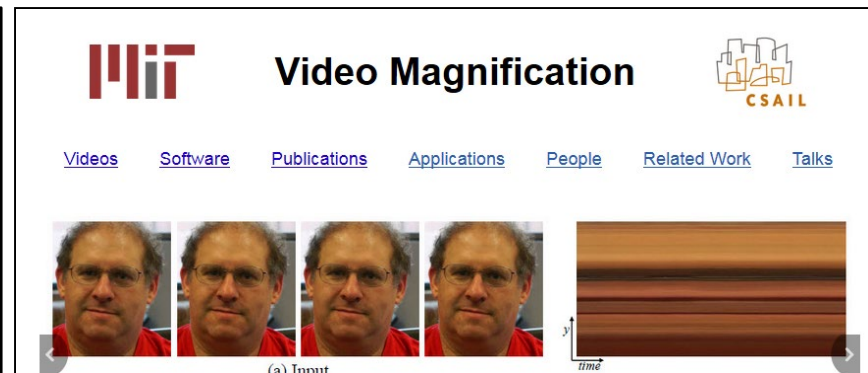
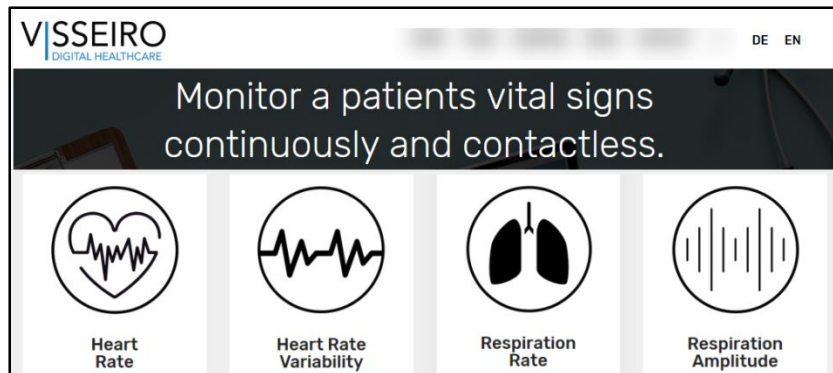
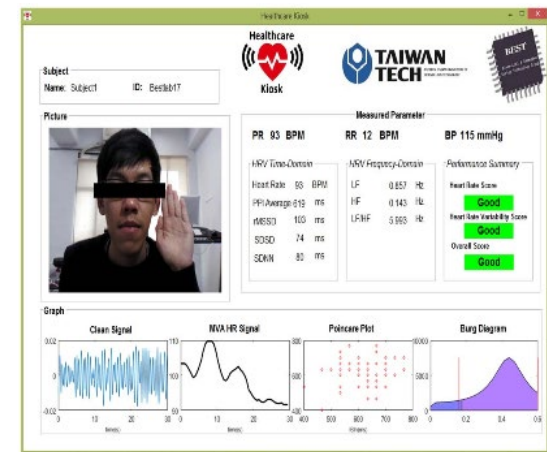
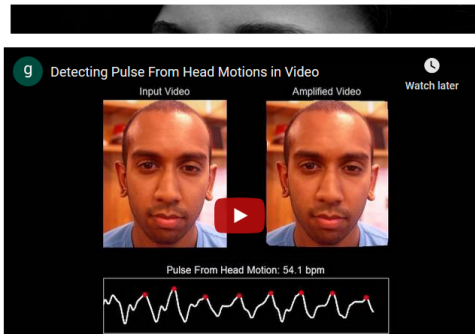
Emotient Facial Expression Analysis Engine

Use facial expressions to understand emotional reactions with Emotient

Contactless vitals

MIT researchers measure your pulse, detect heart abnormalities with smartphone camera

By John Hewitt on June 21, 2013 at 3:30 pm | 5 Comments




Contactless Vital Signs Measurement for Self-Service Healthcare Kiosk in Intelligent Building

Aminuddin Rizal, Yu-Chen Lin, and Yuan-Hsiang Lin*
Electronic and Computer Engineering Department
National Taiwan University of Science and Technology
Taipei, Taiwan
Email: linyh@mail.ntust.edu.tw*

Contactless thermometer (FDA and CE cleared)


CliniCloud Non-contact Thermometer

[Buy Now](#)



Next generation thermometer.

