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EUSEM – EFMI Webinars

”Structured data, Big data, Health analytics, Clinical decision support: How does it change emergency medicine?”

EUSEM – EFMI Webinar 2.

Big Data, Health analytics, Clinical decision support:
How does it change emergency medicine?

Big Data, Health analytics, Clinical decision support: How does it change emergency medicine?

Speakers

- Prof. John Mantas, Dr. Argyro Mavrogiorgou, Dr. Athanasios Kiourtis, Greece, EFMI
- Ass. Prof. Louise Pape-Haugaard, Denmark, EFMI
- Prof. Wolf Hautz, Switzerland, EUSEM

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Learning objectives of the webinar

The participants will be able to

- define the key concepts: Big Data, Artificial Intelligence and eHealth in terms of achievements, opportunities, and benefits of their use in healthcare
- will be familiar with current use of data analytics, especially how data can be prepared for and used in emergency care/emergency medicine and how other data sources can be used in AI.
- understand the relevance of diagnostic error in the ED, to evaluate the potential of computerized diagnostic decision support (CDDS) in the ED and to discuss the limitations of current CDDS.

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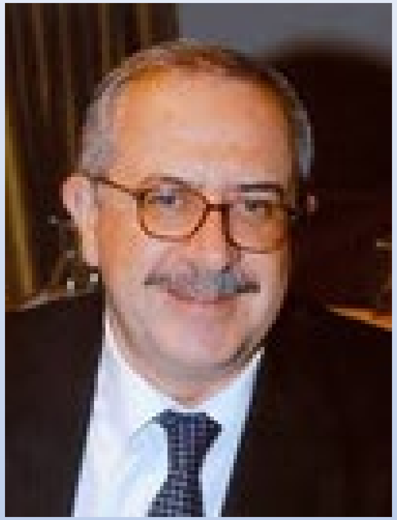
Some practical information

- We have polls during the webinar to advance interaction – please participate
- The attendees can send their questions with the Q&A function and after each panellist the questions will be answered
- At the end of the webinar their will be a discussion you can take part in by raising your hand. The webinar assistant will allow you to join by microphone.
- We also hope that you will give us feedback – After the webinar you will be automatically directed to the survey.

- Please, welcome to join this webinar!



Big Data & Artificial Intelligence in Healthcare

Prof. John Mantas,
Dr. Argyro Mavrogiorgou,
Dr. Athanasios Kiourtis

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European Society for Emergency Medicine (EUSEM)

2ND WEBINAR: ARTIFICIAL INTELLIGENCE AND BIG DATA

Health analytics, Clinical decision support:
How does it change emergency medicine?
Artificial Intelligence and Big Data

Big Data & Artificial Intelligence in Healthcare

Prof. John Mantas, Dr. Argyro Mavrogiorgou, Dr. Athanasios Kiourtis

jmantas@nurs.uoa.gr, margy@unipi.gr, kiourtis@unipi.gr

June 24, 2020

Agenda

- Big Data
  - Motivation & Perception
- Artificial Intelligence
  - Achievements & Motivation
- eHealth & Healthcare
  - Definition
  - Opportunities
- Big Data in Healthcare
- AI in Healthcare
- Benefits
- Real-life Scenarios
- Risks, Concerns & Conclusions

Big Data

I have a question for you…

- What is **Big Data**?
- Are you **producing** Big Data?

Motivation

- Nowadays, **experiments**, **observations**, and **simulations** in many areas of science and business are generating terabytes of data and beyond
  - Finance
  - Education
  - Agriculture
  - Healthcare …
- Traditional computing environments **can not manage such volumes**
- Traditional analysis methods can not be applied
  - Sampling is not efficient
  - Collection of all the data is impossible

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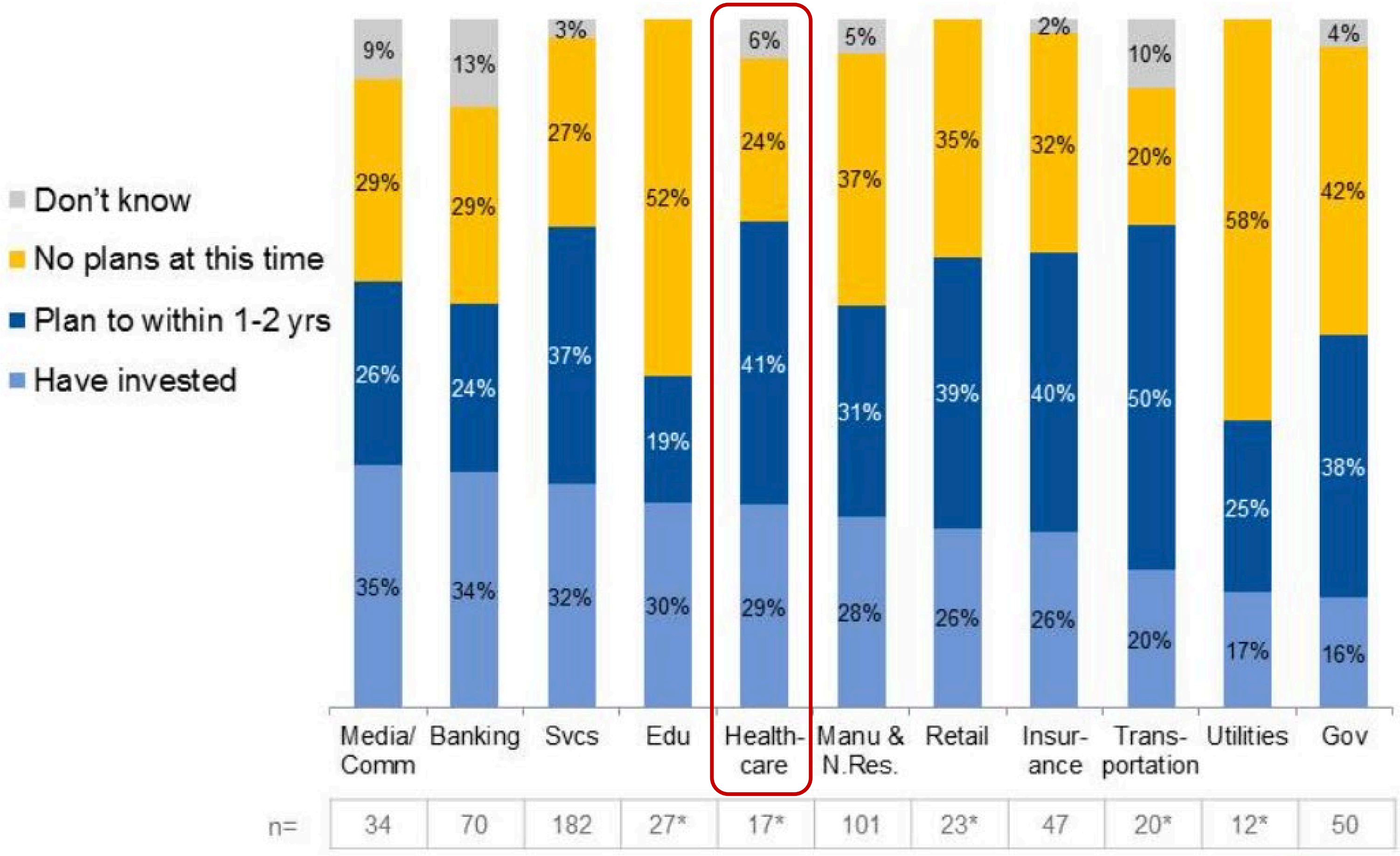
Big Data Vague Perception

- Big Data may sound a vague concept or a trend
  - Marketing and promotional **mischaracterizations** and **misunderstandings**
- **Sometimes meaningless** even in technical situations
  - Big Data once meant petabyte scale, or unstructured chunks of data or data generated from the Internet…
- Big Data means a paradigm change
  - Massive data can be stored, processed and exploited effectively even in real - time situations when having limited time
- Potentialities
  - Science is extending its reach with new discoveries
  - Services are becoming more adaptive, personalized, and focused

Big Data Investments



*Base < 30; results are directional

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Gartner

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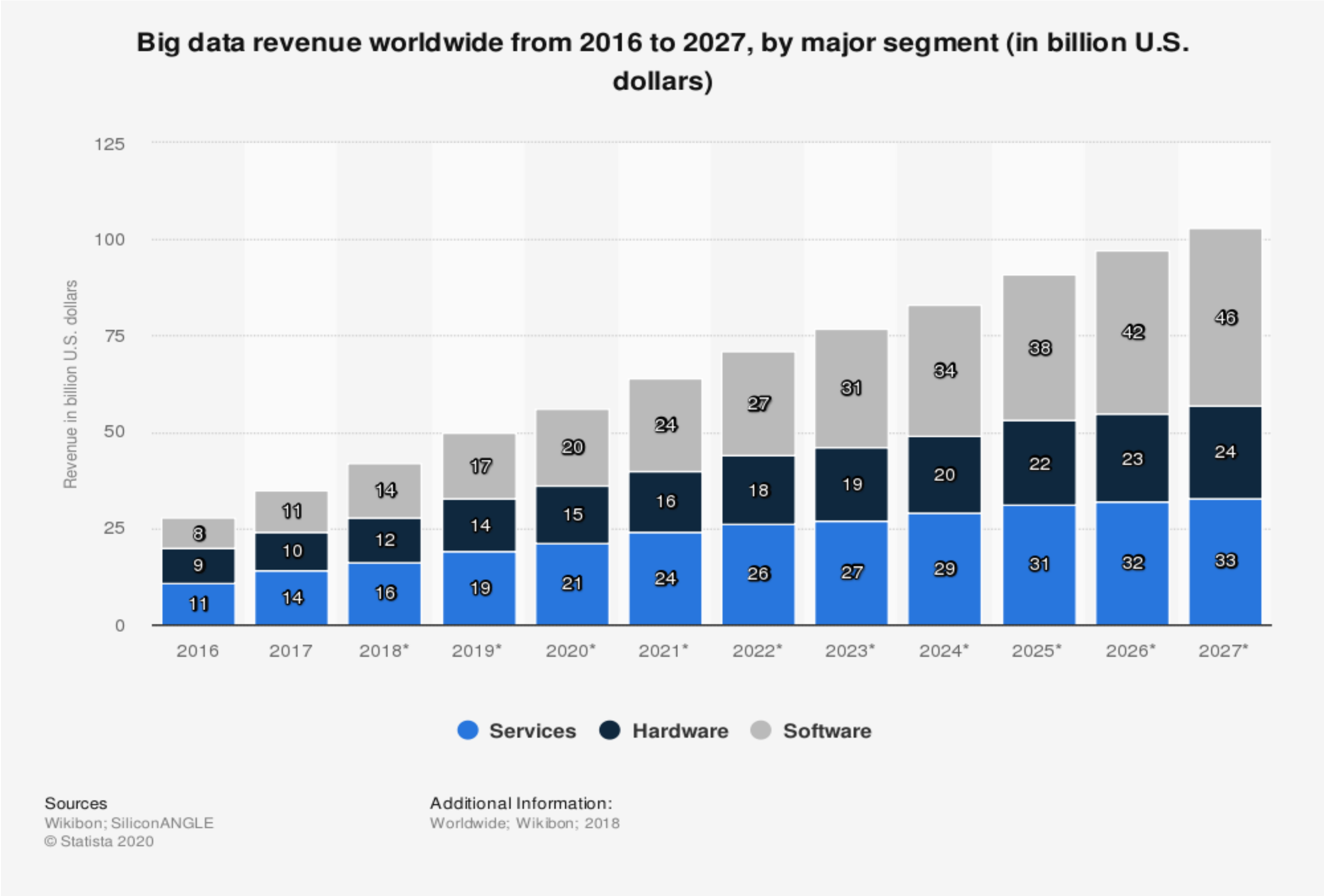
Big Data Profits



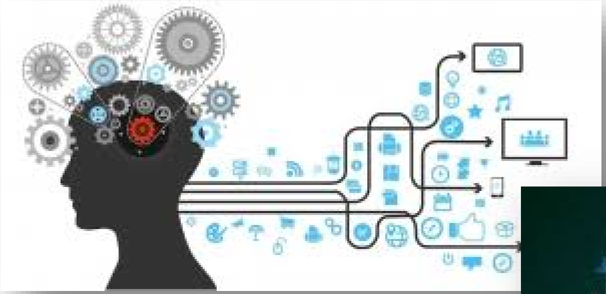
Artificial Intelligence (AI)

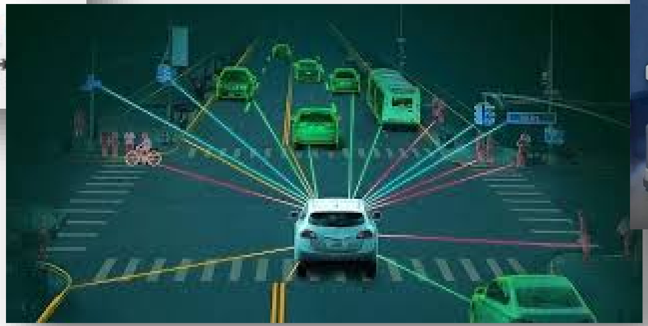
I have a question for you…

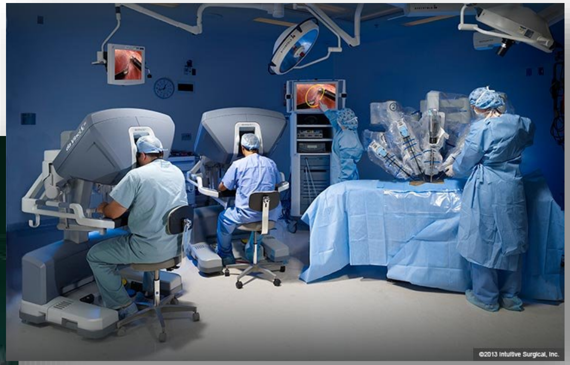
- Have you ever used **Artificial Intelligence**?
- What are the **benefits** of Artificial Intelligence?

