Sundhedsdata og Interoperabilitet

Methods of knowing + Healthcare data

Feb 16, 2026

Chapter 27, Guide to Health Informatics, Enrico Coiera

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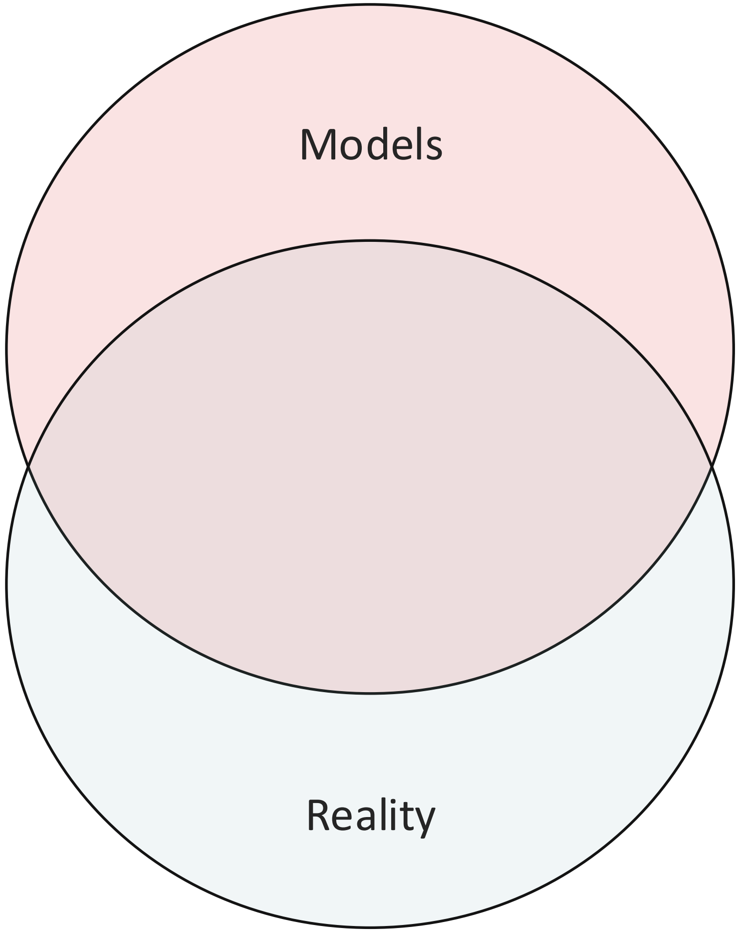
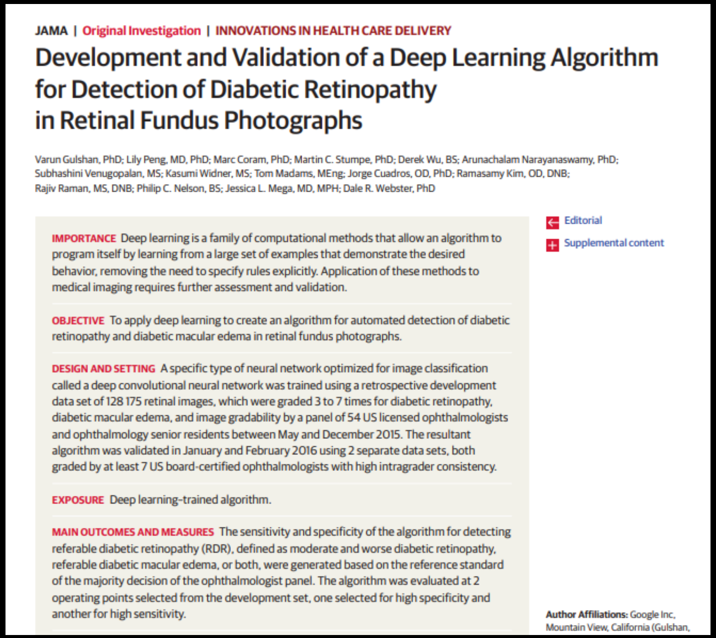


How to model reality and what happens when we assume too much.

Great model != Great value

Can AI detect a disease (diabetic retinopathy) in a retinal image?



JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD

IMPORTANCE Deep learning is a family of computational methods that allow an algorithm to program itself by learning from a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation.

OBJECTIVE To apply deep learning to create an algorithm for automated detection of diabetic retinopathy and diabetic macular edema in retinal fundus photographs.

DESIGN AND SETTING A specific type of neural network optimized for image classification called a deep convolutional neural network was trained using a retrospective development data set of 128 175 retinal images, which were graded 3 to 7 times for diabetic retinopathy, diabetic macular edema, and image gradability by a panel of 54 US licensed ophthalmologists and ophthalmology senior residents between May and December 2015. The resultant algorithm was validated in January and February 2016 using 2 separate data sets, both graded by at least 7 US board-certified ophthalmologists with high intragrader consistency.

EXPOSURE Deep learning–trained algorithm.

MAIN OUTCOMES AND MEASURES The sensitivity and specificity of the algorithm for detecting referable diabetic retinopathy (RDR), defined as moderate and worse diabetic retinopathy, referable diabetic macular edema, or both, were generated based on the reference standard of the majority decision of the ophthalmologist panel. The algorithm was evaluated at 2 operating points selected from the development set, one selected for high specificity and another for high sensitivity.

Editorial

Supplemental content

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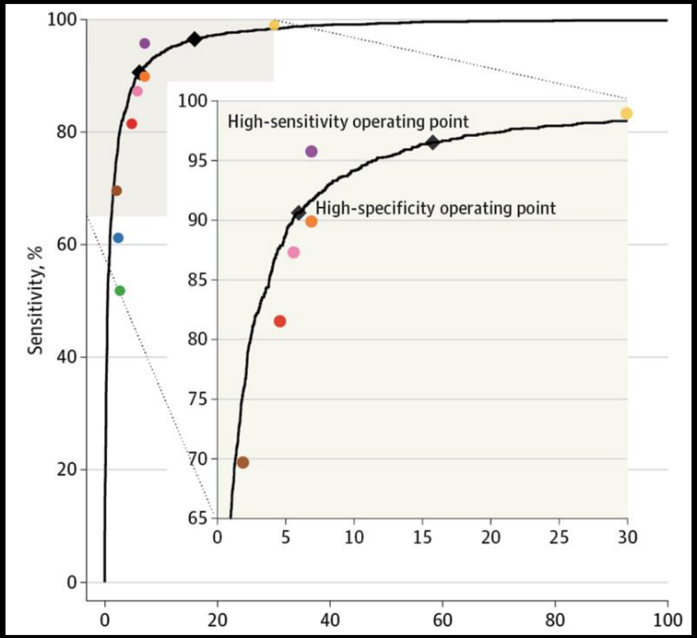
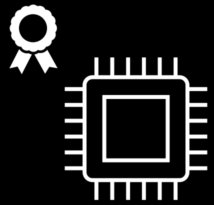


Results of an evaluation of the AI model against 8 senior ophthalmologists.

This study says, yes.

Great model != Great value



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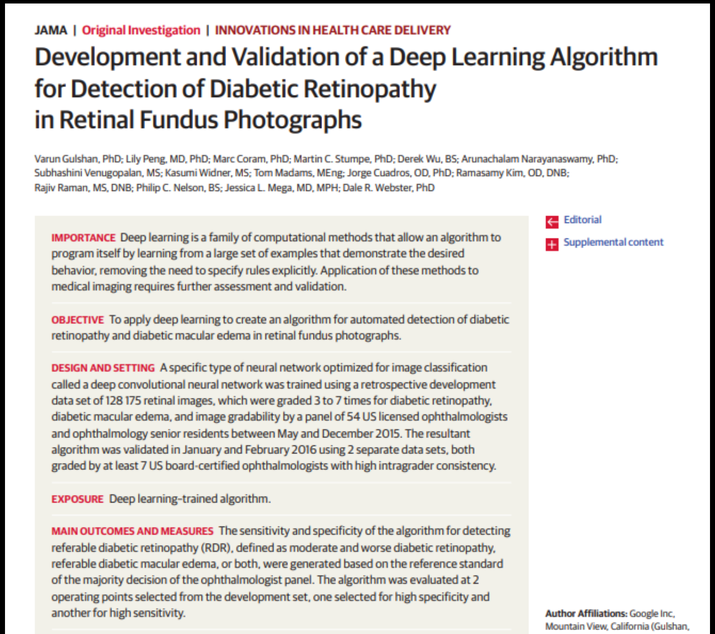

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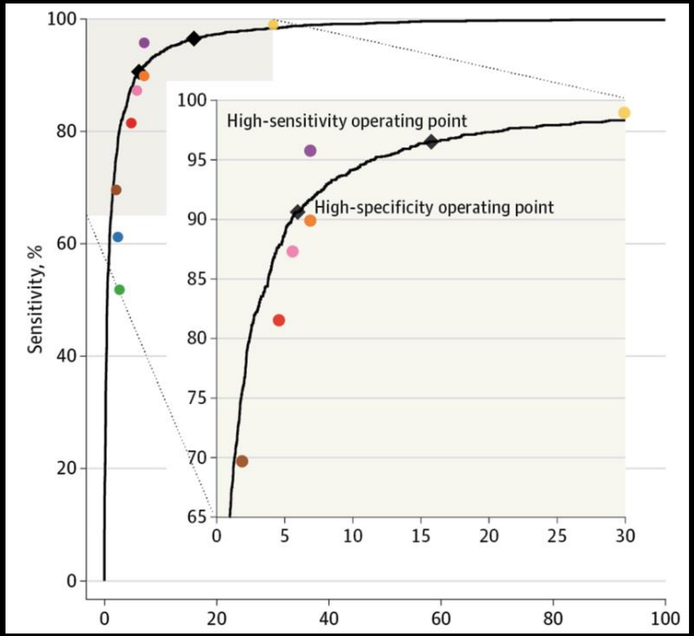

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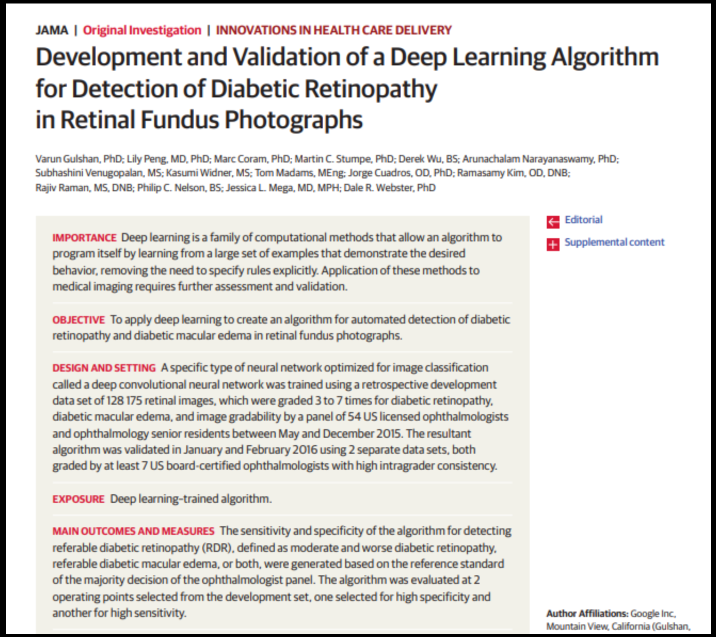
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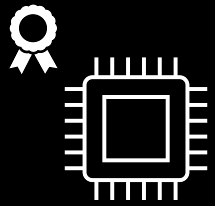