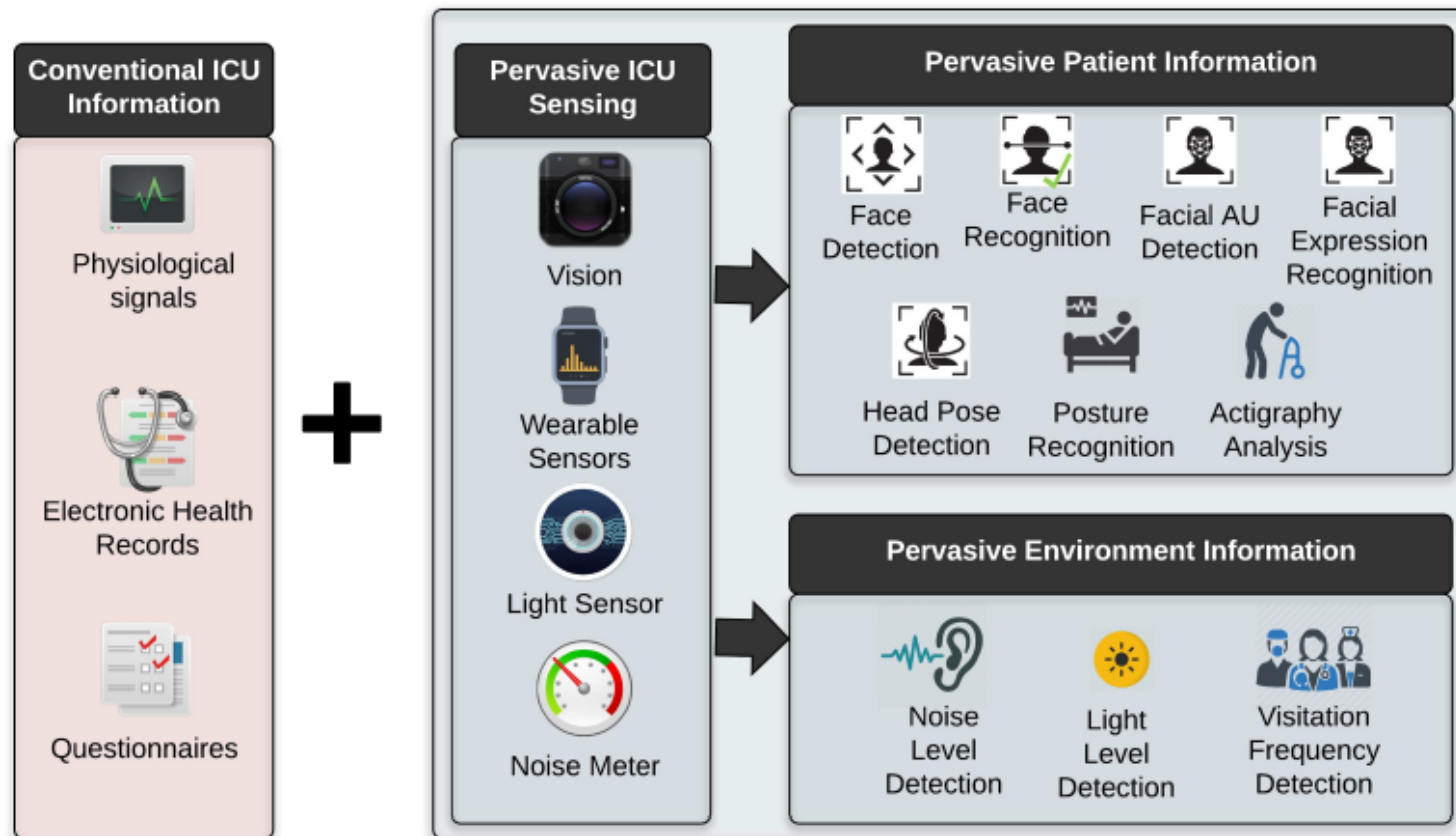
The CliniCloud Thermometer captures temperature with medical-grade accuracy of $\pm 0.2^{\circ}\text{C}$ (0.4°F). It takes just 2 seconds to take a reading from up to 2 in (5 cm) away from skin - easy and hygienic. The device is FDA cleared and has medical CE mark.