Achievements & Excitements

- **Self-driving cars** are as safe as human drivers
- AI defeated human doctors in contest to **diagnose tumors**
- AI promises a **new paradigm for Healthcare** & it will revolutionize the industry
- Machine has surpassed human **intelligence**
- AI can **improve Healthcare** Clinicians work

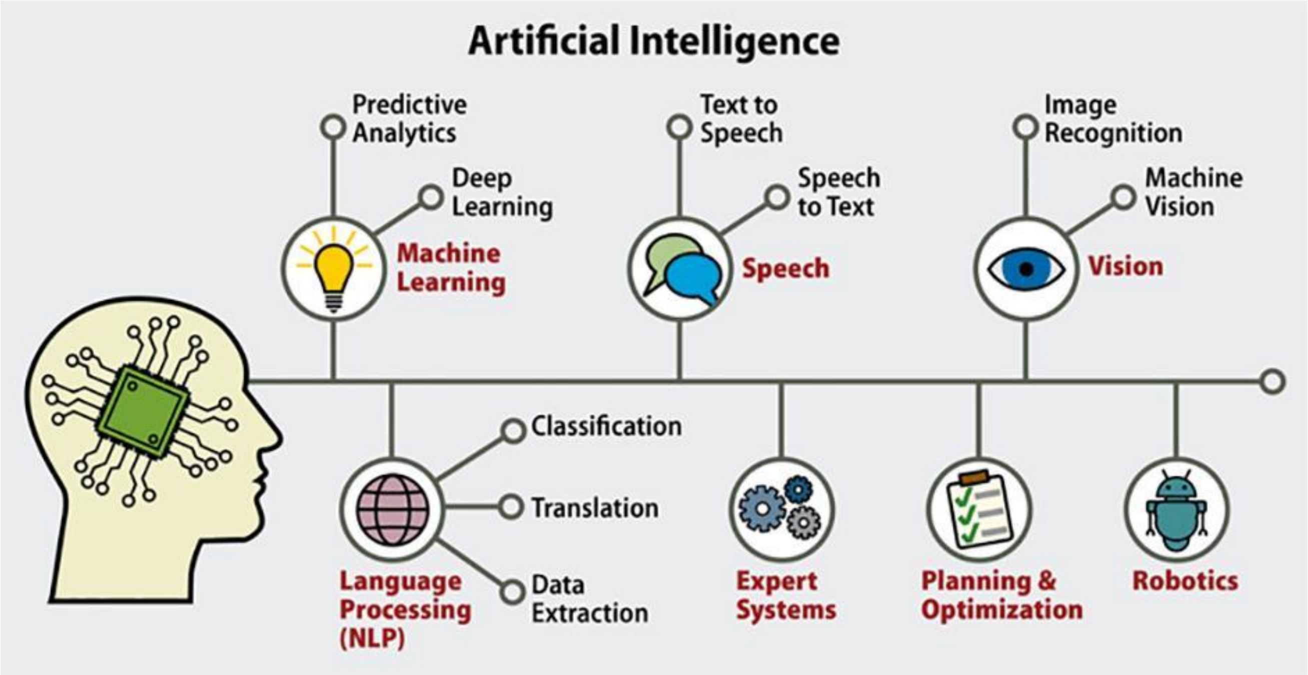






A Subfield of Computer Science

- AI is a machine that **simulates the aspect of learning** or any other feature of human intelligence
- …The theory and development of computer systems able to perform tasks normally requiring human intelligence

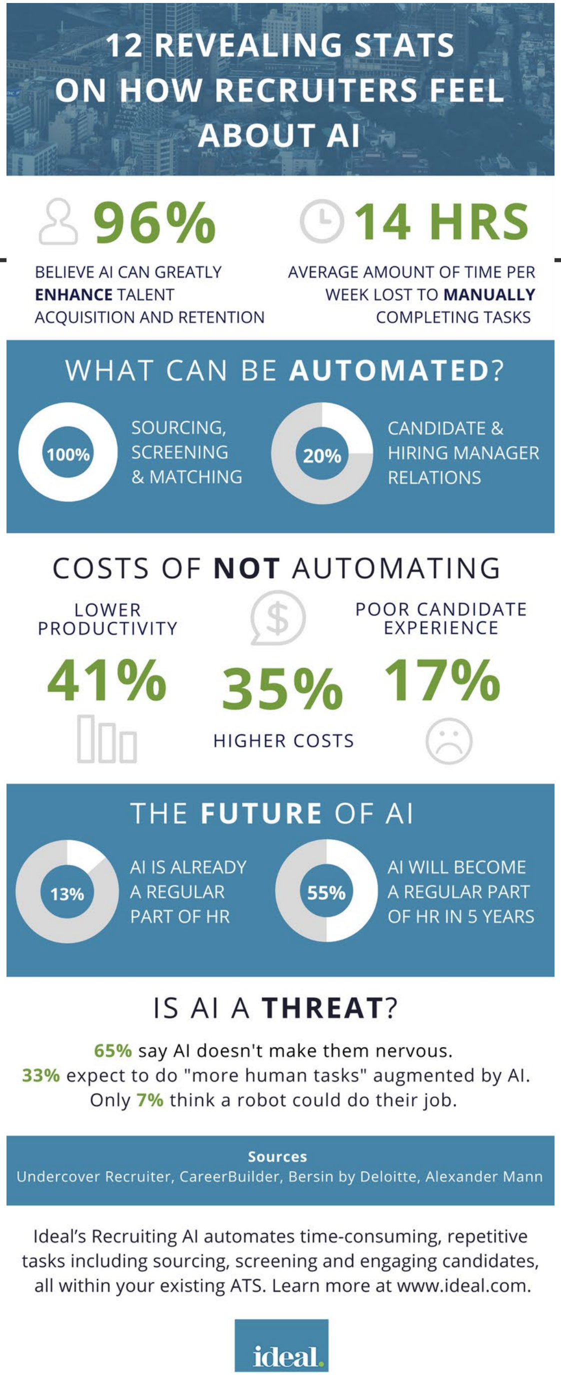


AI Vague Perception

- AI may sound a **vague concept or a trend**

- Benefits
  - **Error reduction**
  - **Daily application**
  - **Digital assistance**
  - **Increased work efficiency**

- Sometimes creates major concerns
  - **Trust related problems**
  - **Safety problems**
  - **Computation problems**



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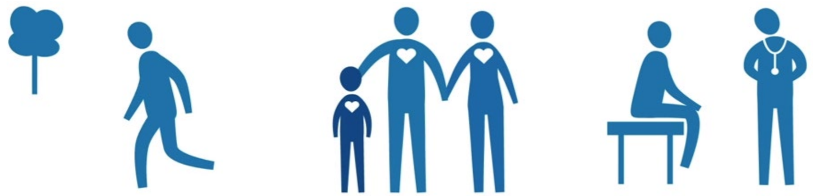
eHEALTH & Healthcare

eHEALTH: What?

~~e~~HEALTH

- Looking after **ourselves**
- Looking after our **loved ones**
- Receiving **care**

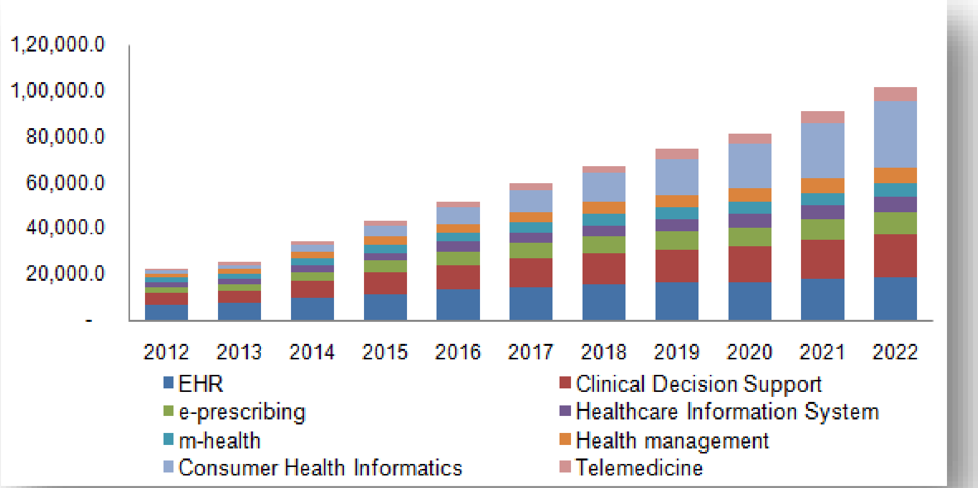


eHEALTH

- Computers, mobiles, tablets, internet and social media that offer:
  - Better healthcare and a healthier life through digital technology

eHEALTH: Why? (1/2)

- Better sharing of information
- Secure digitization of records
- Better quality of data
- Record treatments and test results in almost real-time
- Better diagnosis and appropriate treatments



- Health records available wherever they are needed
- Remote care
- 24-hour condition monitoring
- Management of our own health

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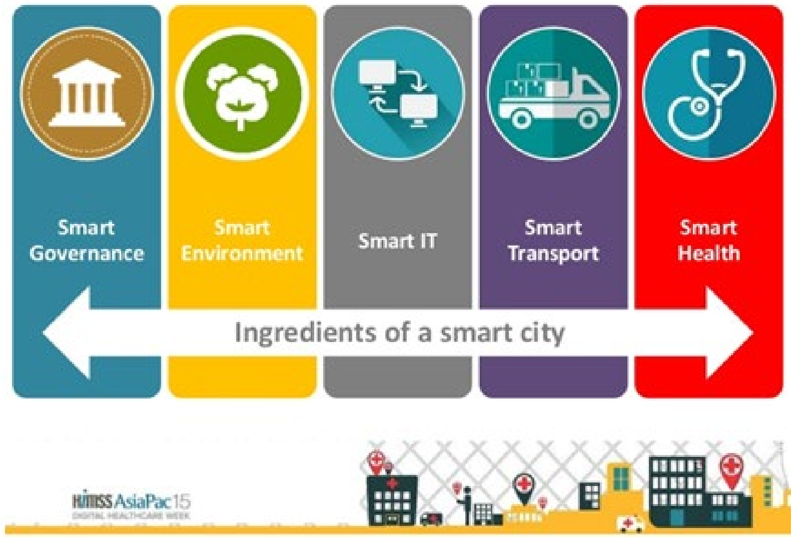
eHEALTH: Why? (2/2)

- Increase of life expectancy
- Growing population of elderly people (long-term care)
- Live at home
- Delivery of high quality and affordable healthcare ecosystem
- Connect people and medical data
- Tackle infectious diseases (Obesity, Tuberculosis, HIV)
- Place patients rather than budgets at the centre of their systems

eHEALTH: New Opportunities

- Revolutionize healthcare
- Improve global health
- Change the way we live our lives
- Use of data to improve healthcare services
- Develop new treatments through expert collaboration