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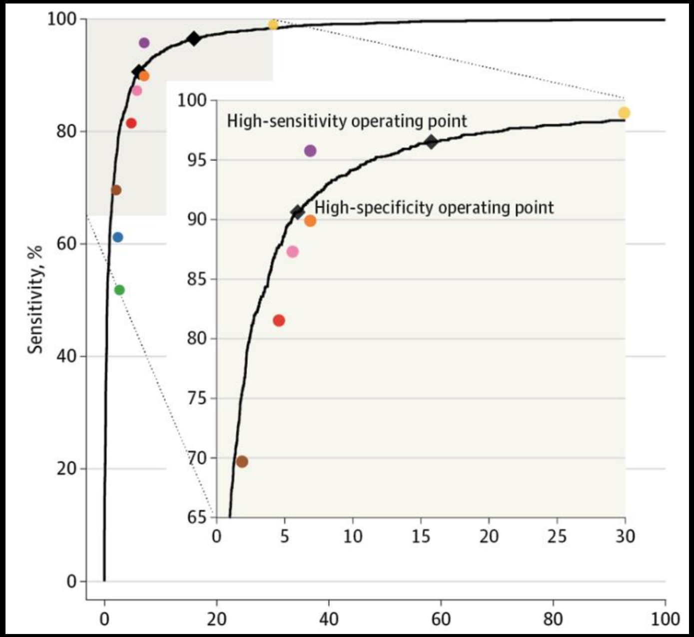
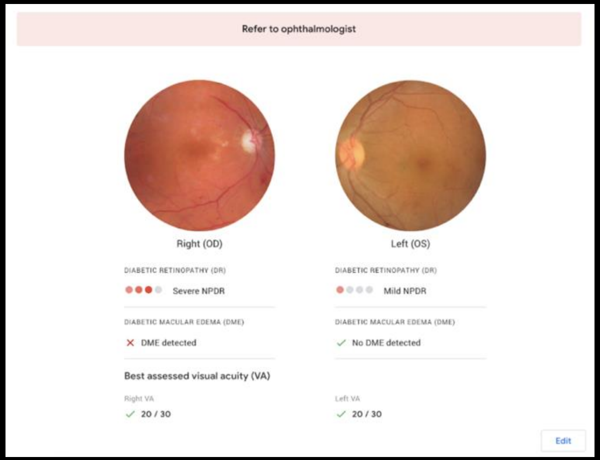


Results of an evaluation of the AI model against 8 senior ophthalmologists.

What happens when we use such a great model in real world?

Great model != Great value

The model was piloted across eleven clinics in Thailand



The system provided a recommendation, referral or dismissal.

The goal was to increase the number of screened patients

Beede, E., Baylor, E., Hersch, F., Iurchenko, A., Wilcox, L., Ruamviboonsuk, P., & Vardoulakis, L. M. (2020, April). A human-centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy. In Proceedings of the 2020 CHI conference on human factors in computing systems (pp. 1-12).

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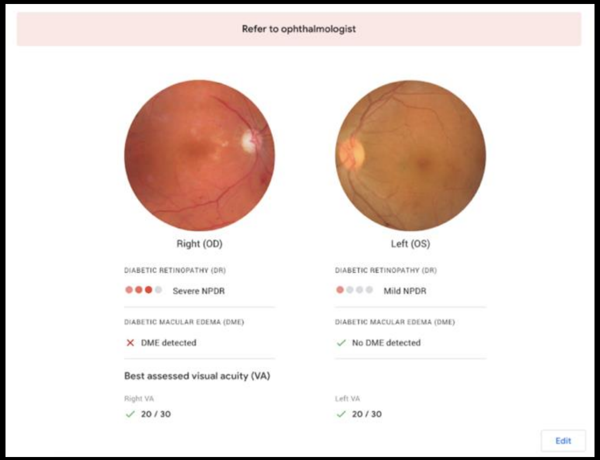
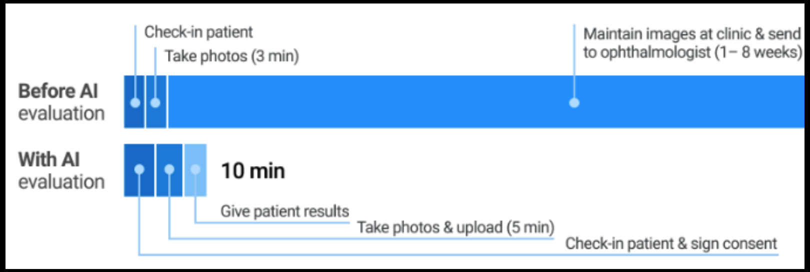


The system provided a recommendation, referral or dismissal.

20% of all the pictures were deemed ungradable by the system

The goal was to increase the number of screened patients

Increased screening time per patient:



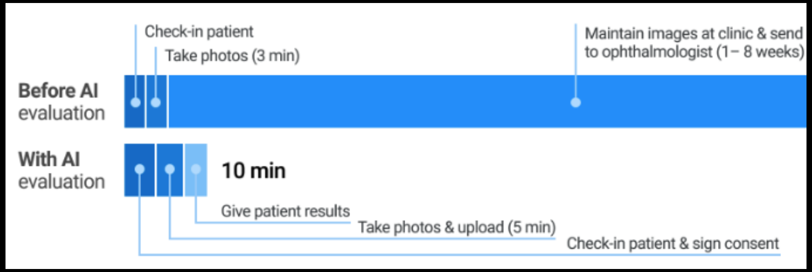
Great model != Great value

20% of all the pictures were deemed ungradable by the system

The data used to train the model was too “curated” and not resembled real world data

<u>Data quality issue</u>

Increased screening time per patient:



The modelling of the work practices used to design the system was inadequate for the problem.

The problem wasn’t waiting for the results. It was the overwhelming number of examinations that had to be conducted within a day.

<u>The system provided support for reality that was not there</u>

Plan for today

How can we create more realistic models of the real world?

Healthcare data intro

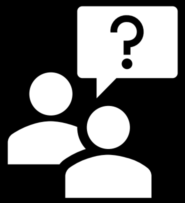
To build any health informatics system, we need realistic models of the world

How can we do that?

How can we create more realistic models of the real world?

We can learn from the data

(Computational discovery systems)



We can learn from the people

(Manual knowledge acquisition)

AI

We can use AI to generate new insights

(Computational discovery systems for new knowledge generation
(not part of this lecture))

https://link.springer.com/article/10.1007/s40264-014-0218-z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Text Mining for Adverse Drug Events: the Promise, Challenges, and State of the Art

Leading Article | Published: 24 August 2014

Volume 37, pages 777–790, (2014) Cite this article

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Rave Harpaz, Alison Callahan, Suzanne Tamang, Yen Low, David Odgers, Sam Finlayson, Kenneth Jung, Paea LePendu & Nigam H. Shah

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Abstract

Text mining is the computational process of extracting meaningful information from large amounts of unstructured text. It is emerging as a tool to leverage underutilized data sources that can improve pharmacovigilance, including the objective of adverse drug event (ADE) detection and assessment. This article provides an overview of recent advances in pharmacovigilance driven by the application of text mining, and discusses several data

Computational discovery systems

1. Association rule mining / data mining / text mining

Purpose: improving medical knowledge, diagnosis, treatment, and patient safety

Discovery systems look for useful patterns in large amounts of clinical data. They can learn simple rules from past cases, find links between medicines and the conditions they treat, spot unexpected benefits or side effects, and pick up signals in free-text notes. These patterns help build CDSSs that support safer and more accurate diagnosis, treatment, and alerts.

Example:
A discovery system, using Natural Language Processing techniques, can scan thousands of free-text adverse event reports written by clinicians. If it repeatedly finds phrases like “rash after starting Drug X” or “patients on Drug X reporting itching”, it can flag a pattern that clinicians have not yet formally recognised.

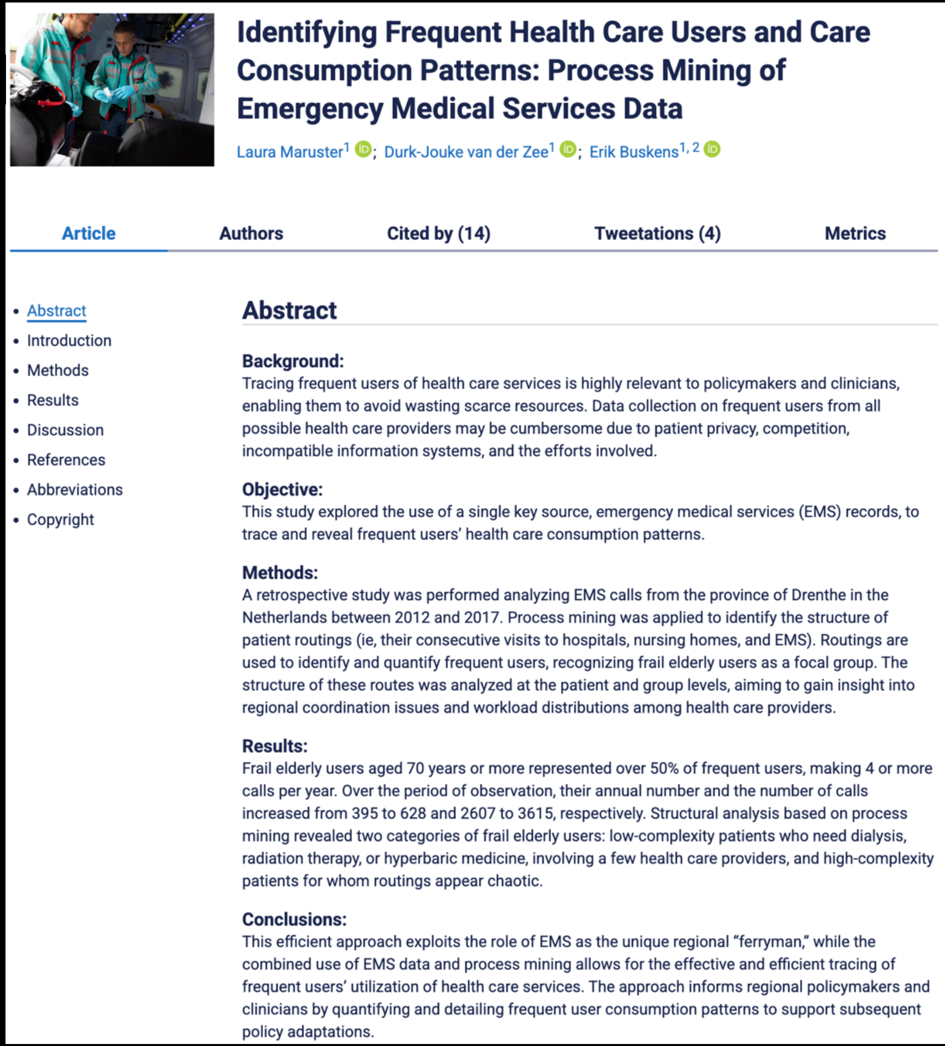
https://www.jmir.org/2021/10/e27499/

Computational discovery systems

1. Association rule mining / data mining / text mining
2. Process mining

Purpose: discovering real care pathways, comparison with guidelines, identifying delays and variations, and supporting quality improvement and training

Process mining in clinical work can be done by extracting time-stamped events from systems such as EHRs, ordering them into sequences for each patient, and then analysing these sequences to identify the most common paths, detect frequent deviations, and measure where steps take longer or vary between clinicians.



Identifying Frequent Health Care Users and Care Consumption Patterns: Process Mining of Emergency Medical Services Data

Laura Maruster[1]; Durk-Jouke van der Zee[1]; Erik Buskens[1,2]

Article | Authors | Cited by (14) | Tweetations (4) | Metrics

- Abstract
- Introduction
- Methods
- Results
- Discussion
- References
- Abbreviations
- Copyright

Abstract

Background:
Tracing frequent users of health care services is highly relevant to policymakers and clinicians, enabling them to avoid wasting scarce resources. Data collection on frequent users from all possible health care providers may be cumbersome due to patient privacy, competition, incompatible information systems, and the efforts involved.