The Intelligent ICU: Using Artificial Intelligence Technology for Autonomous Patient Monitoring

Anis Davoudi¹, Kumar Rohit Malhotra², Benjamin Shickel², Scott Siegel¹, Seth Williams^{3,4}, Matthew Ruppert^{3,4}, Emel Bihorac^{3,4}, Tezcan Ozrazgat-Baslanti^{3,4}, Patrick J. Tighe⁵, Azra Bihorac^{3,4,+}, and Parisa Rashidi^{1,2,4,+*}

¹Biomedical Engineering, University of Florida, Gainesville, 32611, USA



Clinical control tower- prediction monitoring




[Rochester](#) [Saint Marys](#) [Methodist](#) [Arizona](#) [Florida](#) [Mayo Health Systems](#)

[List View](#) [Geo View](#)

find a patient

368

Vitaly Herasevich




<< first < prev 1 2 3 4 5 ... 94 next > last >>


10 patients per page

[Advanced filter](#) [Demo Mode](#)

68 years | Female
11 days in the hospital


Facility: ROSMC
Dept:
Room:
 Palliative

2




Problems List45 total

1. Diabetes Mellitus Type 2 With Unspecified Diabetic Retinopathy Without Macular Edema (HCC)
2. Infection Bloodstream Catheter Related Initial
3. Bacteremia
4. Infection Urinary Tract



24-hour Events3 total


1. Hospital Internal Medicine PROGRESS
2. Nursing Services CARE PLAN
3. Nursing Services CARE PLAN




Open

Ineligible

84 years | Male
1 day in the hospital


Facility: ROSMC
Dept:
Room:
 Palliative

1




Problems List39 total

1. Delirium
2. Palliative Care
3. Failure Heart Biventricular (HCC)
4. Acute And Chronic Respiratory Failure With Hypoxia (HCC)



24-hour Events5 total


1. Respiratory Therapy CARE PLAN
2. Respiratory Therapy CARE PLAN
3. Critical Care Medicine Disch Summ
4. Critical Care Medicine PROGRESS




Open

Ineligible

73 years | Female
33 days in the hospital


Facility: RORMC
Dept:
Room:
 Palliative

2




Problems List37 total

1. Failure Liver (HCC)
2. Do Not Resuscitate Status
3. Fibrillation Atrial (HCC)
4. Hypotension



24-hour Events12 total


1. Spiritual Care PROGRESS
2. GNS General Surgery Disch Summ
3. Critical Care Medicine PROGRESS
4. PTO Physical Therapy PROGRESS




Open

Ineligible

66 years | Male
22 days in the hospital


Facility: RORMC
Dept:
Room:
 Palliative

2




Problems List19 total

1. Hemophagocytic Lymphohistiocytosis (HCC)
2. Abnormal Coagulation Profile
3. Respiratory Failure With Hypoxia (HCC)
4. Sepsis (HCC)



24-hour Events3 total


1. PTO Dysphagia CONSULT
2. Nursing Services CARE PLAN
3. Hematology PROGRESS




Open

Ineligible

81 years | Male
1 day in the hospital


Facility: RORMC
Dept:
Room:
 Palliative

1




Problems List24 total

1. Sepsis (HCC)
2. Cancer Colon Transverse Personal History
3. Post Operative Nausea/Vomiting
4. Malignant Neoplasm Of Colon (HCC)



24-hour Events17 total

1. DX CHEST PORTABLE 1 VIEW
2. DX CHEST PORTABLE 1 VIEW
3. DX CHEST PORTABLE 1 VIEW
4. DX ABDOMEN PORTABLE ANTERIOR POSTERIOR 1 VIEW



Open

Ineligible

© 2018 Mayo Foundation for Medical Education and Research

MAYO
CLINIC

| slide-38

Clinical control tower- viewer

Patient, Test

57 years | Male
4 days in the hospital

Facility:
Dept:
Room:

100 Palliative

Problems List

54 total

1. Anemia Posthemorrhagic Acute (Blood Loss Anemia)
2. Primary Open-Angle Glaucoma Mild Stage Bilateral
3. Age Related Nuclear Cataract Bilateral
4. Uveitis Anterior Acute

24-hour Events

1. Nursing Services CARE PLAN
2. Gastroenterology and Hepatology PROGRESS
3. Gastroenterology and Hepatology Disch Summ
4. Nursing Services CARE PLAN