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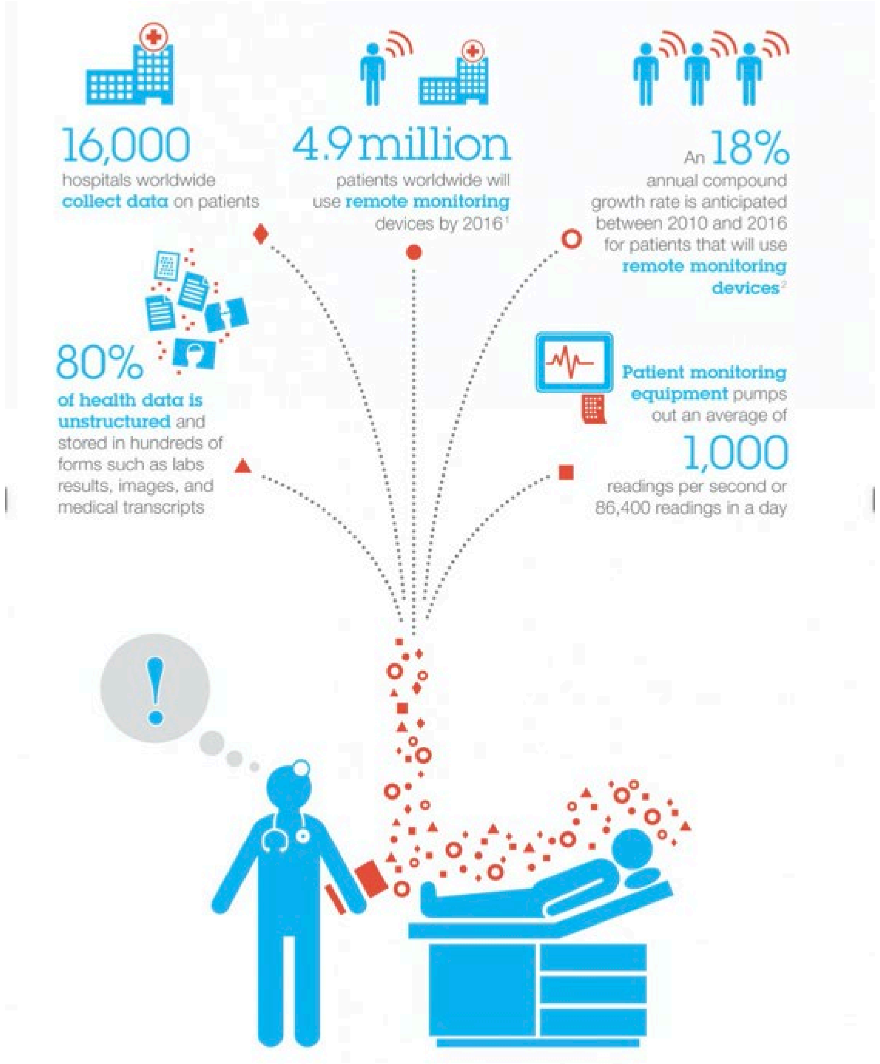
Big Data in Healthcare

Big Data in Healthcare: Why?

- Big Data in Healthcare enables to test exhaustively the following claims:
  - Faster **identification** of high-risk patients
  - Better **understanding** of patients' needs
  - Improved **personalized care**
  - More effective **interventions**
  - Better **decision making**
  - Continuous **observation** and **maintenance** of health records
  - Better **prediction** of health outcomes
  - Closer **monitoring**



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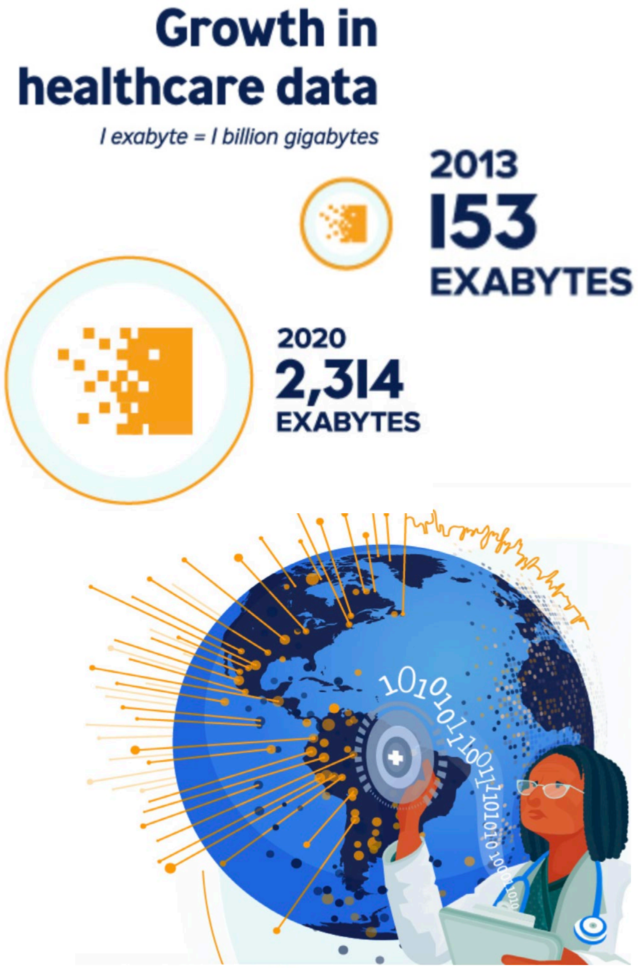
Big Data in Healthcare: How?



- Massive Storage
  - Increasingly **detailed data** for each individual – including genomic, cellular, environmental data, historical patient records, and clinical trials
- Massive Computation
  - **Distributed** and **parallel computation** on commodity hardware
- Powerful Analytics
  - Allowing to **process** large amounts of data in batch or in real-time

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Big Data in Healthcare: What?

- **Right living**
  - Informed lifestyle choices that promote well-being and the active engagement of citizens in their own care
- **Right care**
  - Evidence-based care that is proven to deliver needed outcomes for each citizen while ensuring safety
- **Right provider**
  - Care provider (e.g. nurse, physician) that is most appropriate to deliver prescribed clinical impact
- **Right value**
  - Sustainable approaches that continuously enhance healthcare value by reducing cost at the same or better quality
- **Right innovation**
  - Innovation to advance the frontiers of medicine and boost R&D productivity in discovery, development, and safety

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AI in Healthcare

AI in Healthcare: Why?

- AI as a powerful tool and partner:
  - **Man + Machine = enhanced human capabilities**
- AI can help human
  - **Unlock the power of big data** and gain insight into patients
  - **Support** evidence-based decision making, improving quality, safety, and efficiency
  - **Coordinate** care and foster communication
  - **Improve** patient experience and outcomes
  - **Deliver** value and reduce costs
  - **Improve** health system performance & optimization

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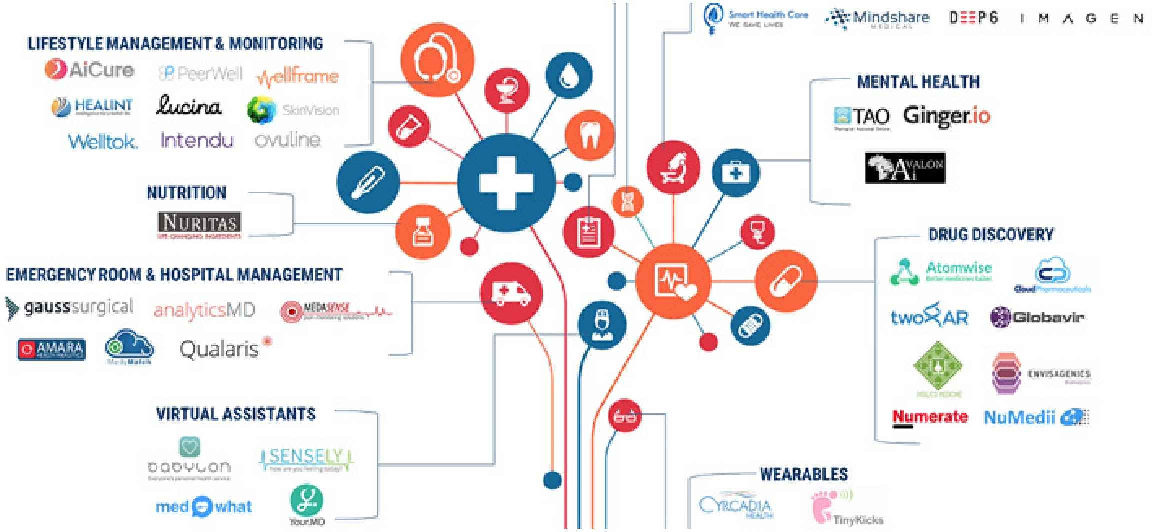
AI in Healthcare: How?

- Lifestyle Management & Monitoring
  - Continuous monitoring of lifestyle choices
- Emergency Room & Hospital Management
  - Adaptation to real-time emergency requirements
- Wearables
  - Increase in wearable devices usage
- Drug Discovery
  - Drugs & Prescriptions
- Mental Health
  - Clinical pathways



AI in Healthcare: What?

- Improving effectiveness
  - Quality [Experience, Outcomes]
  - Safety [Ways to ensure patients in safety]
  - Efficiency [Usability, Productivity]
  - Access to Care

- Controlling costs

- AI-powered automation
  - Medical robotics
  - Machine learning
  - Natural Language Processing
  - AI voice technology

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Big Data & AI in Healthcare:
Should it be an Option or an Obligation?

Big Data & AI in Healthcare: Benefits

- **Right living**
  - Targeted disease prevention
  - Data-enabled adherence programs
- **Right care**
  - Alignment around proven pathways
  - Coordinated care across providers
- **Right provider**
  - Shifting volume to right care setting
  - Reducing Emergency rooms/readmission rates
- **Right value**
  - Payment innovation and alignment
  - Provider-performance transparency
- **Right innovation**
  - Accelerating discovery in Research & Development

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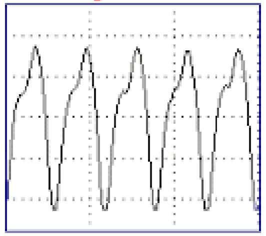
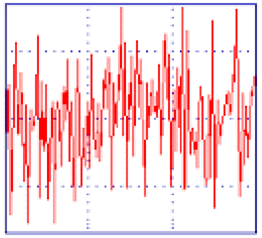
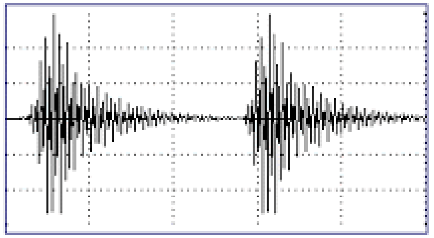
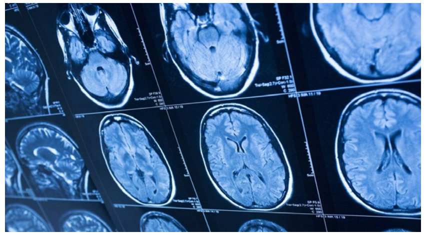
Big Data in Healthcare: Real-life Scenarios