Objective:
This study explored the use of a single key source, emergency medical services (EMS) records, to trace and reveal frequent users' health care consumption patterns.

Methods:
A retrospective study was performed analyzing EMS calls from the province of Drenthe in the Netherlands between 2012 and 2017. Process mining was applied to identify the structure of patient routings (ie, their consecutive visits to hospitals, nursing homes, and EMS). Routings are used to identify and quantify frequent users, recognizing frail elderly users as a focal group. The structure of these routes was analyzed at the patient and group levels, aiming to gain insight into regional coordination issues and workload distributions among health care providers.

Results:
Frail elderly users aged 70 years or more represented over 50% of frequent users, making 4 or more calls per year. Over the period of observation, their annual number and the number of calls increased from 395 to 628 and 2607 to 3615, respectively. Structural analysis based on process mining revealed two categories of frail elderly users: low-complexity patients who need dialysis, radiation therapy, or hyperbaric medicine, involving a few health care providers, and high-complexity patients for whom routings appear chaotic.

Conclusions:
This efficient approach exploits the role of EMS as the unique regional "ferryman," while the combined use of EMS data and process mining allows for the effective and efficient tracing of frequent users' utilization of health care services. The approach informs regional policymakers and clinicians by quantifying and detailing frequent user consumption patterns to support subsequent policy adaptations.

Example:
A hospital's EHR logs every step in a patient's journey, such as admission -> CT scan -> stroke unit -> rehabilitation. A process mining tool can analyse thousands of these sequences to find the most common pathway. It can also spot delays (e.g., long waits for imaging) or frequent deviations from the recommended guidelines.

How can we create more realistic models of the real world?

Computational discovery systems

1. Association rule mining / data mining / text mining
2. Process mining
3. Literature-based discovery

Purpose: generation of new clinical hypotheses

Literature-based discovery systems analyse research papers to uncover hidden links between diseases, treatments, and biological mechanisms. By identifying concepts that appear in two separate bodies of literature, these systems can generate new clinical hypotheses that may guide further research or treatment development.

Example:
A discovery system scans thousands of research papers. One group of papers shows that fish oil lowers blood viscosity and platelet stickiness. Another group shows that Raynaud's syndrome is worsened by high viscosity and platelet activity. The system identifies shared factors and suggests that fish oil might help people with Raynaud's, a finding later confirmed by studies.

How can we create m

Computational discovery systems

1. Association rule mining / data mining / text mining
2. Process mining
3. Literature-based discovery
4. Biological model discovery

Purpose: generation of new clinical hypotheses, representing physiological functions

https://www.nature.com/articles/s41746-025-01920-8

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Article | Open access | Published: 25 August 2025

Digital twins for noninvasively measuring predictive markers of right heart failure

Justen R. Geddes, Christopher W. Jensen, Cyrus Tanade, Arash Ghorbannia, Marat Fudim, Manesh R. Patel & Amanda Randles

npj Digital Medicine 8, Article number: 545 (2025) | Cite this article

Abstract

Digital twins offer a promising approach to advancing healthcare by providing precise, noninvasive monitoring and early detection of diseases. In heart failure (HF), a leading cause of mortality worldwide, they can improve patient monitoring and clinical outcomes by simulating hemodynamic changes indicative of worsening HF. Current techniques are limited by their invasiveness and lack of scalability. We present a novel framework for HF digital twins that predicts patient-specific hemodynamic metrics in the pulmonary arteries using 3D computational fluid dynamics to address these limitations. We introduce a strategy to determine the minimal geometric complexity required for accurate pressure prediction and explore the effects of varying boundary conditions. By validating our digital twins against invasively-measured data, we demonstrate their potential to improve HF management by enabling continuous, noninvasive monitoring and early identification of worsening HF. This proof-of-concept study lays the groundwork for integrating digital twin technology into personalized HF care.

Biological model discovery uses patient data to build computational models that describe how physiological systems behave. These models can represent normal and abnormal function, detect changes in a patient's condition in real time, and generate new hypotheses about biological mechanisms, metabolic pathways, or disease processes.

Example:
During cardiac bypass surgery, sensors collect real-time data about a patient's heart function. A learning system uses this data to build a digital twin of the patient's cardiovascular system. By comparing the twin's expected behaviour with the patient's actual measurements, clinicians can spot early signs of instability. In research, the same model can be used to test ideas about how the heart responds to stress or medication.

c models of the real world?

Computational discovery systems

1. Association rule mining / data mining / text mining
2. Process mining
3. Literature-based discovery
4. Biological model discovery
5. Drug discovery

Purpose: guiding drug discovery


Since 2020, AlphaFold has accelerated the pace of science and fueled a global wave of biological discovery — an achievement recognized with a Nobel Prize

Five years ago, AlphaFold 2 solved the protein structure prediction problem, unlocking new avenues of biological research and providing our first major proof point that AI can be a powerful tool to advance science.

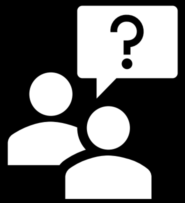
Proteins are the complex, microscopic machines that drive every process in a living cell. Composed of long, unique chains of amino acids, they precisely fold into a 3D structure that largely defines the protein's function - making knowledge of this shape critical for drug discovery and understanding disease.

https://deepmind.google/blog/alphafold-five-years-of-impact/

It works by analysing the structures of weakly active drugs, identifying the chemical features linked to their activity, and using these features to guide the design of new compounds.

Example:
Suppose several existing drugs show only mild anti-inflammatory effects. A system can study their chemical structures and notice that all effective compounds share a particular ring shape and side chain. It suggests that these features are key to the activity. Chemists can then design a new molecule that includes these features, instead of testing hundreds of random variations.

How can we create more realistic models of the real world?



AI

Computational discovery systems

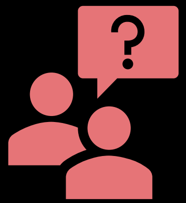
- reveal how care is actually delivered
- generate new scientific hypotheses
- model physiological processes
- guide drug development

Manual knowledge acquisition

Computational discovery systems for new knowledge generation (not part of this lecture)

Hubert D. Zając | hdz@di.ku.dk

How can we create more realistic models of the real world?



Manual knowledge acquisition

1. Interview

Purpose: gaining an in-depth understanding of actions, motivations, and reasoning

Interviews are the most common method for improving our understanding of certain phenomena. It involved talking to your participants and can range from highly structured, almost like asking a questionnaire, to completely unstructured, like a conversation. They are usually audio- or video-recorded for further analysis.

Example:
An interview may be used to understand real work practices. For example, one may ask an emergency nurse to walk through how they triage a patient with chest pain to understand what they look for first, what questions they ask, and what triggers escalation, providing insight into the actual decision-making process.

How can we create more realistic models of the real world?

Manual knowledge acquisition

1. Interview
2. Observation

Purpose: gaining an in-depth understanding of actions, motivations, and reasoning (focusing on what and how)

Observation involves watching participants in real settings (or using simulated cases when necessary) to see how they make judgements, what information they use, and how decisions unfold. Collected data may include notes, audio, or video. Analysis usually encompasses ethnographic methods such as grounded theory or thematic analysis.

Example:
A researcher shadows a triage nurse and notices that, although the nurse says they follow a formal checklist, in practice they rely heavily on quick visual cues and experience to prioritise patients – an insight that would not emerge from interviews alone.

How can we create more realistic models of the real world?

Manual knowledge acquisition

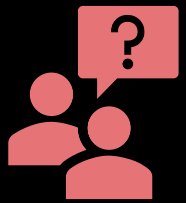
1. Interview
2. Observation
3. Process tracing

Purpose: uncovering the detailed steps, thoughts, and cues involved in real-world tasks (focusing on how and why)

Process tracing captures the moment-to-moment sequence of actions and thoughts involved in a task. This can include think-aloud protocols, eye-tracking, stress measurements, event logs, or retrospective explanations based on video. The resulting data show how a task is really carried out, often revealing hidden steps, shortcuts, and cognitive demands that are not visible from interviews or guidelines.

Example:
A pharmacist is asked to check a complex medication order while thinking aloud. As they work, their mouse clicks, eye movements, and verbal reasoning are recorded. Later analysis shows that they repeatedly jump between two screens to cross-check doses, revealing a hidden usability issue in the prescribing system that slows down safe verification.

How can we create more realistic models of the real world?



Manual knowledge acquisition

1. Interview
2. Observation
3. Process tracing
4. Conceptual methods

CONSTRUCTS / ELEMENTS

	LEFT POLE	RIGHT POLE	SELF NOW	DAUGHTER	DAUGHTER	MOTHER	FATHER	HUSBAND	FRIEND 1	FRIEND 2	FRIEND 3	FRIEND 4	FRIEND 5	FRIEND 6	NON GRATA	IDEAL SELF
1.	CHOKE BACK	SPEAKS HIS MIND	1	1	7	4	1	5	4	7	7	7	2	5	4	7
2.	FARSIGHTED	IMPULSIVE	7	4	7	7	2	1	7	2	2	2	7	3	3	3
3.	STRONG CHARACTER	PATIENT	7	7	5	7	7	5	7	6	6	6	7	5	4	4
4.	PROTECTOR	UNEMOTIONAL (NO BLOOD)	1	1	1	1	1	1	1	2	1	1	2	2	4	2
5.	CHEERFUL	EMBITTERED	1	3	1	1	6	6	2	4	5	5	1	5	2	1
6.	NERVIOUS/ ANXIOUS	CALM	1	1	1	1	5	5	3	5	5	5	1	5	6	5
7.	GENEROUS	STINGY	1	3	1	1	4	2	1	4	3	3	1	3	4	2
8.	CONCERN ABOUT OTHERS	SELFISH	1	1	1	1	4	3	1	3	3	3	1	3	7	3
9.	LISTEN	BLOCKHEAD	1	1	1	1	4	3	1	3	2	2	1	2	2	3
10.	SNOOTY	SLOVENLY	3	3	3	3	3	1	1	1	3	3	3	3	1	3
11.	AMBITIOUS	COMFORMIST	7	2	6	7	4	2	6	2	2	2	6	2	4	5
12.	GOOD PERSON	BAD PERSON	2	2	2	2	2	2	2	2	2	2	2	3	4	3
13.	HARD-WORKING	LAZY	1	1	1	1	1	1	1	3	3	3	1	3	1	3
14.	FLOOZY	FAITHFUL	7	7	7	7	7	5	5	5	7	7	7	7	1	7
15.	LOVES HERSELF	DOES NOT LOVE HERSELF	7	7	7	7	4	1	6	1	5	6	4	6	4	1
16.	HAPPY	SAD/ DEPRESSED	7	5	5	1	1	1	7	4	2	7	4	4	2	1
17.	ROMANTIC	NO ROMANTIC	1	1	1	4	4	1	1	1	1	3	1	3	4	1

1. very much so *2. quite a lot* *3. a little* — *4 middle point* — *5. a little* *6 .quite a lot* *7. very much so*

Figure 2. Example of the repertory grid of a patient of the clinical sample.

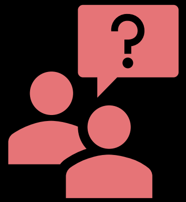
https://doi.org/10.1111/bjc.12050D

Purpose: mapping out the key concepts in a clinical domain and clarifying how they relate to one another

Conceptual methods capture the structure of a domain by identifying its core concepts, such as diseases, symptoms, signs, and tests, and describing the relationships between them. Techniques like repertory grids help clinicians articulate how strongly concepts are related by rating them along structured dimensions, revealing the underlying ontology that supports accurate modelling of clinical decision-making.

Example:
A researcher asks clinicians to rate how strongly different symptoms (e.g., fever, rash, joint pain) relate to several infectious diseases. The ratings show which symptoms are most distinctive for each condition, helping build a clear conceptual map of the diagnostic space.