Organ Status

☒ hide normal values

Interval: ☐ 15 mins ☐ 30 mins ☐ 1 hour ☐ 2 hours ☐ 4 hours ☒ 8 hours ☐ 1 day ☐ 1 week

	3/1	3/2	3/3	3/4	3/5
all Lab/Vital/Event	16:00	00:00	08:00	16:00	00:00
Creatinine (mg/dL)		1.85		1.69	1.68
Potassium (mmol/L)		3.9		3.8	3.6
Leukocytes (x10(9)/L)		3.2	2.8	3	2.5
Hematocrit (%)		21.8	23.7	23.4	23.9
Hemoglobin (g/dL)		7.3	7.7	7.6	7.7

In Review Actions

☐ Palliative care team contacted

☐ Primary care team contacted

Goals

☐ Case review
23 hours, 59 minutes remaining

☐ Palliative note
Not started

Notes

none

New In Review Following Goals of Care Complete

☒ ☒ ☐ ☐

■ Artificial Intelligence
 ■ High Value Data – Eliminate Noise
 ■ Defined Process
 ■ Defined QI Goals
 ■ Communication

Real time monitoring

SCIP-4 glucose control metric

Task: EMR solution to help providers maintain 100% adherence with SCIP-4.

- Not disruptive.
- Zero data entry



© 2014 Mayo Foundation for Medical Education and Research

Control of implementation process



<input type="checkbox"/>	ICU: MB 6G 6-572(SM) NA
<input type="checkbox"/>	ICU: MB 6G 6-566(SM) NA
<input type="checkbox"/>	ICU: MB 6G 6-582(SM) NA
<input checked="" type="checkbox"/>	ICU: MB 6B 6-508(SM) NA
<input checked="" type="checkbox"/>	ICU: MB 6B 6-528(SM) NA
<input checked="" type="checkbox"/>	ICU: MB 6B 6-520(SM) NA
<input checked="" type="checkbox"/>	ICU: MB 6B 6-530(SM) NA

Close

Fedosov V, Dziadzko M, Dearani JA, Brown DR, Pickering BW, Herasevich V. Decision Support Tool to Improve Glucose Control Compliance After Cardiac Surgery. AACN Adv Crit Care. 2016 Jul;27(3):274-282. PMID: 27959310.

Ethics guidelines for trustworthy AI

Published April 8, 2019



- **Human agency and oversight:** AI systems should enable equitable societies by supporting human agency and fundamental rights, and not decrease, limit or misguide human autonomy.
- **Robustness and safety:** Trustworthy AI requires algorithms to be secure, reliable and robust enough to deal with errors or inconsistencies during all life cycle phases of AI systems.
- **Accountability:** Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes.

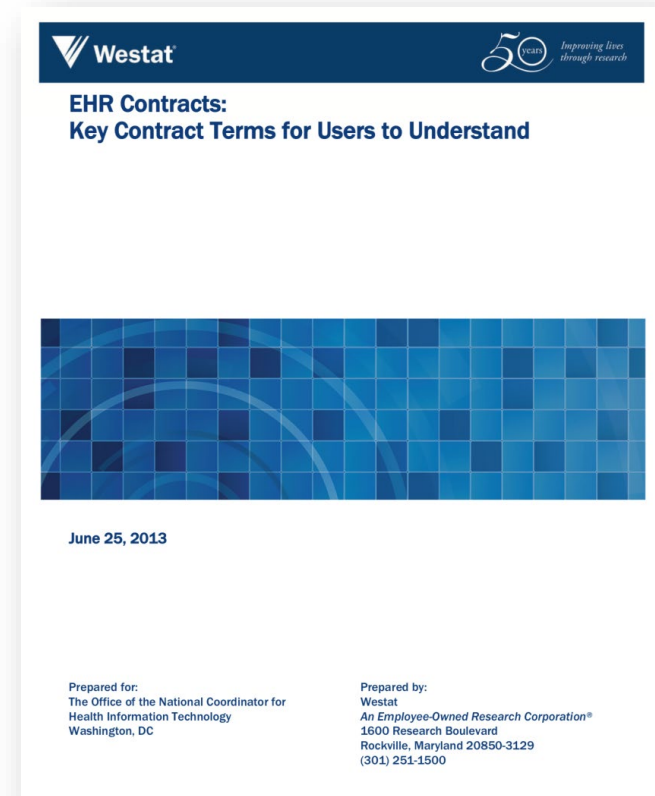
FDA framework for artificial intelligence-based medical devices (proposal)



- The artificial intelligence technologies granted marketing authorization and cleared by the agency so far are generally called “locked” algorithms that don’t continually adapt or learn every time the algorithm is used.
- A new approach to these technologies would address the need for the algorithms to learn and adapt when used in the real world.