Medical Signal Processing

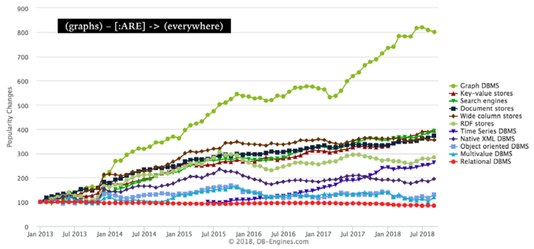




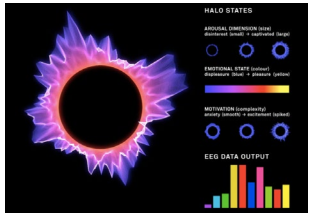


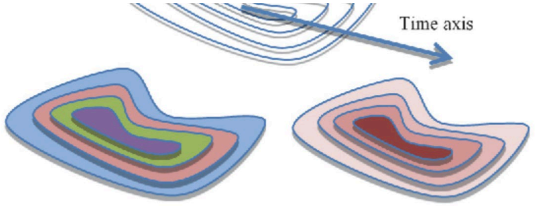


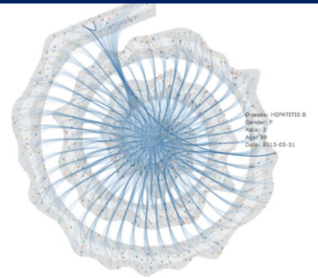
Data Analysis



Visualization & Results

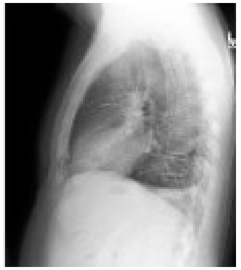




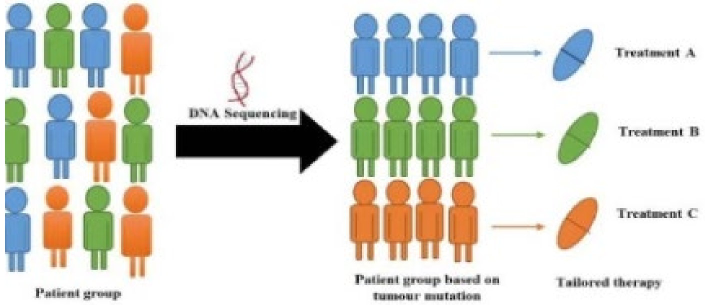


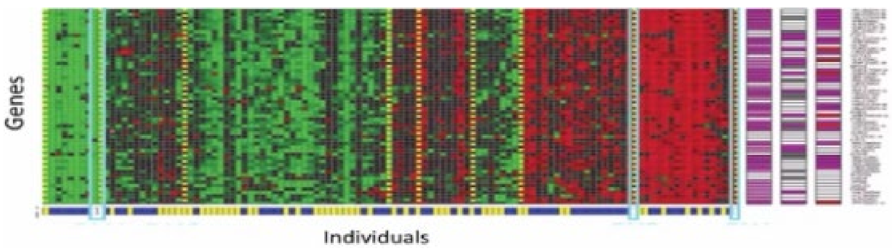
AI in Healthcare: Real-life Scenarios

Classification of disease severity



Treatment design & Pattern recognition





Medical Dictation

Big Data & AI in Healthcare: Risks & Concerns

- Security & Privacy
  - Concentrate and analyze so much data gives **too much power and responsibility** to the institutions, organizations, private entities in terms of information that can be delivered or leaked
- Data analysis challenge
  - Massive data sometimes is **difficult and messy** to extract
- Cost
  - **Biggest barrier** for Big Data & AI in Healthcare even though applications are open source
- Recent technologies
  - Continuous tools in market require consolidation, and difficult to find experts

Conclusions

- The adoption of Big Data & AI in Healthcare:
  - provides infrastructure and analytics for massive data
  - improves healthcare systems
  - boosts the productivity of research
  - raises security concerns
  - requires right healthcare policies to make the change possible in healthcare
  - roadmap towards **emergency medicine**
    - **improve care, decrease errors,** and **increase efficiency**

Thank you

감사합니다
Natick
Grazie
Danke
Ευχαριστίες
Dalu
Obrigado
Thank You
Köszönöm
Tack
Спасибо
Dank
Gracias
谢谢
Merci
Seé
ありがとう

Data is generated, registered, shared, used and stored – what are the challenges?

Ass. Prof. Louise Pape-Haugaard

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European Society for Emergency Medicine (EUSEM)

2ND WEBINAR: ARTIFICIAL INTELLIGENCE AND BIG DATA

Health analytics, Clinical decision support:
How does it change emergency medicine?
Artificial Intelligence and Big Data

Big Data & Artificial Intelligence in Healthcare

Associate Prof. Louise Pape-Haugaard, Aalborg University, Department of Health Science & Technology, Research Group Medical Informatics

Institutional Officer in EFMI Board

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June 24, 2020

Agenda

- The life story of health data:
  - Data is generated, registered, stored, shared, used and re-stored – what are the challenges from a medical informaticians perspective?
- Incoming data from ambulances: how data can be prepared for and efficiently used in emergency medicine?
- Data from emergency care/emergency medicine and other data sources can be used in AI

The life story of health data:

Data is generated, registered, stored, shared, used and re-stored – what are the challenges from a medical informaticians perspective?

From cradle to grave

- Health data is any data related to health conditions, reproductive outcomes, causes of death and quality of life

- Myriad of (health) data is generated or shared from patients
  - Genetics
  - Pharmacies
  - Labs
  - Hospitals
  - Health agencies
  - Social (media) data
  - Quantified self-data
  - …

- Structured or unstructured data

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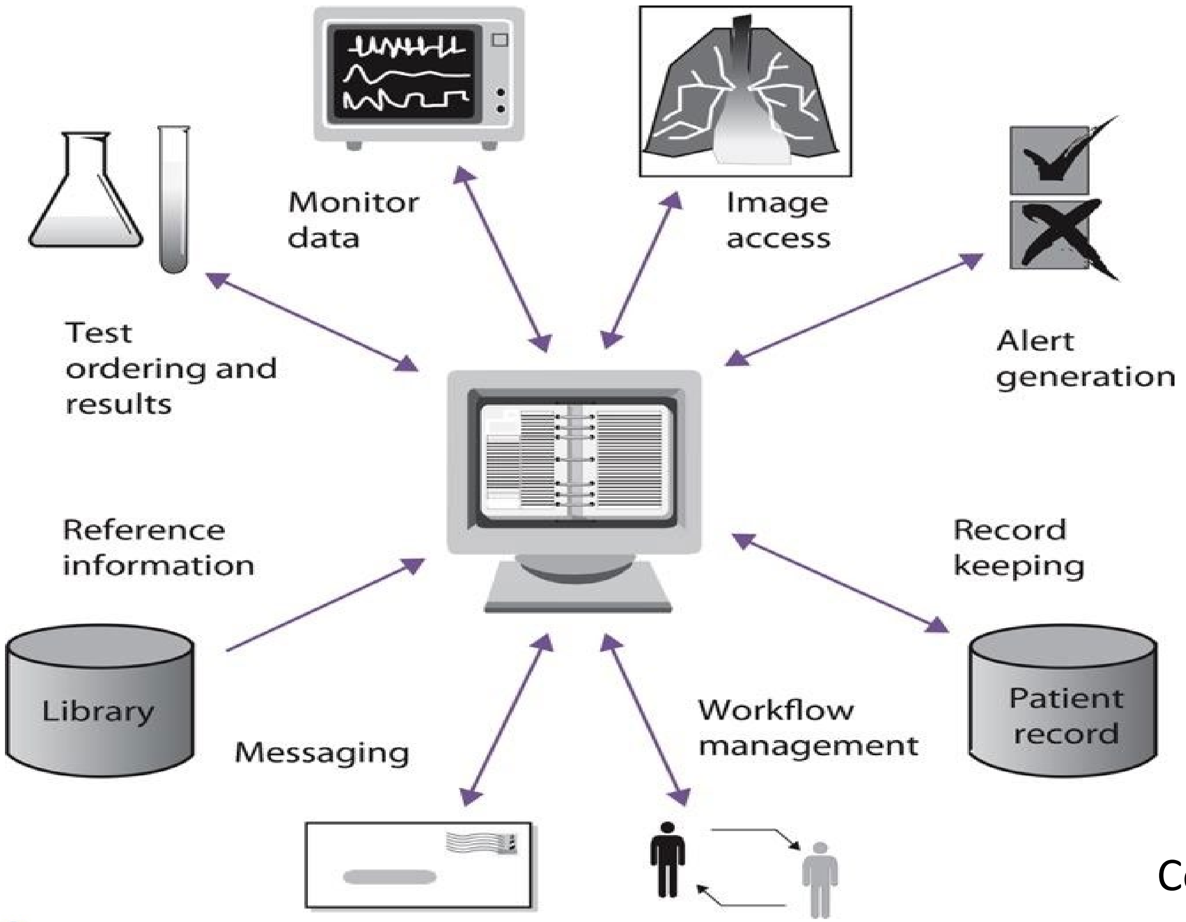
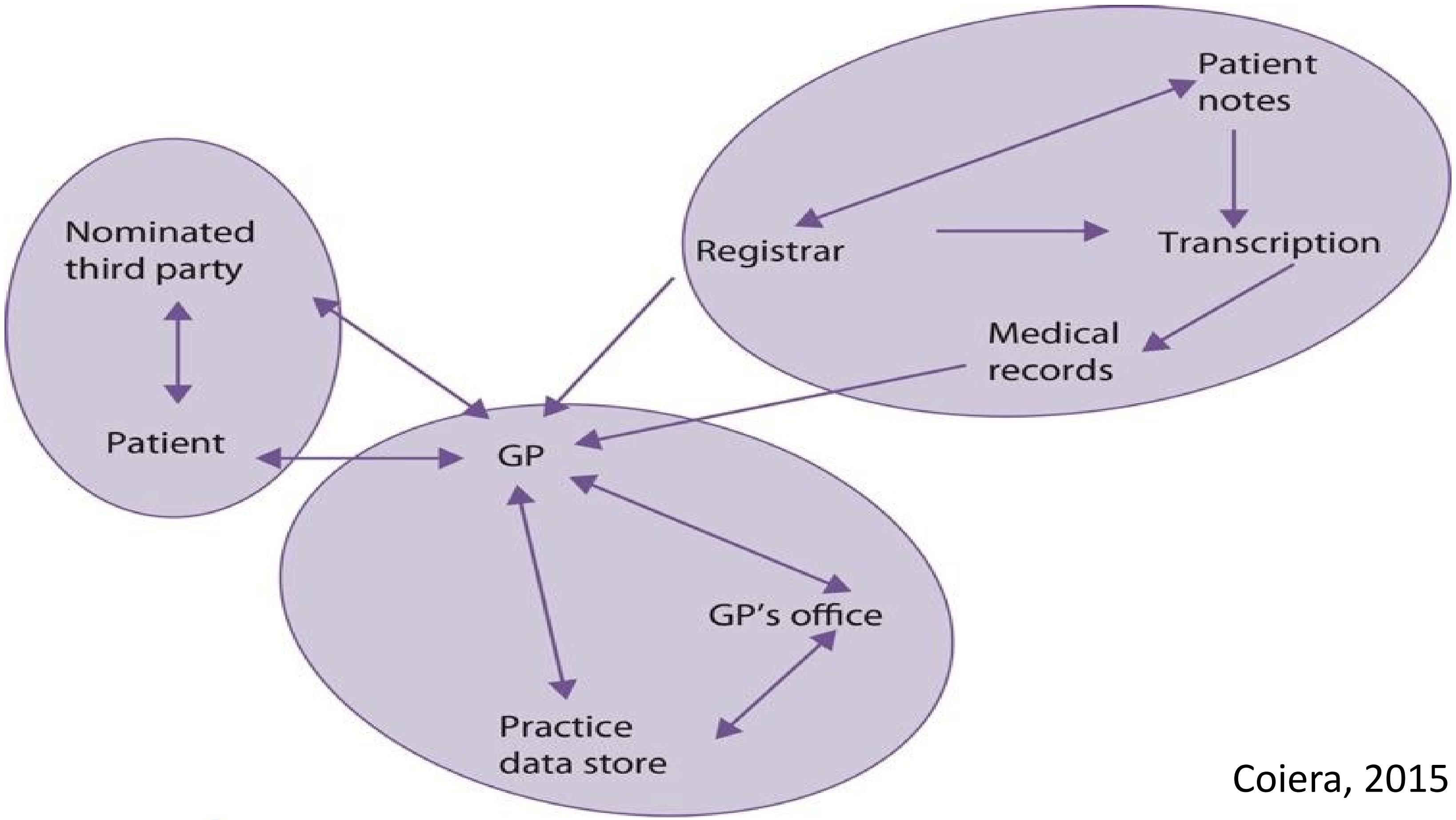
Regular health data