How can we create more realistic models of the real world?



Manual knowledge acquisition

1. Interview
2. Observation
3. Process tracing
4. Conceptual methods
5. Case-driven knowledge acquisition

Purpose: discovering new clinical knowledge case-by-case

Experts add rules that fix specific failures and add them to the system of knowledge that misclassified the case. Cornerstone cases are then re-checked to ensure no new errors are introduced. Over time, this produces a knowledge base that grows organically from real clinical examples and remains maintainable despite many contributors.

Example:
A clinical decision support system provides wrong advice for a child with a fever. The paediatrician adds one new rule explaining how fever behaves differently in young children. The system is then checked against a small set of earlier example cases to make sure nothing else breaks, and from that point on it handles similar paediatric fever cases correctly.

Hubert D. Zając | hdz@di.ku.dk

How can we create more realistic models of the real world?

Manual knowledge acquisition

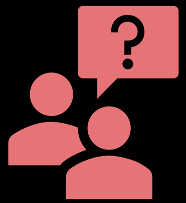
1. Interview
2. Observation
3. Process tracing
4. Conceptual methods
5. Case-driven knowledge acquisition
6. Crowdsourcing

Purpose: building and refining clinical knowledge based on insights from many participants rather than relying on a single expert.

Crowdsourcing gathers contributions from multiple users to identify key concepts, relationships, and decision patterns in a clinical domain. This is often achieved through structured tasks, rating exercises, or collaborative platforms.

Example:
A group of clinicians each lists the drugs they would prescribe for common infections. Their combined responses reveal consistent first-line choices and highlight areas of disagreement, helping shape a shared, evidence-aligned treatment knowledge base.

How can we create more realistic models of the real world?



Manual knowledge acquisition

1. Interview
2. Observation
3. Process tracing
4. Conceptual methods
5. Case-driven knowledge acquisition
6. Crowdsourcing
7. Systematic review

Purpose: building and refining clinical knowledge based on the best available scientific evidence

Systematic review uses a formal, transparent process to search for, appraise, and synthesise all relevant research on a specific question, e.g., the effectiveness of treatments for a disease. The resulting evidence summary forms our understanding of best practice.

Example:
Researchers review all high-quality studies comparing different antibiotics for pneumonia. They combine the findings, identify which drug works best in which situations, and translate those recommendations into decision rules.

How can we create more realistic models of the real world?

AI

Computational discovery systems

- Reveal how care is delivered
- Generate new scientific hypotheses
- Model physiological processes
- guide drug development

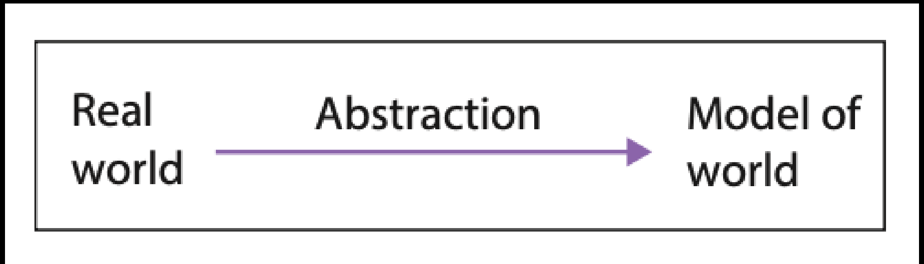
Manual knowledge acquisition

- Capture how people act and think, tracing the detailed steps of tasks in real world
- Map core domain concepts and their relationships
- Build knowledge based on real-world cases, consensus, and literature

Computational discovery systems for new knowledge generation (not part of this lecture)

Modelling the world

Simpler than the original
Never capturing reality in full



Several models of the same phenomenon can differ
Captured at a specific point in time

Modelling the world

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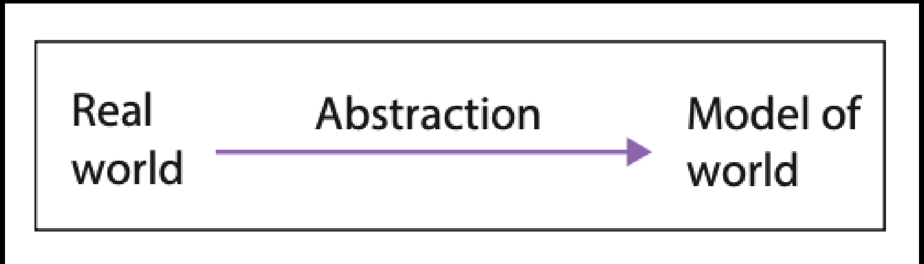
Never capturing reality in full



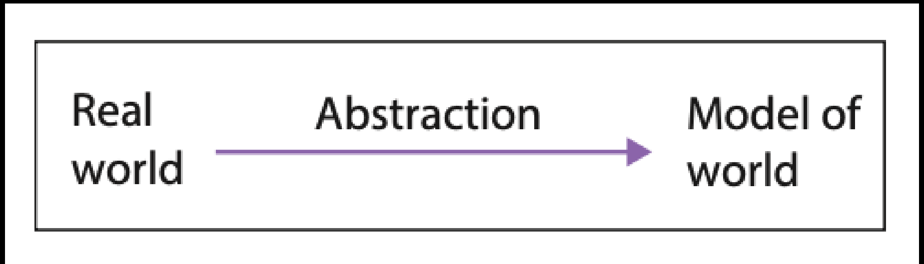
How can we learn about the real world to model how radiologists handle X-rays?

Several models of the same phenomenon can differ
Captured at a specific point in time

Modelling the world

Simpler than the original
Never capturing reality in full

Discuss this question with your neighbour/group for 5-10 min



How can we learn about the real world to model how radiologists handle X-rays?

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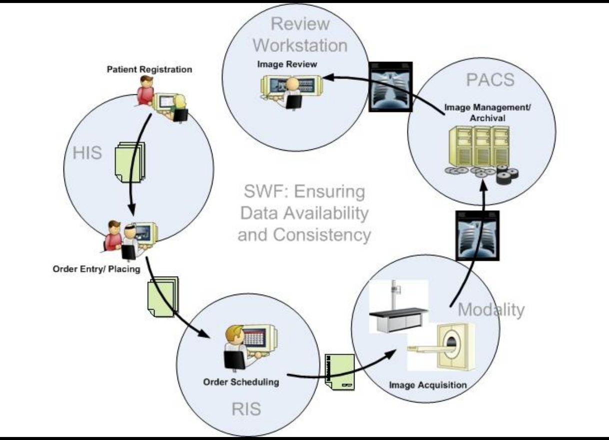
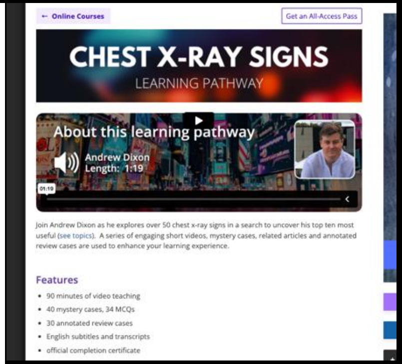
Modelling the world

Workflow guidelines, e.g., IHE proposed scheduled workflow for radiologists





Courses on image interpretation

Software intro courses, e.g. to PACS

Interviews

How can we learn about the real world to model how radiologists handle X-rays?

Observations

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Event logs, e.g., from EHR or PAC systems

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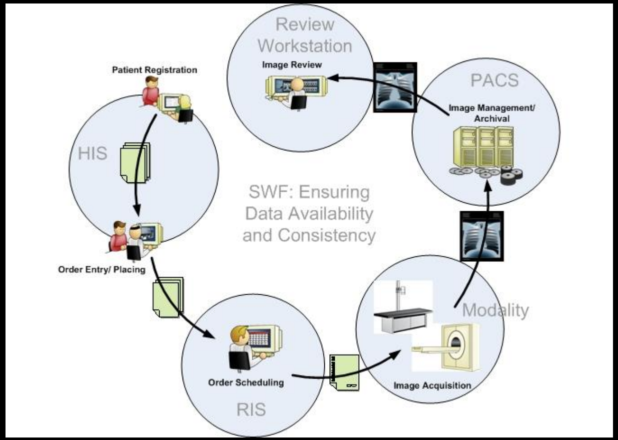
Clinical guidelines, e.g., https://www.ahajournals.org/doi/10.1161/STR.0000000000000513

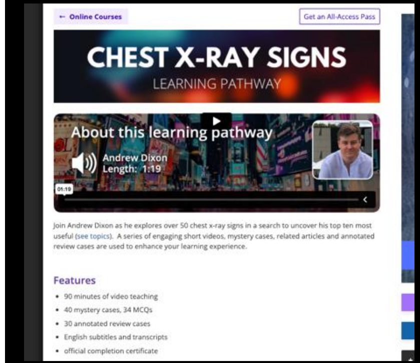
Modelling the world

How can we learn about the real world to model how radiologists handle X-rays?

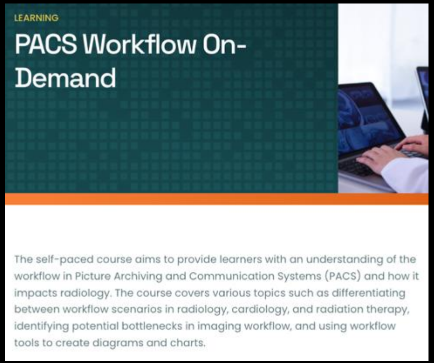
Idealised version ⟷ Real version



Interviews



Observations



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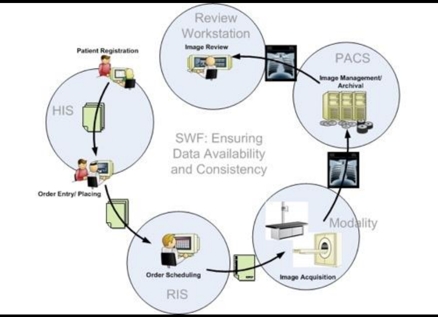
Modelling the world

How can we learn about the real world to model how radiologists handle X-rays?

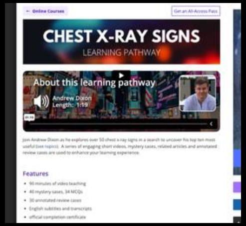
Idealised version

Real version



Workflow guidelines, e.g., IHE proposed scheduled workflow for radiologists

Software intro courses, e.g. to PACS



Courses on image interpretation

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Interviews

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Idealised version

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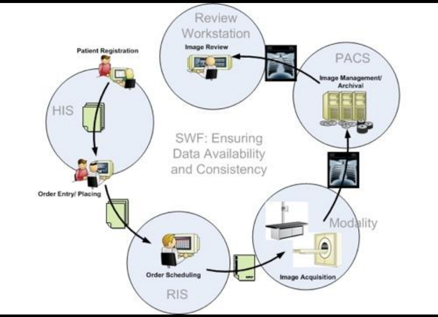

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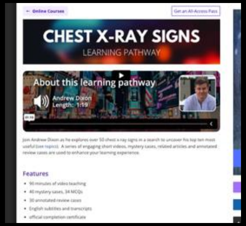

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CXR-003	ACC20260112003	2026-01-12T08:37	Order accepted	Task	RIS System	system							
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CXR-004	ACC20260112004	2026-01-12T08:43	Order placed	ServiceRequest	Dr. Kumar	clinician							indication=Chest pain
CXR-004	ACC20260112004	2026-01-12T08:44	Order accepted	Task	RIS System	system							
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CXR-001	ACC20260112001	2026-01-12T09:14	Image acquisition start	ImagingStudy	Tech. Hansen	radiographer	CR						
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CXR-003	ACC20260112003	2026-01-12T09:27	Images uploaded to PACS	ImagingStudy	Tech. Hansen	radiographer	CR	1.2.840.11361	2	4			views=PA and Lateral
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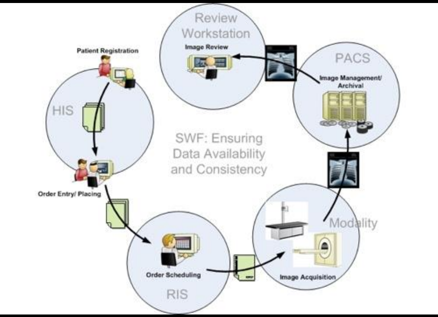
Event logs, e.g., from EHR or PAC systems

Modelling the world

How can we learn about the real world to model how radiologists handle X-rays?