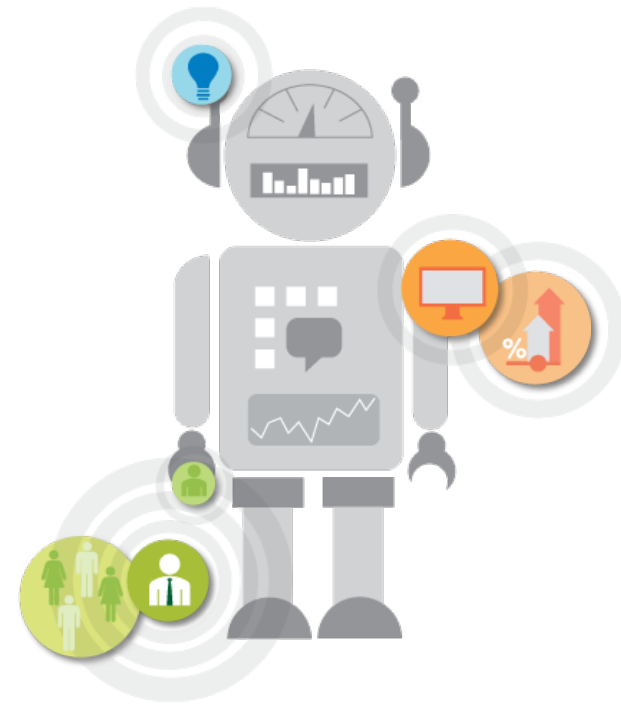
But still.... EHR (Artificial intelligence) contracts

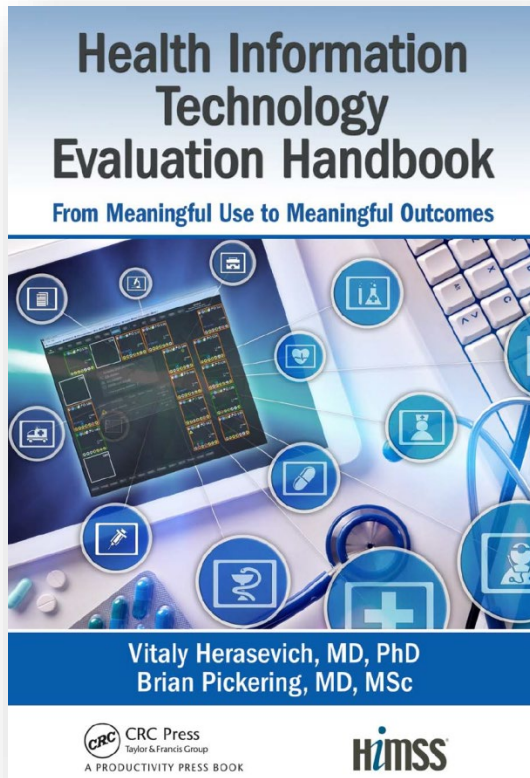
- Customer agrees to defend, indemnify and hold harmless **EHR technology** developer and its employees, officers, directors, or contractors (collectively, “EHR technology developer Indemnitees”) from any claim by or on behalf of any patient of Customer, which is brought **against any EHR technology developer** Indemnitee **regardless of the cause** if such claim arises **for any reason** whatsoever out of the **operation of the EHR Software** licensed to Customer under this Agreement.



The next generation of EHRs will be different

1. Interoperability
2. Functional modules.
3. Note creation will be automated
(combining images, text and voice).
4. Interaction with EMR will use
Speech Recognition
5. Video Recognition will mimic
clinician's interaction with patients
6. AI will be center of clinical
decision support.





ISBN-10: 1498766471

Thank You!



vitaly@mayo.edu



Google → “Clinical informatics Mayo”