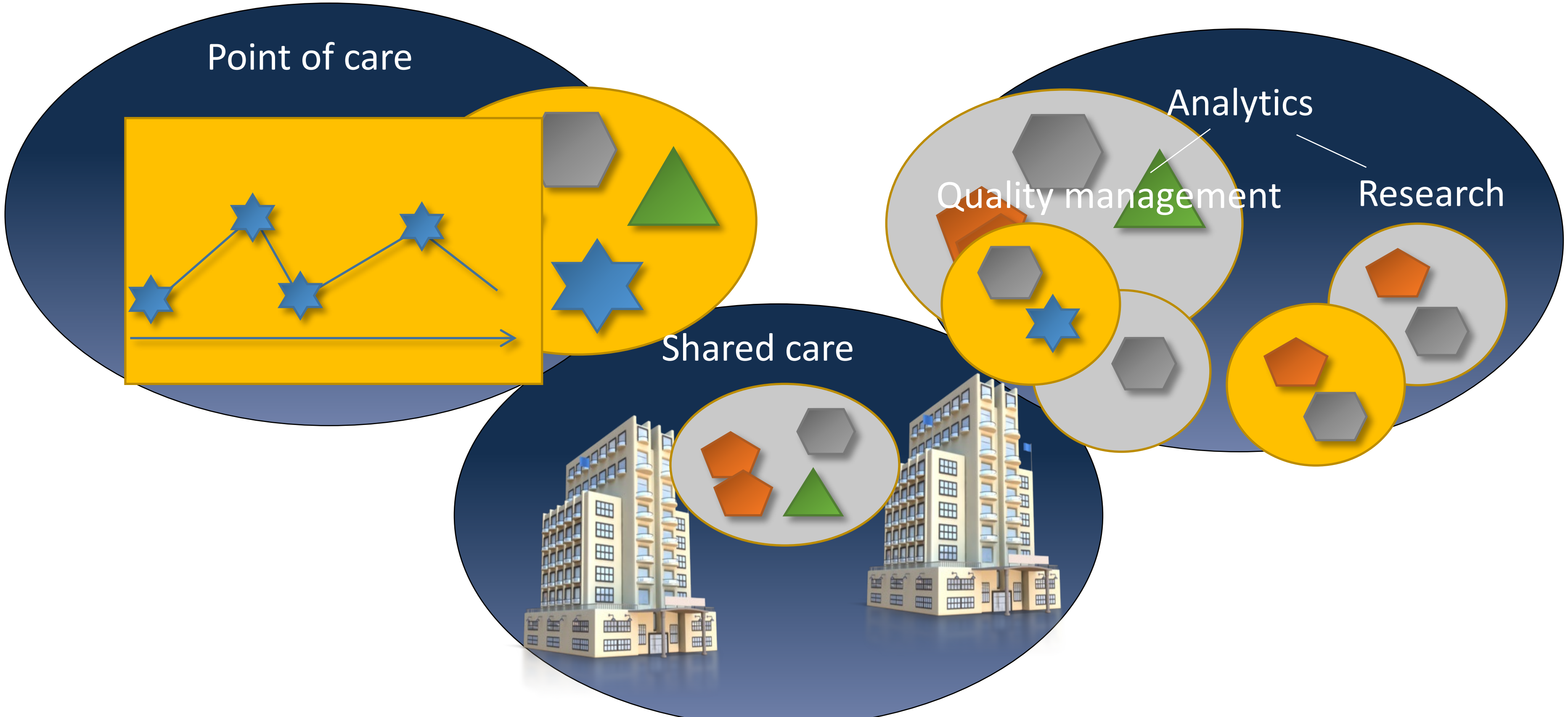
Coiera, 2015

Regular health data: from cradle to grave



Coiera, 2015

What are the challenges from a medical informaticians perspective?



The life story of health data:

Incoming data from ambulances: how data can be prepared for and efficiently used in emergency medicine

Based on papers:

1) Blendal, RG & Pape-Haugaard, L 2018, An International Minimal Patient Care Report Exemplified in FHIR to Facilitate Standardisation and Interoperability of Emergency Medical Services Data. i A Bygholm, L Pape-Haugaard, K Niss, O Hejlesen & C Zhou (red), Proceedings from The 16th Scandinavian Conference on Health Informatics 2018 Aalborg, Denmark August 28–29, 2018. Linköping University Electronic Press, Linköping Electronic Conference Proceedings, bind 151, s. 85-91

2) Waidtløv Gustafson, J, Jones, CH & Pape-Haugaard, L 2018, Designing a Dashboard to Visualize Patient Information. i A Bygholm, L Pape-Haugaard, K Niss, O Hejlesen & C Zhou (red), Proceedings from The 16th Scandinavian Conference on Health Informatics 2018 Aalborg, Denmark August 28–29, 2018. Linköping University Electronic Press, Linköping Electronic Conference Proceedings, bind 151, s. 23-29

Simple clinical trauma case

- The local EM services have been called to the local horse riding club to examine Kathrine Smith, a 24-year old women who has fallen off her horse. Katherine is conscious but has pain in her pelvic area, she rates it an 8 out of 10. The EMS personnel notes that she has no known allergies and is an otherwise healthy young woman. Due to the height of the fall, horse was in mid jump, she is put in a hard collar and taped to the hard spine board to ensure spinal stability. Once in the ambulance her vitals are measured Temp: 36.2C, HR: 90/min, RR: 22/min, BP: 110/ 65 mmHg, SpO2: 98%OA and GCS 15. She is given a 50 mcg bolus of Fentanyl for the pain along with an additional 75 mcg via IV during the ambulance ride. The iliac crest feels tender when palpated. The EMS personnel suspects a pelvic fracture, performs a triage and transport her to the ED.

- The clinical case has been adapted from C. Nickson, “Trauma! pelvic fractures i.” https://lifeinthefastlane.com/trauma-tribulation-027/

Simple clinical trauma case

Prehospital

- Comprehensive amount af data e.g.
  - Incident location
  - Patient status
  - Vital signs

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Patient data handover

Support

- Trauma clinicians in decision making
- Increase patient safety

Trauma care

- Complex patient handovers from prehospital care
- Decision making processes are challenged by stress
- Verbal handovers may not include all key data

Simple clinical trauma case

Just to simplify the clinical trauma case….

STORY
…Kathrine Smith, a 24-year old women . The EMS personnel notes that she has no known allergies and is an otherwise healthy young woman
..fallen off her horse… horse was in mid jump..
..is conscious but has pain in her pelvic area, she rates it an 8 out of 10.
…put in a hard collar and taped to the hard spine board to ensure spinal stability…
Once in the ambulance her vitals are measured Temp: 36.2C, HR: 90/min, RR: 22/min, BP: 110/ 65 mmHg, SpO2: 98%OA and GCS 15
She is given a 50 mcg bolus of Fentanyl for the pain along with an additional 75 mcg via IV during the ambulance ride
The iliac crest feels tender when palpated. The EMS personnel suspects a pelvic fracture …
..Performs a triage..

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Simple clinical trauma case

… and divided into categories based on the inter-national minimal patient care report

STORY	IMPCR CATEGORY
...Kathrine Smith, a 24-year old women . The EMS personnel notes that she has no known allergies and is an otherwise healthy young woman	Patient + Additional patient information
..fallen off her horse... horse was in mid jump..	Injury
..is conscious but has pain in her pelvic area, she rates it an 8 out of 10.	Vital signs + Diagnose/symptoms
...put in a hard collar and taped to the hard spine board to ensure spinal stability...	Procedure
Once in the ambulance her vitals are measured Temp: 36.2C, HR: 90/min, RR: 22/min, BP: 110/ 65 mmHg, SpO2: 98%OA and GCS 15	Vital signs
She is given a 50 mcg bolus of Fentanyl for the pain along with an additional 75 mcg via IV during the ambulance ride	Medication
The iliac crest feels tender when palpated. The EMS personnel suspects a pelvic fracture ...	Diagnose/symptoms
..Performs a triage..	Triage

IMPCR category: Internationa Minimal Patient Care Report)

Simple clinical trauma case

… and to see how it can be shared

STORY	IMPCR CATEGORY	FHIR RESOURCE
...Kathrine Smith, a 24-year old women . The EMS personnel notes that she has no known allergies and is an otherwise healthy young woman	Patient + Additional patient information	Patient, AllergyIntol Observation
..fallen off her horse... horse was in mid jump..	Injury	Observation
..is conscious but has pain in her pelvic area, she rates it an 8 out of 10.	Vital signs + Diagnose/symptoms	Observation.Vitalsig
...put in a hard collar and taped to the hard spine board to ensure spinal stability…	Procedure	Procedure
Once in the ambulance her vitals are measured Temp: 36.2C, HR: 90/min, RR: 22/min, BP: 110/ 65 mmHg, SpO2: 98%OA and GCS 15	Vital signs	Observation.Vitalsig
She is given a 50 mcg bolus of Fentanyl for the pain along with an additional 75 mcg via IV during the ambulance ride	Medication	MedicationAdminist
The iliac crest feels tender when palpated. The EMS personnel suspects a pelvic fracture ...	Diagnose/symptoms	Condition
..Performs a triage..	Triage	Questionnaire

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IMPCR category: Internationa Minimal Patient Care Report)

Structured data from simple clinical trauma case

- *If* data is organized and structured …
- … it *can* be used efficiently when assesing the patient
- ….*either* by simple use of vizualisation of data on dashboard
- …*or* by use of decision support

The life story of health data:

Data from emergency care/emergency medicine and other data sources can be used in AI

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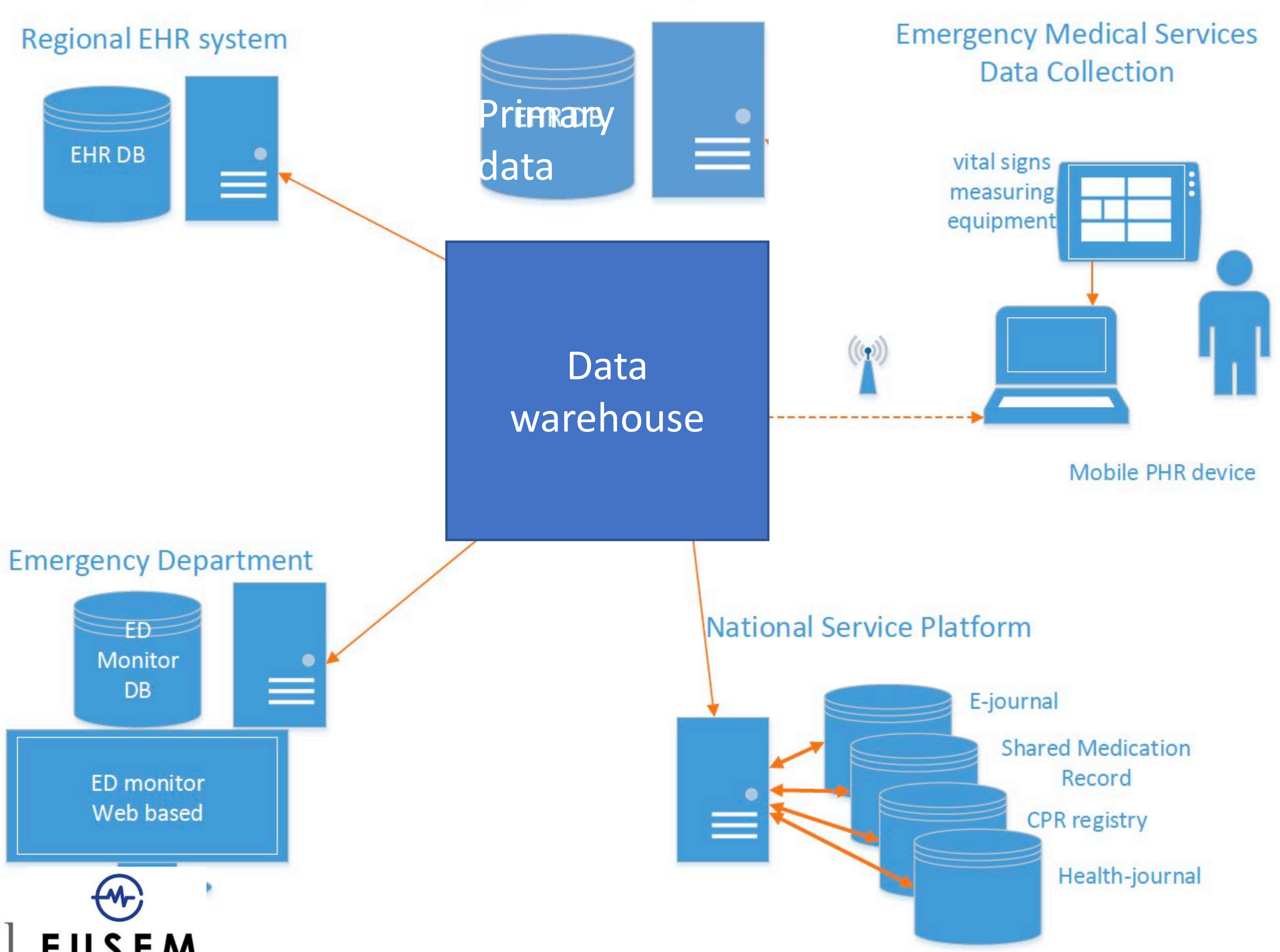
Data from emergency care/emergency medicine and other data sources

- Big (health) data can be identified in the V-model
  - Volume
  - Variability
  - Velocity

- When applying AI to health data it is a must to be able to propagate back through data to understand the decision or prediction
- This is not as easy as it may sound
  - Domain complexity due to high variability in health data
  - Level of data quality amongst others suffers of inregularity in data due to recording mistakes, patient relocation, lack of visits
  - Temporality due to the non-deterministic ways diseases evolve in
  - Data volume – how to gain access to data

Data from emergency care/emergency medicine and other data sources



Operational flow

- From the data warehouse
  - Extract training data
  - Training, validating and testing →prediction model
- Then extract input data
- Apply your choosen model
- Outcome will be the prediction probabilities