Idealised version ⟷ Real version



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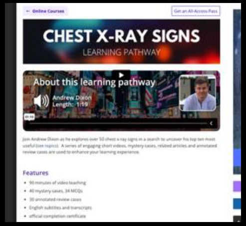

Courses on image interpretation

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Interviews

Why here?

Observations

radiology_event_log

case_id	accession_number	event_time	activity	fhir_resource	actor	role	modality	study_uid	seri	instan	report_i	icd11_code	notes
TEST-001	TEST001	2026-01-12T07:45	Order placed	ServiceRequest	Admin User	system							indication=TRAINING CASE - DO NOT PROCESS
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Event logs, e.g., from EHR or PAC systems

Say / do problem

- People recall an idealised version of their past actions - a natural by-product of wanting to be helpful
- Details and repetitive choices fade into the background and become invisible
- Managers often describe how work *should* happen, not how it *does*
- Front-line practices differ from the tidy, high-level view
- Idealised accounts mask the messy reality of real work

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What can we do about it?

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What can we do about it?

- Ask better questions
- Conduct observations
- Look at the data

How can we learn how radiologists handle X-rays?

Do you look at X-Rays in a systematic way?

Is it a good question? Why and why not?

How can we learn how radiologists handle X-rays?

How do you typically approach reviewing an X-ray?

Is it a good question? Why and why not?

How can we learn how radiologists handle X-rays?

Ask better questions

Think about the last chest X-ray you reviewed yesterday before lunch. Walk me through what you actually did, step by step.

Is it a good inquiry? Why and why not?

Ask good questions / Summary

Don’t ask Yes/No questions

Avoid priming, leading your interviewees

Avoid “double-barreled” questions – 1 question – 1 topic

When specific – ask about concrete examples, stories, etc.

Say / do problem

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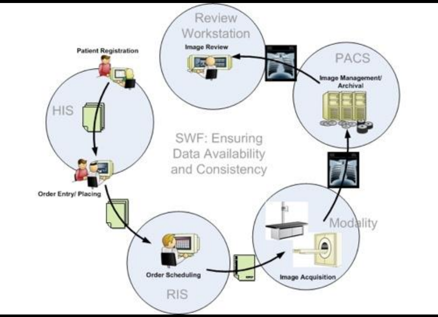

Workflow guidelines, e.g., IHE proposed scheduled workflow for radiologists

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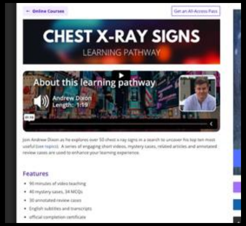
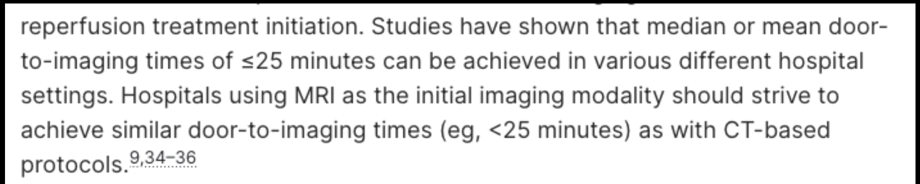


Courses on image interpretation



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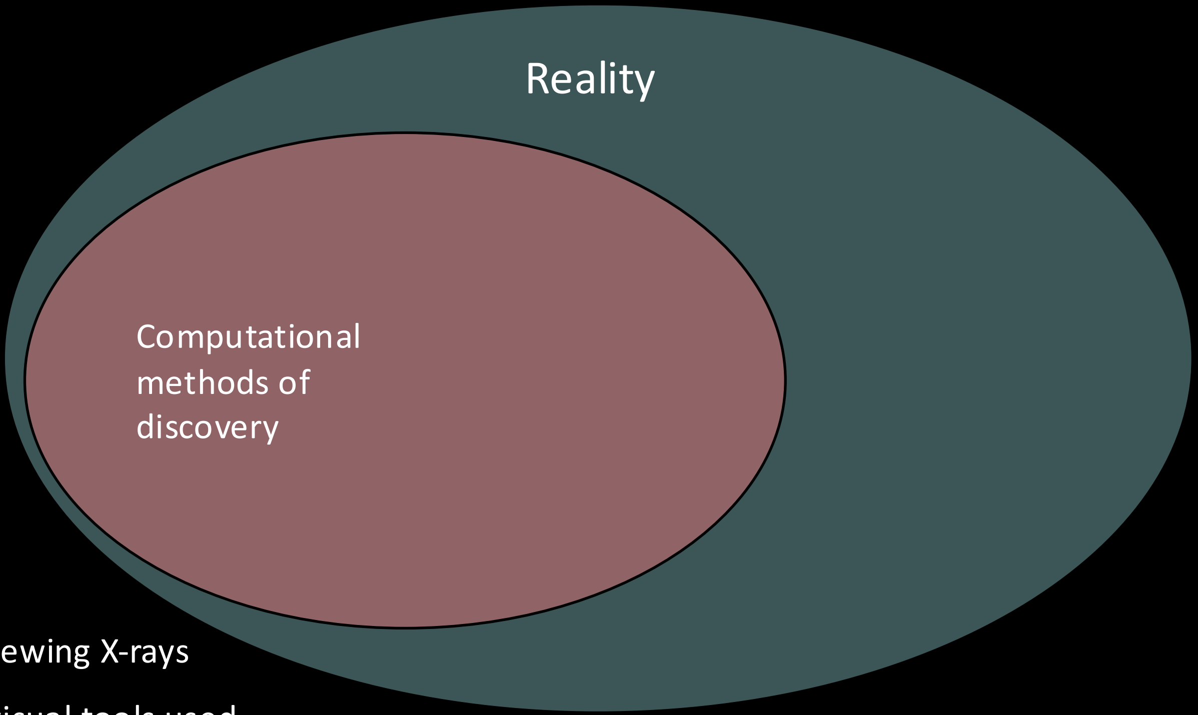
Event logs, e.g., from EHR or PAC systems

How can we learn how radiologists handle X-rays?

How can we create more realistic models of the real world?

Event logs, e.g., from EHR or PAC systems



Computational discovery

Digital timing patterns, e.g. time spent viewing X-rays

Reading patterns at scale, e.g., types of visual tools used

Formal workflow sequences, e.g., use of past examinations or frequency of switching between apps

Recorded diagnostic outputs, e.g., error rates, turnaround times

Hubert D. Zając | hdz@di.ku.dk

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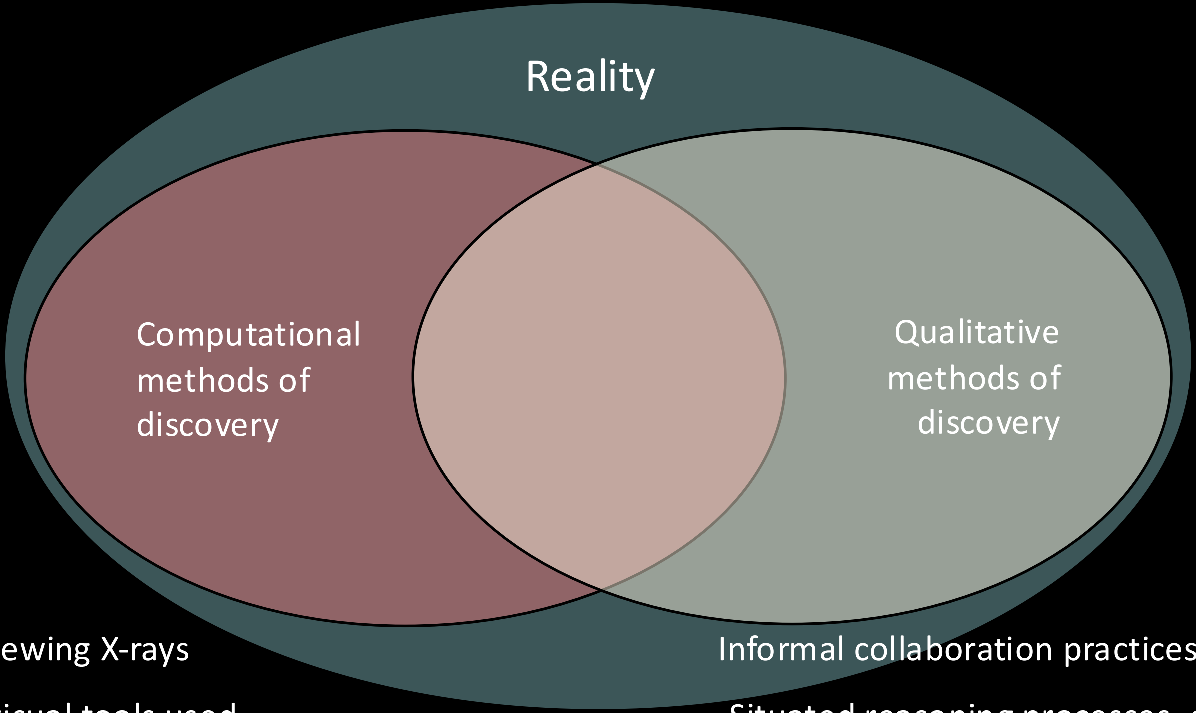

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Qualitative discovery

Informal collaboration practices, e.g., joint interpretation of an X-ray

Situated reasoning processes, e.g., interpretation systems/methods

Unwritten expertise and norms, e.g., knowledge of special handling of certain diseases

Workarounds and adaptive strategies, e.g., strategies for dealing with system breakages

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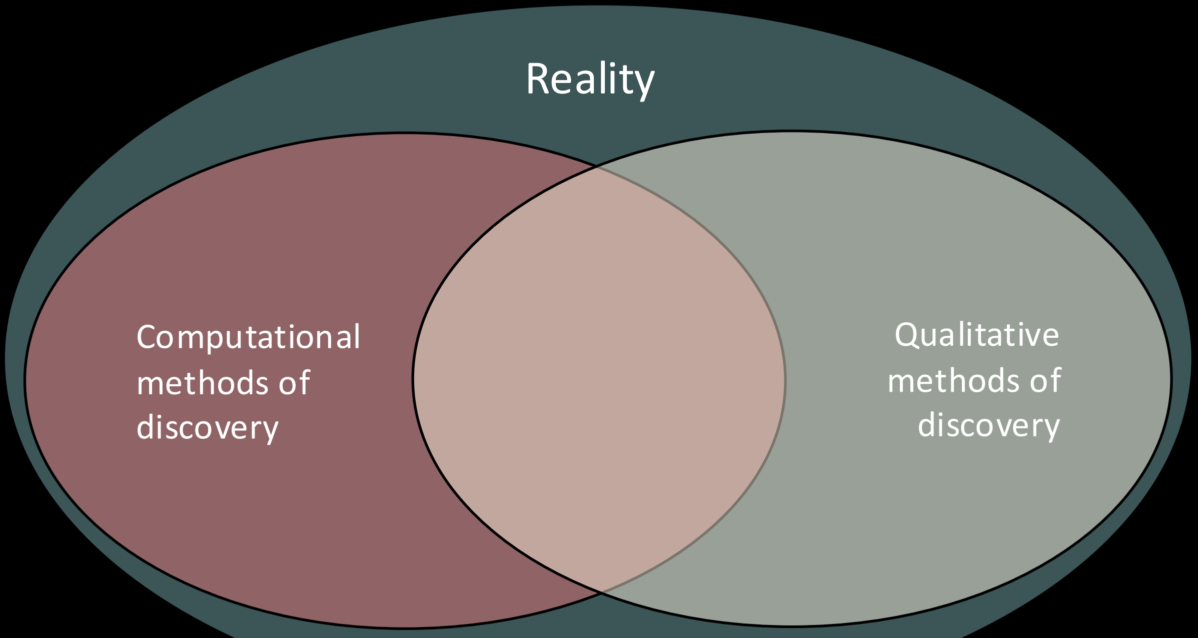

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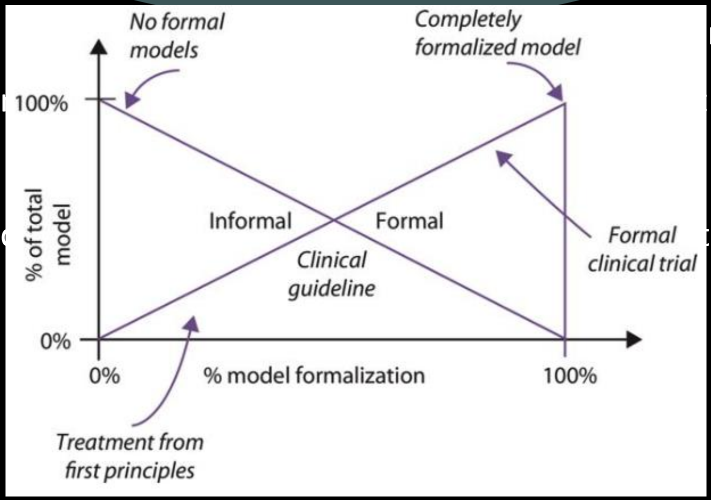

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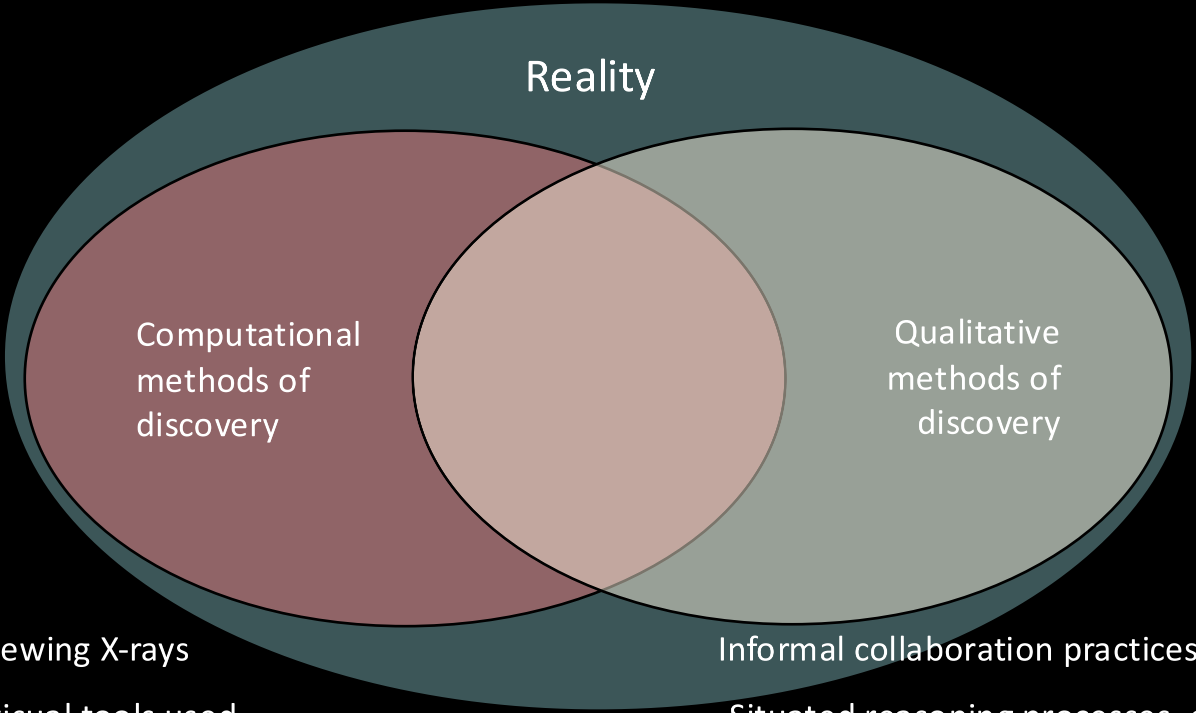

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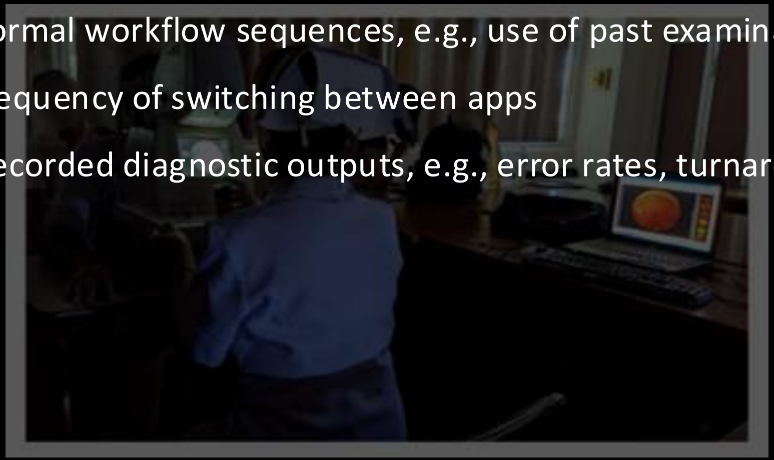

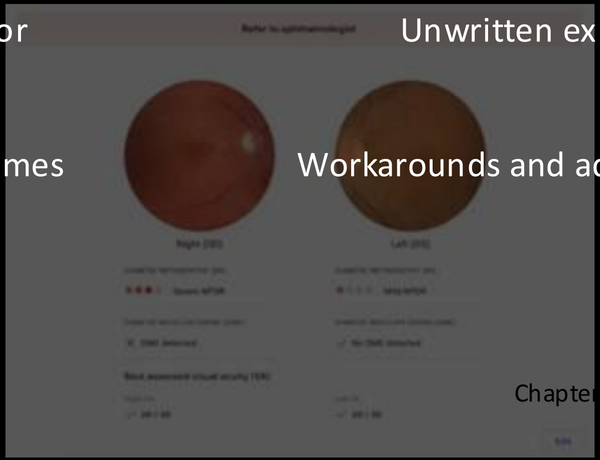

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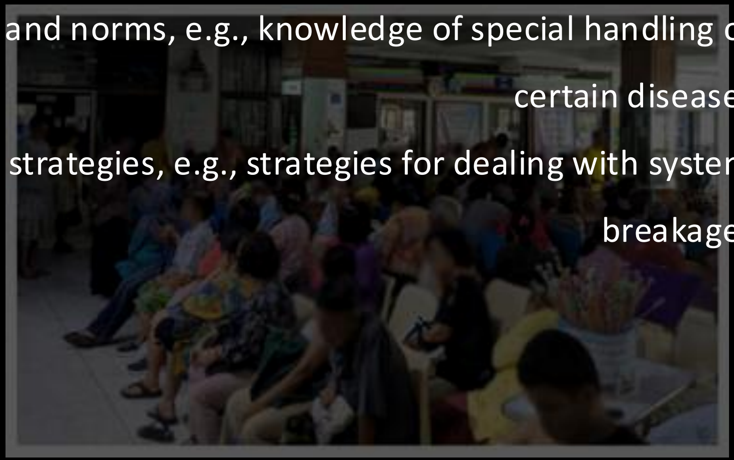
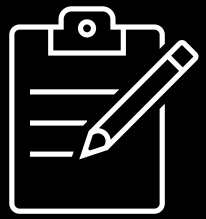


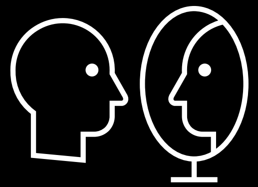
Intro to assignment 2, Part I

Assignment objective

Conduct real-world observations



Gain experience with qualitative data



Experience the say/do problem

Conduct real-world observations

Think of what you are going to observe and plan accordingly.

1. Write down goals for the observation
2. Prepare an observation guide, i.e., a list of questions you'd like to answer throughout the observation to help you structure it.
3. Collect your data
    - If you received permission, record the observations and take pictures
    - Write down observation notes, usually divided into,
        - Descriptive - accurately document what you see. Aim to capture factual data like time, actions, settings, conversations, objects, and avoid interpretation. For example, instead of noting that a classroom appears "comfortable," (interpretation) write that the room includes soft lighting and a sofa (descriptive)
        - Reflexive - record your thoughts, ideas, questions, and concerns during the observation.

If the work is not naturally verbose, ask your participants to follow a think-aloud protocol

- This means that they describe their actions, thoughts, and feelings while performing an activity. You may need to remind them about it.

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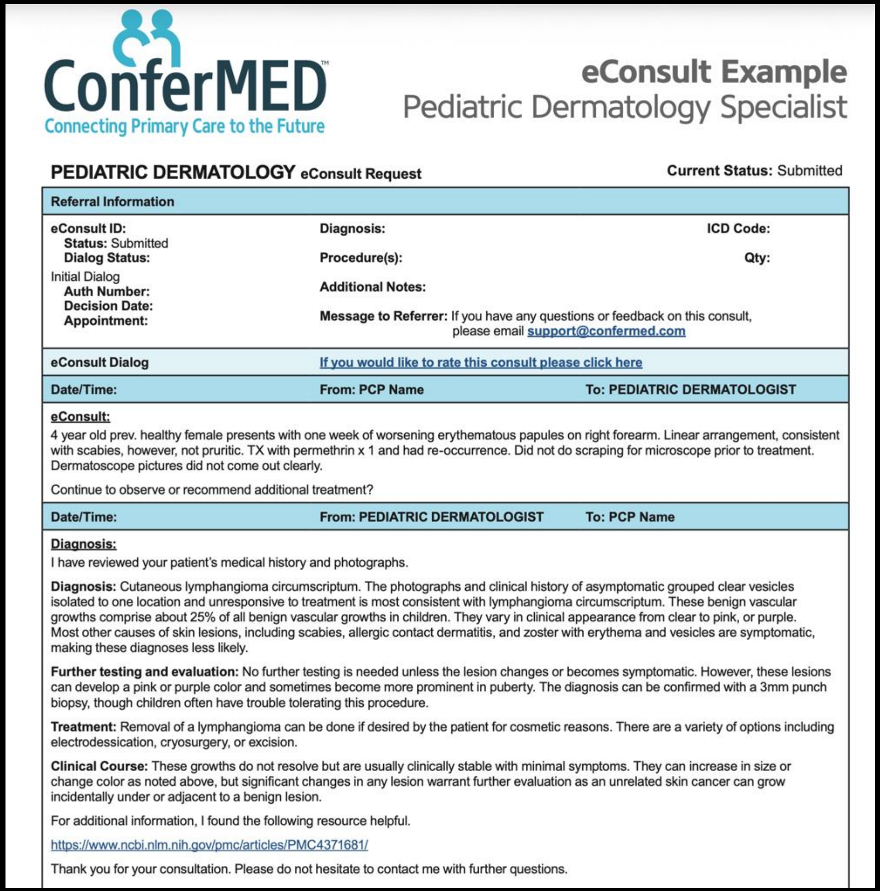
Healthcare data 101

What kind of healthcare data do you know?