- Predictions could be: the probability for a patient to be in need of life support, to be readmitted, etc

- But we still need to have data to train the model in order to predict anything

Thank you

Correspondance: lph@hst.aau.dk

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Computerized diagnostic decision support (CDDS) in the ER

Prof.Dr.med. Wolf Hautz

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MEDICINE

Computerized diagnostic decision support (CDDS) in the ER

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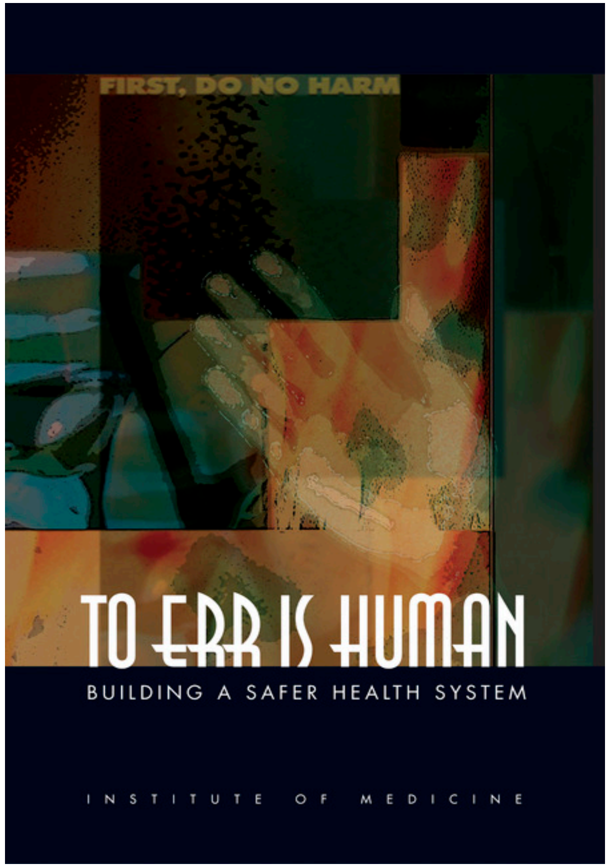
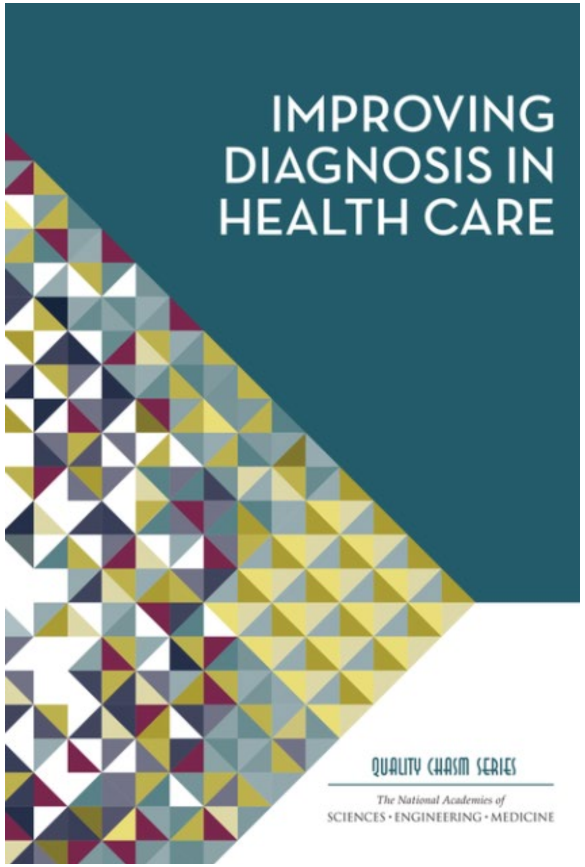
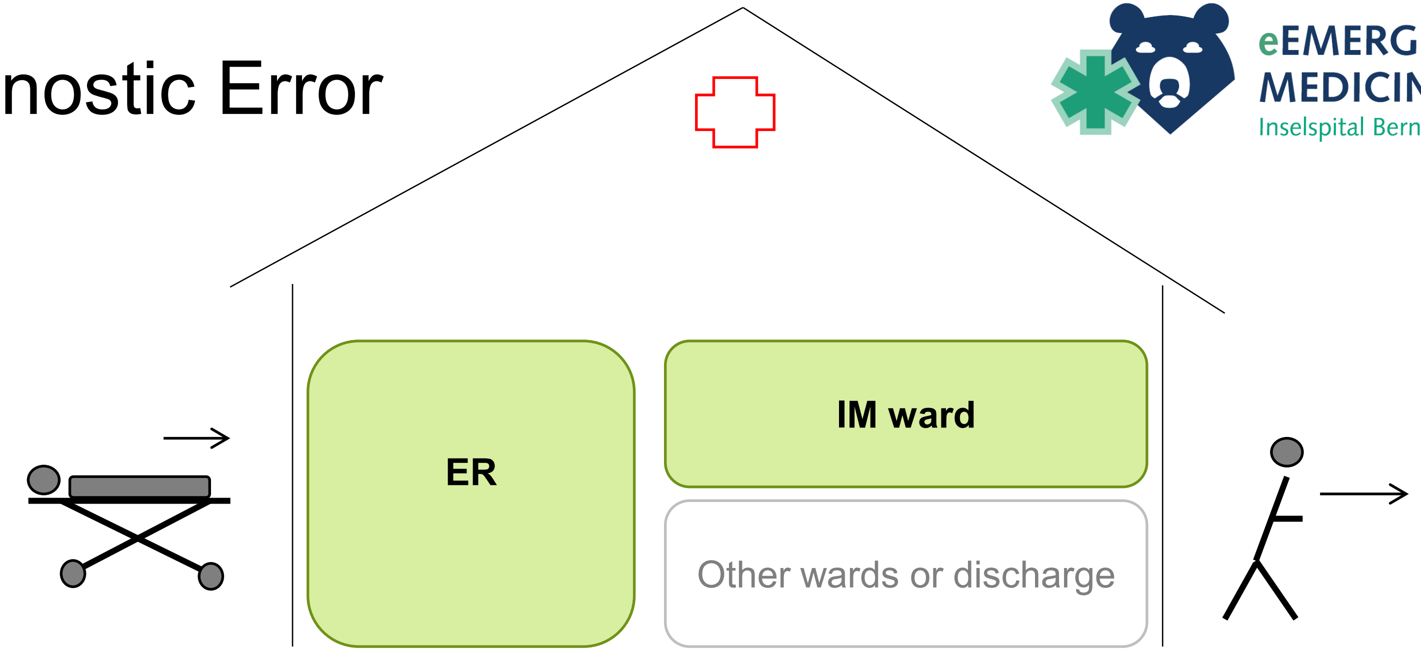
Error in Medicine





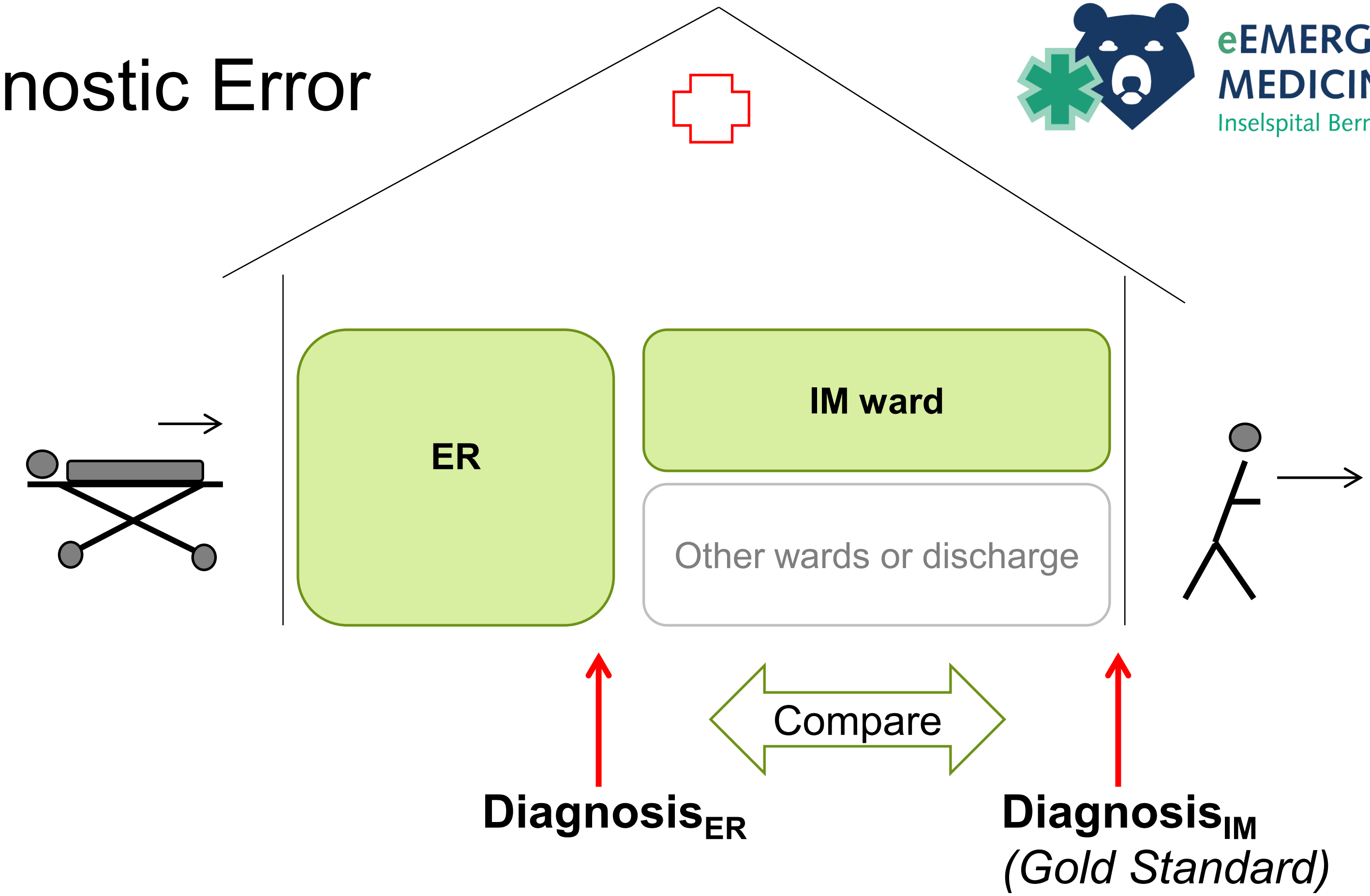
National Academies of Sciences, Engineering, and Medicine. **Improving Diagnosis in Health Care.** Washington, DC: The National Academies Press, 2015.
Institute of Medicine (US) Committee on Quality of Health Care in America, Kohn LT, Corrigan JM, Donaldson MS, eds. **To Err is Human: Building a Safer Health System.** Washington (DC): National Academies Press (US); 2000.