How can we create more realistic models of the real world?

Examples of computational types of healthcare data

1. **Text data**
   - Discharge summaries, patient journals, referrals, reports



ConferMED
Connecting Primary Care to the Future

eConsult Example
Pediatric Dermatology Specialist

PEDIATRIC DERMATOLOGY **eConsult Request** **Current Status:** Submitted

Referral Information

eConsult ID:
Status: Submitted
Dialog Status:
Initial Dialog
Auth Number:
Decision Date:
Appointment:

Diagnosis: **ICD Code:**
Procedure(s): **Qty:**
Additional Notes:
Message to Referrer: If you have any questions or feedback on this consult, please email support@confermed.com

eConsult Dialog If you would like to rate this consult please click here

Date/Time:	**From: PCP Name**	**To: PEDIATRIC DERMATOLOGIST**

eConsult:
4 year old prev. healthy female presents with one week of worsening erythematous papules on right forearm. Linear arrangement, consistent with scabies, however, not pruritic. TX with permethrin x 1 and had re-occurrence. Did not do scraping for microscope prior to treatment. Dermatoscope pictures did not come out clearly.

Continue to observe or recommend additional treatment?

Date/Time:	**From: PEDIATRIC DERMATOLOGIST**	**To: PCP Name**

Diagnosis:
I have reviewed your patient's medical history and photographs.

Diagnosis: Cutaneous lymphangioma circumscriptum. The photographs and clinical history of asymptomatic grouped clear vesicles isolated to one location and unresponsive to treatment is most consistent with lymphangioma circumscriptum. These benign vascular growths comprise about 25% of all benign vascular growths in children. They vary in clinical appearance from clear to pink, or purple. Most other causes of skin lesions, including scabies, allergic contact dermatitis, and zoster with erythema and vesicles are symptomatic, making these diagnoses less likely.

Further testing and evaluation: No further testing is needed unless the lesion changes or becomes symptomatic. However, these lesions can develop a pink or purple color and sometimes become more prominent in puberty. The diagnosis can be confirmed with a 3mm punch biopsy, though children often have trouble tolerating this procedure.

Treatment: Removal of a lymphangioma can be done if desired by the patient for cosmetic reasons. There are a variety of options including electrodessication, cryosurgery, or excision.

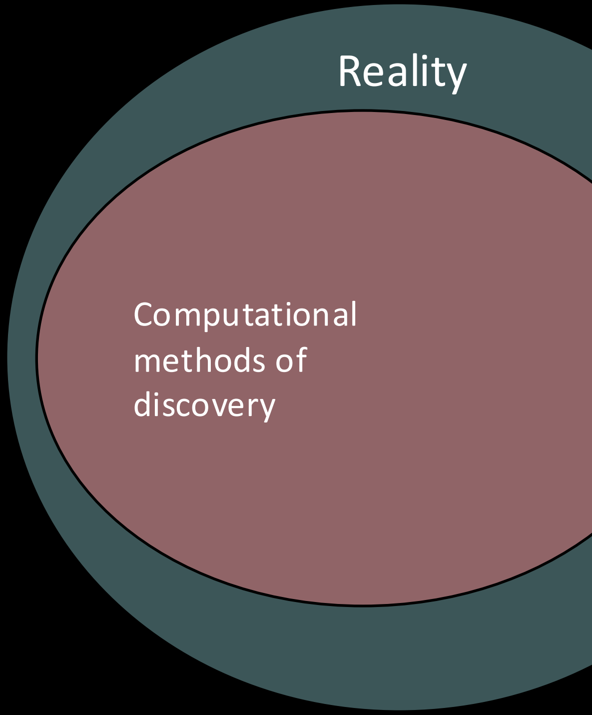
Clinical Course: These growths do not resolve but are usually clinically stable with minimal symptoms. They can increase in size or change color as noted above, but significant changes in any lesion warrant further evaluation as an unrelated skin cancer can grow incidentally under or adjacent to a benign lesion.

For additional information, I found the following resource helpful.

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4371681/

Thank you for your consultation. Please do not hesitate to contact me with further questions.

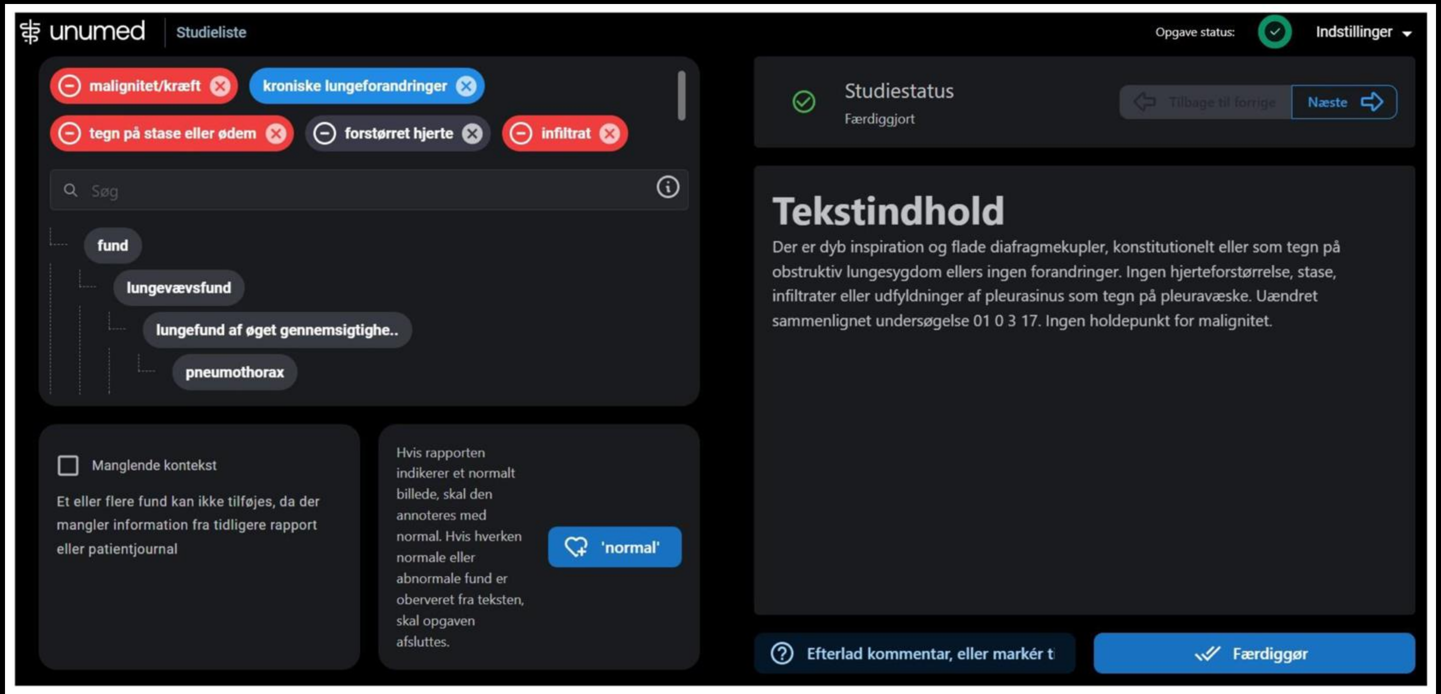
Sample report from a ConferMED clinicl.

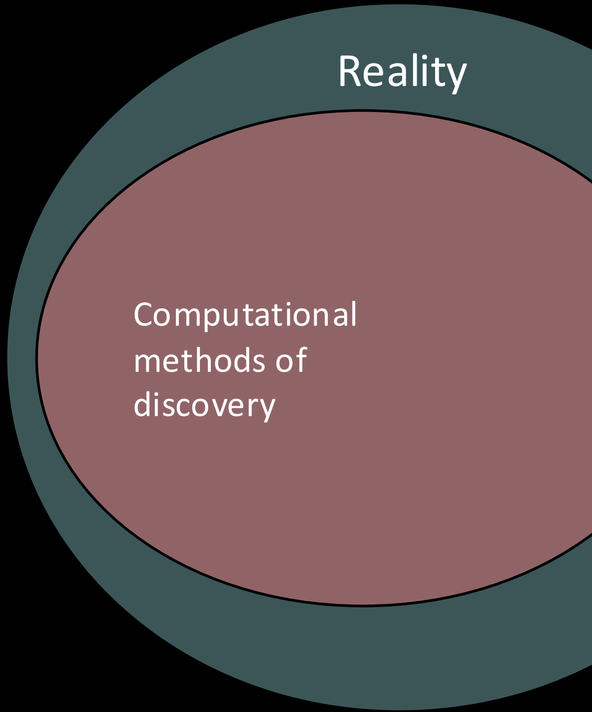


How can we create more realistic models of the real world?

Examples of computational types of healthcare data

1. **Text data**
    - Discharge summaries, patient journals, referrals, reports
2. **Structured data**
    - Diagnoses (ICD codes), procedures, lab results, vitals





Li D, Pehrson LM, Bonnevie R, Fraccaro M, Thrane J, Tøttrup L, Lauridsen CA, Butt Balaganeshan S, Jankovic J, Andersen TT, et al. Performance and Agreement When Annotating Chest X-ray Text Reports—A Preliminary Step in the Development of a Deep Learning-Based Prioritization and Detection System. Diagnostics. 2023; 13(6):1070. https://doi.org/10.3390/diagnostics13061070