Diagnostic Error



Hautz et al: BMJopen 2016;11:e011585 // Hautz et al: Scand J Trauma Resuc Emerg Med 2019;27:74

Diagnostic Error



Hautz et al: BMJopen 2016;11:e011585 // Hautz et al: Scand J Trauma Resuc Emerg Med 2019;27:74

Diagnostic Error

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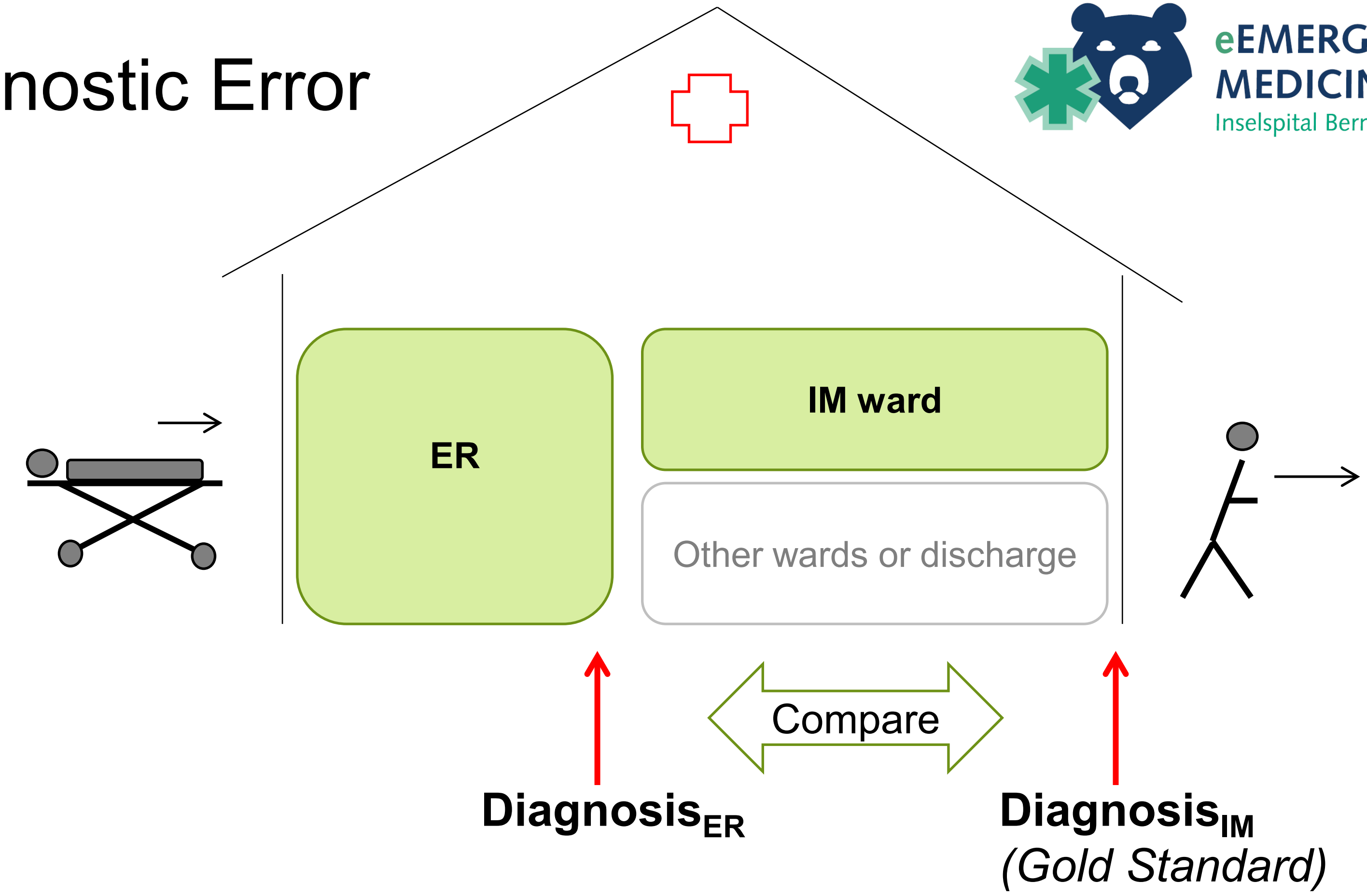

755 Patients	**Error (12.3%)**	**No Error**	**Relevance [95%CI]**
Hospital stay (day)	10.3	6.9	*d*= 0.47 [0.26-0.7]
Mortality (%)	8.6	3.78	OR=2.4 [1.05-5.5]

Hautz et al: BMJopen 2016;11:e011585 // Hautz et al: Scand J Trauma Resuc Emerg Med 2019;27:74

Probelematic Complaints

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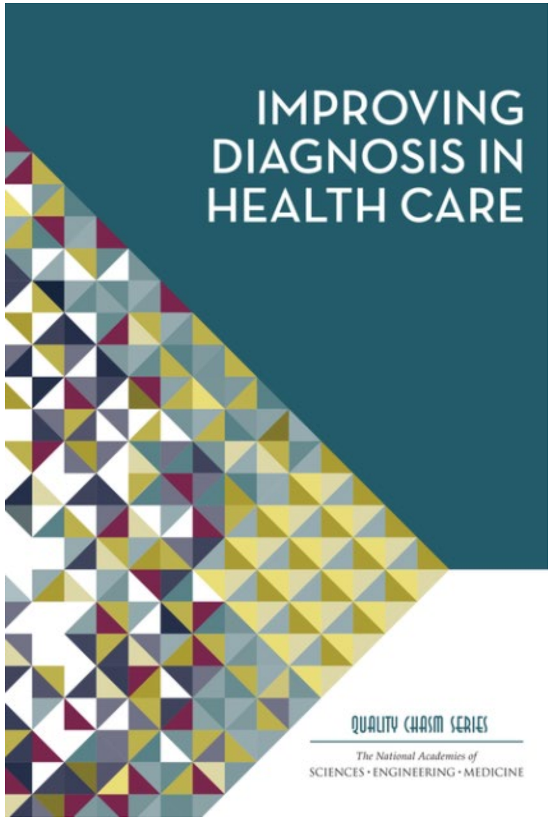
Non-Specific Complaints

Unsepecific Diagnoses
30.3% vs. 23.1%, p=0.001; OR=1.82 (95%CI 1.16-2.9)

Hospital stay
6.51 vs. 5.22 days, p=0.025

Sauter TC, Capaldo G, Hoffmann M, Birrenbach T, Hautz SC, Kämmer JE, Exadaktylos AK, Hautz WE.
Non-specific complaints at emergency department presentation result in unclear diagnoses and lengthened hospitalization: a prospective observational study.
Scand J Trauma Resusc Emerg Med. 2018 Jul 16;26(1):60.

“Improving the diagnostic process represents a moral, professional, and public health imperative”



Causes of diagnostic error

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Mainly: Human Error

- ❑ Incomplete History
- ❑ Fixation error
- ❑ Lack of knowledge
- ❑ Ignoring clinical findings

Zwaan L, Thijs A, Wagner C, van der Wal G, Timmermans DRM. **Relating Faults in Diagnostic Reasoning With Diagnostic Errors and Patient Harm.** Acad Med. 2012;87(2):149-156.
Norman GR, Monteiro SD, Sherbino J, Ilgen JS, Schmidt HG, Mamede S. **The Causes of Errors in Clinical Reasoning: Cognitive Biases, Knowledge Deficits, and Dual Process Thinking.** Acad Med. 2017;92(1):23-30.
Croskerry P. **The importance of cognitive errors in diagnosis and strategies to minimize them.** Acad Med. 2003;78(8):775–780.

Causes of diagnostic error

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Inselspital Bern University Hospital

Mainly: Human Error

❑ Incomplete History	✓ Point to relevant questions
❑ Fixation error	✓ Offer differential diagnoses
❑ Lack of knowledge	✓ Close knowledge gaps
❑ Ignoring clinical findings	✓ Recommend Diagnostic steps

Zwaan L, Thijs A, Wagner C, van der Wal G, Timmermans DRM. **Relating Faults in Diagnostic Reasoning With Diagnostic Errors and Patient Harm.** Acad Med. 2012;87(2):149-156.
Norman GR, Monteiro SD, Sherbino J, Ilgen JS, Schmidt HG, Mamede S. **The Causes of Errors in Clinical Reasoning: Cognitive Biases, Knowledge Deficits, and Dual Process Thinking.** Acad Med. 2017;92(1):23-30.
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Decision support internationally

1/3 of patients in the U.S. use decision support tools

15 billion Visits per month ada

58% patients in germany google **prior** and 62% **after** consulting a physician

Bertelsmann Stiftung: **Wer suchet, der findet – Patienten mit Dr. Google zufrieden.** Gesundheitsinfos Daten, Analysen, Perspektiven. Nr. 2, 2018.
Gann B. **Giving patients choice and control: health informatics on the patient journey.** Yearb Med Inform. 2012;7:70-73.
Fox S, Duggan M. **Health Online 2013**. January 2013. http://www.pewinternet.org/2013 /01/15/health-online-2013/

Do these tools actually work?

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Inselspital Bern University Hospital

***Table 1**: Previous randomized controlled trials on decision support systems in emergency care.*

Trial	Sample	Condition	Primary outcome	Key findings	Key limitations
Apkon 2005[24] Primary care	1902 members of the military	Patients with appoint-ments	"Quality of care"	No difference in primary outcome, intervention group slightly more expensive	No ER patients, highly selected population, not targeted at diagnosis
Dexheimer 2013[48] Paediatric ER	704 children	Asthma	Time to disposition	No differences in primary outcome, system usage low	Post-hoc identification of eligible patients, specific condition, focus on management
Roukema 2008[49] Paediatric ER	164 children	Fever	Time in ER	No differences in primary outcome, more laboratory testing in intervention group	Small sample size, limited adherence to protocol
Roy 2009[50] 20 French ERs	1768 adults	Suspected pulmonary embolism	Appropriate-ness of diagnostic workup	Better diagnostic workup and slightly less tests in intervention group	No patient outcomes assessed, automated scoring of primary outcome, rare condition

Do these tools actually work?

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***Table 3**: DR-CDDS and their key characteristics*

System	Field	Technology	Languages	EHR integration	Studies
Diagnosaurus	General	Not disclosed	EN	Unknown	-
DxPlain	General	Bayesian logic	EN	Unknown	4
Gideon	Infections	Unknown	EN	No	-
Iliad	Internal Medicine	Bayesian logic	EN	No	2
Infera	General	Clinical Rules Engine	EN	Yes	-
Isabel	General	Statistical NLP	EN,ES, DE	Yes	10
Pairs	General	NLP, Bayesian probabilistic belief networks	EN	No	-
Pepid	General	Unknown	EN	Yes	2
SimulConsult	General	Bayesian pattern matching	EN	Unknown	2
VisualDx	General	Neural Network	EN, DE, FR, CHN	Yes	4

Do these tools actually work?

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An 87-year-old man presented to the emergency room with a history of constant abdominal pain that had started 2 days ago. The pain was initially in the lower abdomen and then spread across the entire abdominal area. The pain intensified during the past 2 hours. There was no nausea, vomiting, diarrhoea, blood in faeces, fever or shivers. The patient has a history of anteroseptal myocardial infarction 15 years ago, and has used enalapril and furosemide for hypertension and cardiac congestive insufficiency.

Physical examination:
The patient was oriented, reporting suffering severe abdominal pain.
BP: 60/30 mmHg; Pulse: 112/ min, regular; Temperature: 37.7° C; Respiration: 32/min. Distended jugular veins. Heart: regular rhythm, ejection systolic murmur (2/6) at the base.
Lungs: crepitation in the bases of both lungs. Abdomen: distended, tympanic abdomen, diffusely painful, with defence response and reduced peristaltic sounds. Digital rectal examination: no abnormalities found. Fecal *occult blood* test: negative. Symmetric peripheral pulses:

Lab tests:
Ht 29%; white cell count: 22400/mm^3 with 95% granulocytes; urea: 46; creatinine: 3.0; glucose , amylase and liver functions: normal; pH 7.28, pCO_2 37, pO_2 61 (with 80% oxygen); HCO_3: 17.

EKG: old anteroseptal infarction

Imaging tests:
Chest X-ray: pulmonary congestion and infiltrate in the left lower lobe.
Abdominal X-ray: air-fluid levels; no indication of intestine obstruction; no free air in abdominal cavity.
Abdominal ultrasound: No fluid in the abdominal cavity; no aneurysm.
Abdominal CT scan: No additional information.

Diagnosis: Bacterial pneumonia with sepsis

Do these tools actually work?

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Diagnosis: Bacterial pneumonia with sepsis

Counted as correct if the CDSS lists **either** pneumonia **OR** sepsis among the **first five** (or three) differentials, e.g.:

- Diverticulitis
- Urinary tract infection
- Sepsis
- Pulmonary embolism
- Left ventricular failure

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Do these tools actually work?

Diagnosis: Bacterial pneumonia with sepsis

Counted as correct if the CDSS lists **either** pneumonia **OR** sepsis among the **first five** (or three) differentials, e.g.:

- Diverticulitis
- Urinary tract infection
- Sepsis
- Pulmonary embolism
- Left ventricular failure

If your patient has bacterial pneumonia with sepsis and your resident suggests the above differentials, what would you say to him?

What does the literature say?

Riches et al. 2016: Meta-Analysis von 36 heterogenous studies (only 2 RCTs), no improved diagnostic accuracy as compared to clinicians alone

Patterson et al. 2019: 42 studies, 83% positive effect, heterogenous outcomes, mixed study quality

Conclusion: Numerous studies suggest that clinical decision support interventions are effective in changing physician practice with respect to process outcomes such as guideline adherence; however, many studies are small and poorly controlled. Future studies should consider the inclusion of more specific information in regard to design choices, attempt to improve on uncontrolled before-after designs, and focus on clinically relevant outcomes wherever possible. [Ann Emerg Med. 2019;74:285-296.]

Patterson BW, Pulia MS, Ravi S, et al. **Scope and Influence of Electronic Health Record–Integrated Clinical Decision Support in the Emergency Department: A Systematic Review.** Ann Emerg Med. January 2019.
Riches N, Panagioti M, Alam R, et al. **The Effectiveness of Electronic Differential Diagnoses (DDX) Generators: A Systematic Review and Meta-Analysis.** PLOS ONE. 2016;11(3):e0148991.

Economic effects?

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A Randomized Outpatient Trial of a Decision-Support Information Technology Tool

Michael Apkon [1], Jennifer A Mattera, Zhenqiu Lin, Jeph Herrin, Elizabeth H Bradley, Michael Carbone, Eric S Holmboe, Cary P Gross, Jared G Selter, Amy S Rich, Harlan M Krumholz

Affiliations + expand

PMID: 16287768 DOI: 10.1001/archinte.165.20.2388

Abstract

Background: Decision-support information technology is often adopted to improve clinical decision making, but it is rarely rigorously evaluated. Congress mandated the evaluation of Problem-Knowledge Couplers (PKC Corp, Burlington, Vt), a decision-support tool proposed for the Department of Defense's new health information network.

Methods: This was a patient-level randomized trial conducted at 2 military practices. A total of 936 patients were allocated to the intervention group and 966 to usual care. Couplers were applied before routine ambulatory clinic visits. The primary outcome was quality of care, which was assessed based on the total percentage of any of 24 health care quality process measures (opportunities to provide evidence-based care) that were fulfilled. Secondary outcomes included medical resources consumed within 60 days of enrollment and patient and provider satisfaction.

Results: There were 4639 health care opportunities (2374 in the Coupler group and 2265 in the usual-care group), with no difference in the proportion of opportunities fulfilled (33.9% vs 30.7%; P = .12). Although there was a modest improvement in performance on screening/preventive measures, it was offset by poorer performance on some measures of acute care. Coupler patients used more laboratory and pharmacy resources than usual-care patients (logarithmic mean difference, 71 dollars). No difference in patient satisfaction was observed between groups, and provider satisfaction was mixed.

Economic effects?

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Original Investigation | Diabetes and Endocrinology

September 28, 2018

Evaluation of Artificial Intelligence–Based Grading of Diabetic Retinopathy in Primary Care

Yogesan Kanagasingam, PhD[1,2]; Di Xiao, PhD[1]; Janardhan Vignarajan, BSc (Hons)[1]; et al

Author Affiliations | Article Information

JAMA Netw Open. 2018;1(5):e182665. doi:10.1001/jamanetworkopen.2018.2665

Design, Setting, and Participants Diagnostic study of patients with diabetes seen at a primary care practice with 4 physicians in Western Australia between December 1, 2016, and May 31, 2017. A total of 193 patients consented for the study and had retinal photographs taken of their eyes. Three hundred eighty-six images were evaluated by both the AI-based system and an ophthalmologist.

Economic effects?

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Main Outcomes and Measures Sensitivity and specificity of the AI system compared with the gold standard of ophthalmologist evaluation.

Results Of the 193 patients (93 [48%] female; mean [SD] age, 55 [17] years [range, 18-87 years]), the AI system judged 17 as having diabetic retinopathy of sufficient severity to require referral. The system correctly identified 2 patients with true disease and misclassified 15 as having disease (false-positives). The resulting specificity was 92% (95% CI, 87%-96%), and the positive predictive value was 12% (95% CI, 8%-18%). Many false-positives were driven by inadequate image quality (eg, dirty lens) and sheen reflections.

Are symptom checkers any better?

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Semigran et al.
Assessment of self-diagnosis and triage recommendation:
45 Vignettes
Correct Diagnoses: 34% (95% CI= 31%-37%)

What factors affect diagnostic accuracy?

Better performance for frequent diagnoses.

Correct diagnosis depends on urgency:
80% in life-threatening emergencies
34% Self-Care cases

Semigran HL, Linder JA, Gidengil C, Mehrotra A. **Evaluation of symptom checkers for self diagnosis and triage: audit study.** BMJ. July 2015:h3480.

Special situations: COVID-19?

Problem:
Exponetially increasing numbers of patients
Fear among the public
Frequent changes in testing criteria

Literatur
H1N1 Swine-Flu: Online Triage prevents >100,000 ER visits

Hollander JE, Carr BG. Virtually Perfect? Telemedicine for Covid-19. New England Journal of Medicine. March 2020.
Kellermann AL, Isakov AP, Parker R, Handrigan MT, Foldy S. Web-Based Self-Triage of Influenza-Like Illness During the 2009 H1N1 Influenza Pandemic. Annals of Emergency Medicine. 2010;56(3):288-294.e6

Online Triage Tool COVID-19

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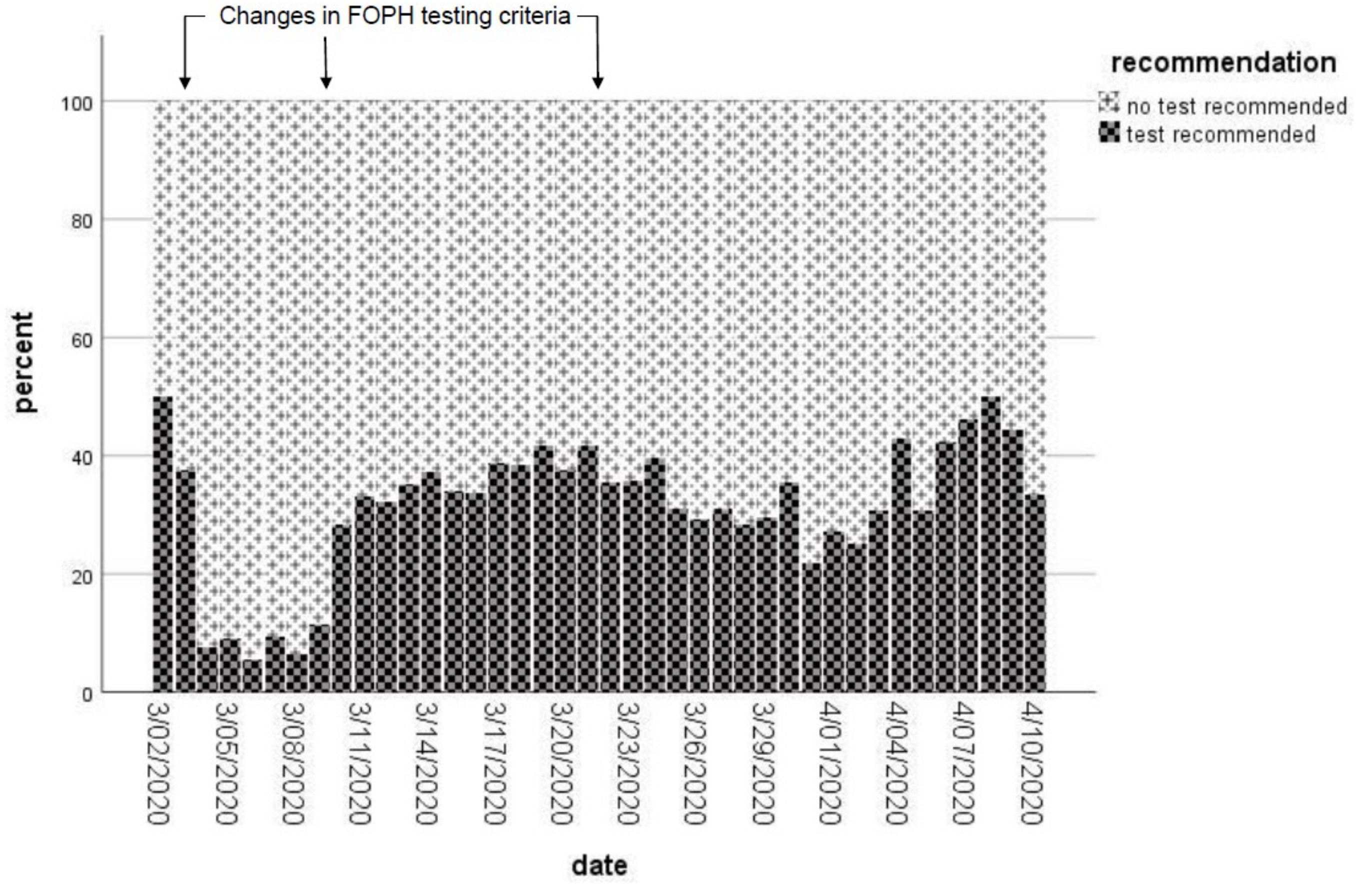
15.000 Visits in less than 3 weeks



Hautz WE, Exadaktylos AK, Sauter TC. **Online forward triage during the COVID-19 outbreak**, EMJ under review

Online Triage Tool COVID-19

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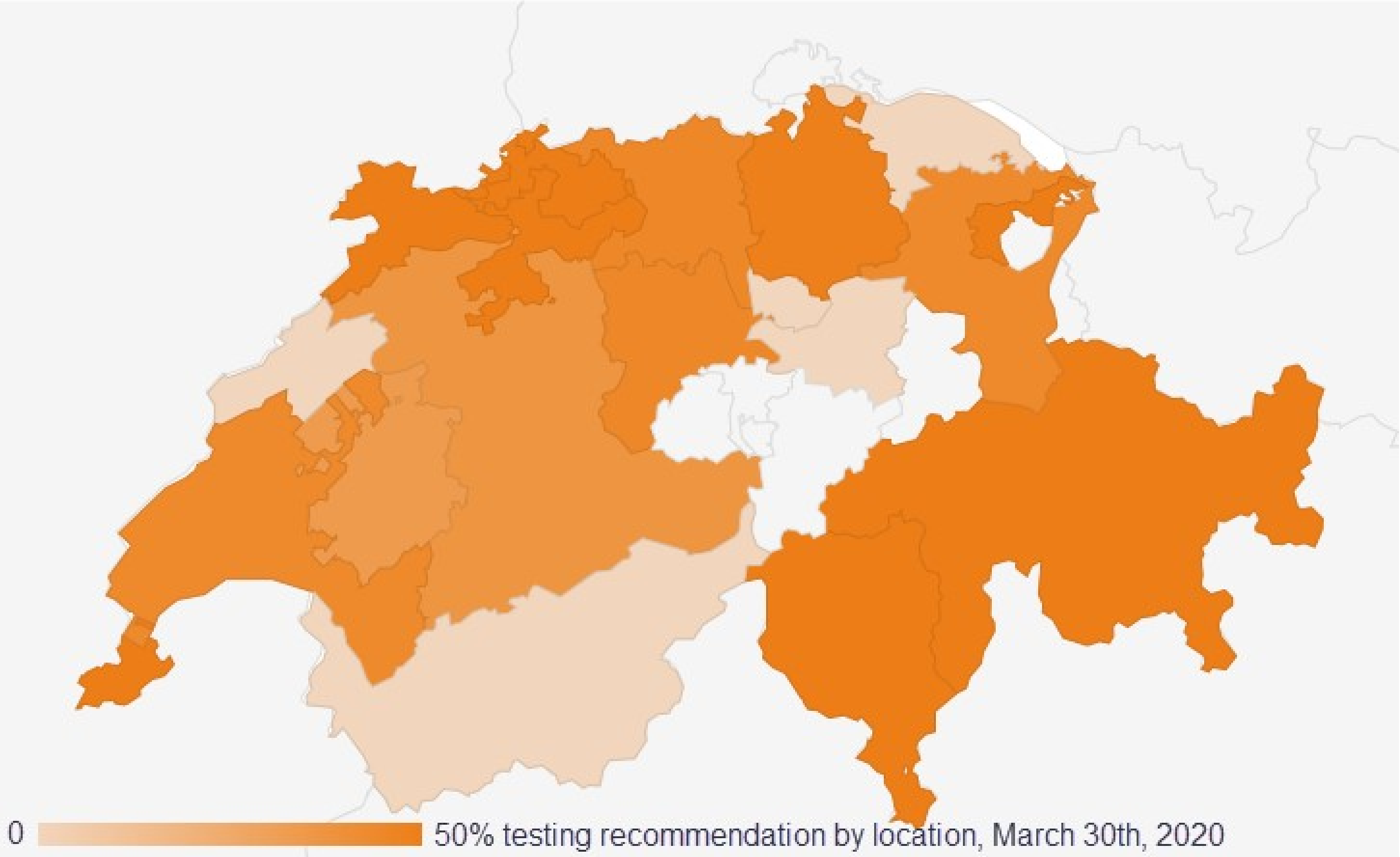

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Summary

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Computerized diagnostic decision support holds (and makes) great promises.

Research generally does not support most claims but is very limited.

CDDS currently may have a role in highly specific situations.

The economic impact of CDDS is far from clear.

Thank you for joining us! Please fill in the survey.
See you next time!