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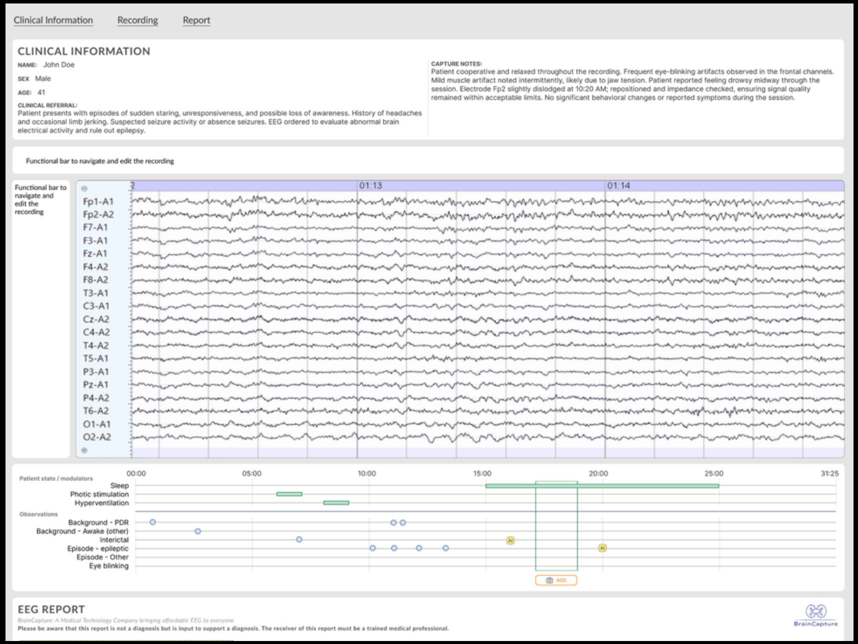
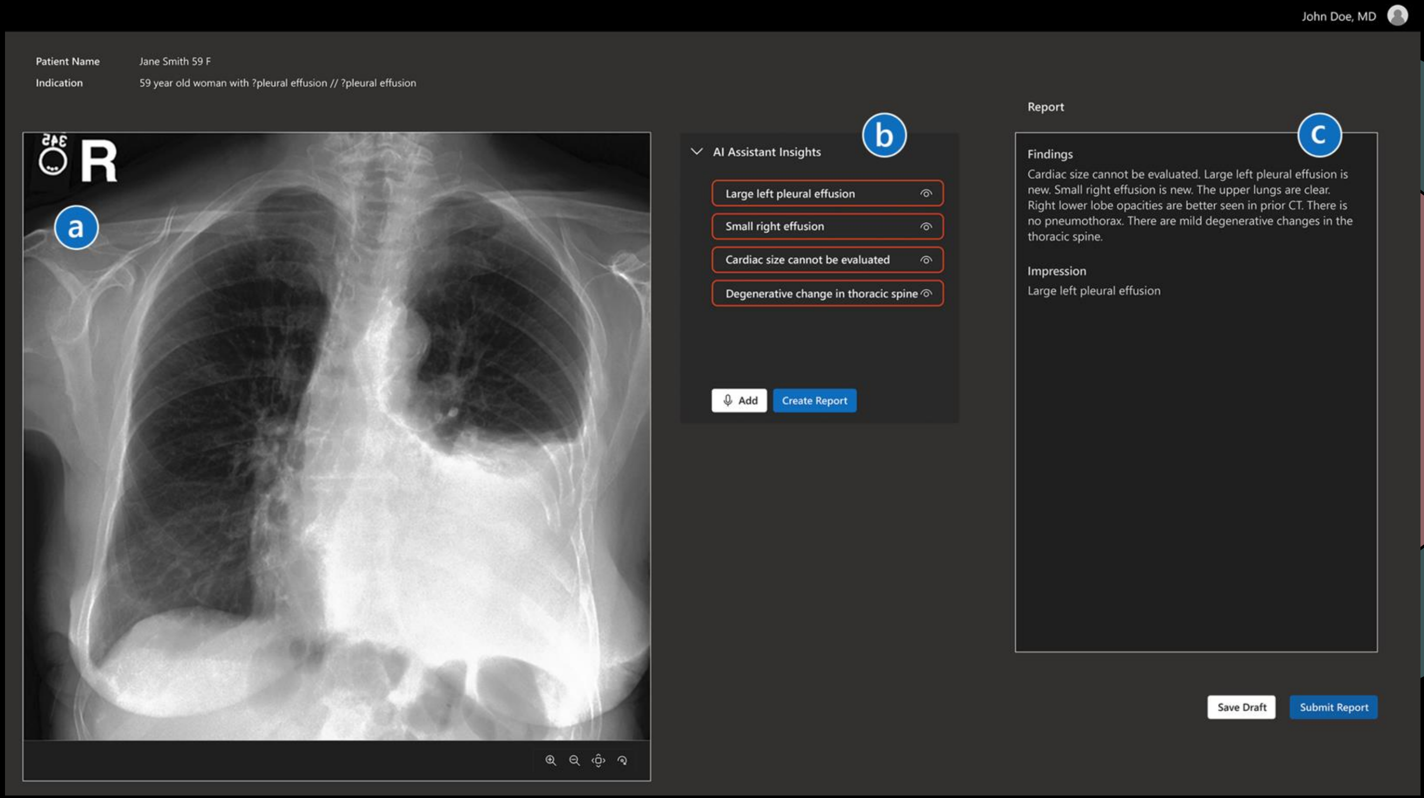


EEG reporting prototype. With Braincapture



Nur Yildirim et al. Multimodal Healthcare AI: Identifying and Designing Clinically Relevant Vision-Language Applications for Radiology. https://doi.org/10.1145/3613904.3642013

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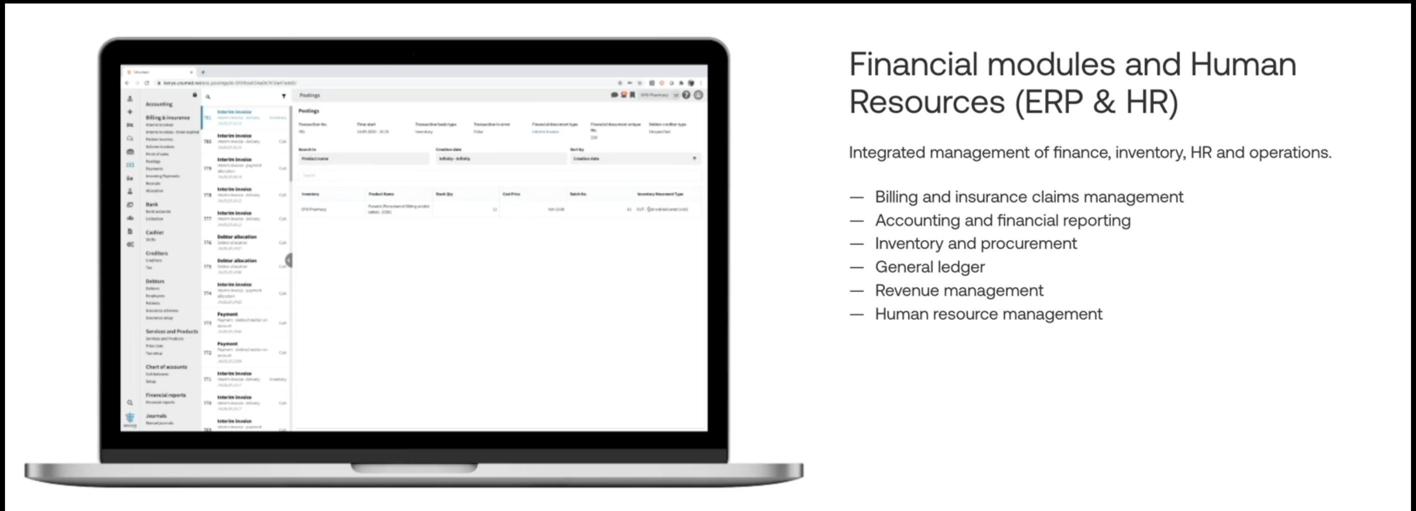
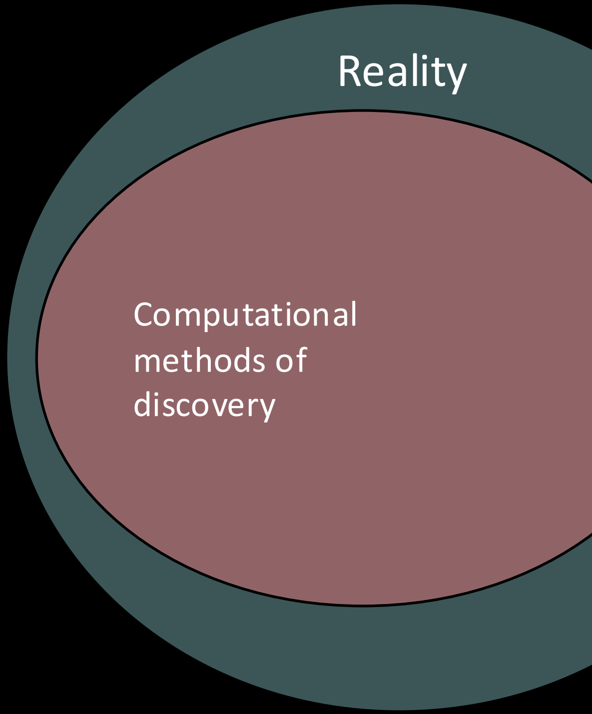


Unumed.com



Hubert D. Zając | hdz@di.ku.dk

How can we create more realistic models of the real world?

Examples of computational types of healthcare data

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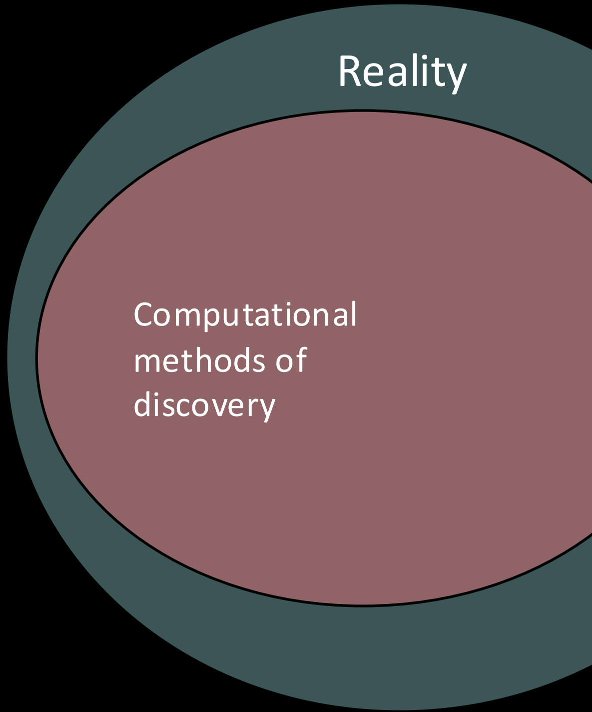
   - X-ray, MRI, CT
   - ECG, EEG
4. **Administrative & operational data**
   - Appointments, billing, resource use, schedules
5. **Patient-generated data**
   - Wearable data, questionnaires



https://www.apple.com/healthcare/

How can we create more realistic models of the real world?

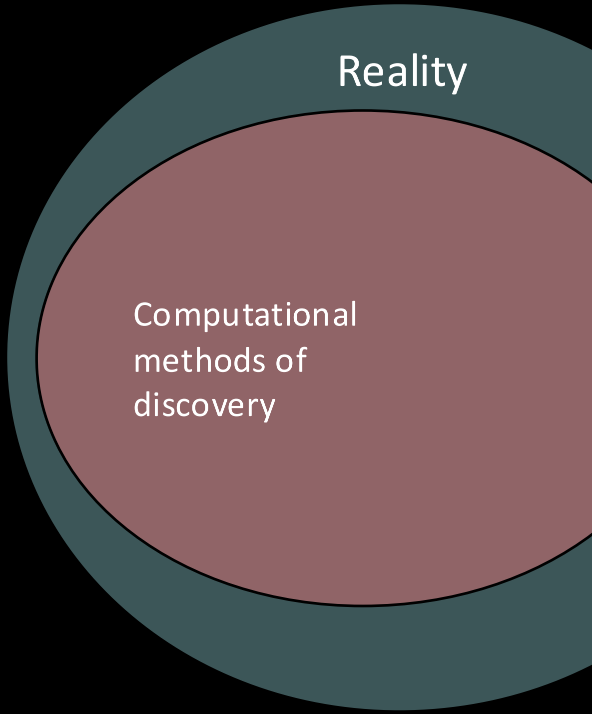
Computational types of healthcare data

1. **Electronic Health Record (EHR, clinical) data:**
   - **Unstructured data**: discharge summaries, patient journals, referrals, reports
   - **Structured clinical data**: longitudinal records of patient health, including diagnoses, treatment plans, diagnostic codes (ICD), procedure codes (CPT), medication lists, lab results, etc.
   - **Imaging and signal data**: X-ray, MRI, CT, ultrasound, ECG, EEG
   - **Temporal/sequential data**: Timestamps of activities, event logs from medical devices, workflow sequences in EHR systems, care pathway trajectories

2. **Administrative data (Enterprise Resource Planning, Human Resources)**: billing records, insurance claims, appointment attendance, length of stay, readmission rates

3. **Patient-generated data (Different platforms, both internal e.g., EHR, or external, e.g., Apple Health):**
   - **Sensor/device data**: continuous glucose monitoring readings, heart rate variability from wearables, accelerometer activity data, sleep stage measurements
   - **Survey responses**: patient-reported outcome scores, quality of life questionnaires, pain scales, satisfaction ratings

4. **Genomic data (distinct public, private systems)**: e.g., gene sequences
5. **Clinical trials registers (e.g., https://euclinicaltrials.eu)**
6. **Pharmacological data (e.g., UpToDate Lexidrug, or Computerised Physician Order Entry - CPOE)**: information about medication



Metadata

Data about data. It gives context and helps you understand the data.

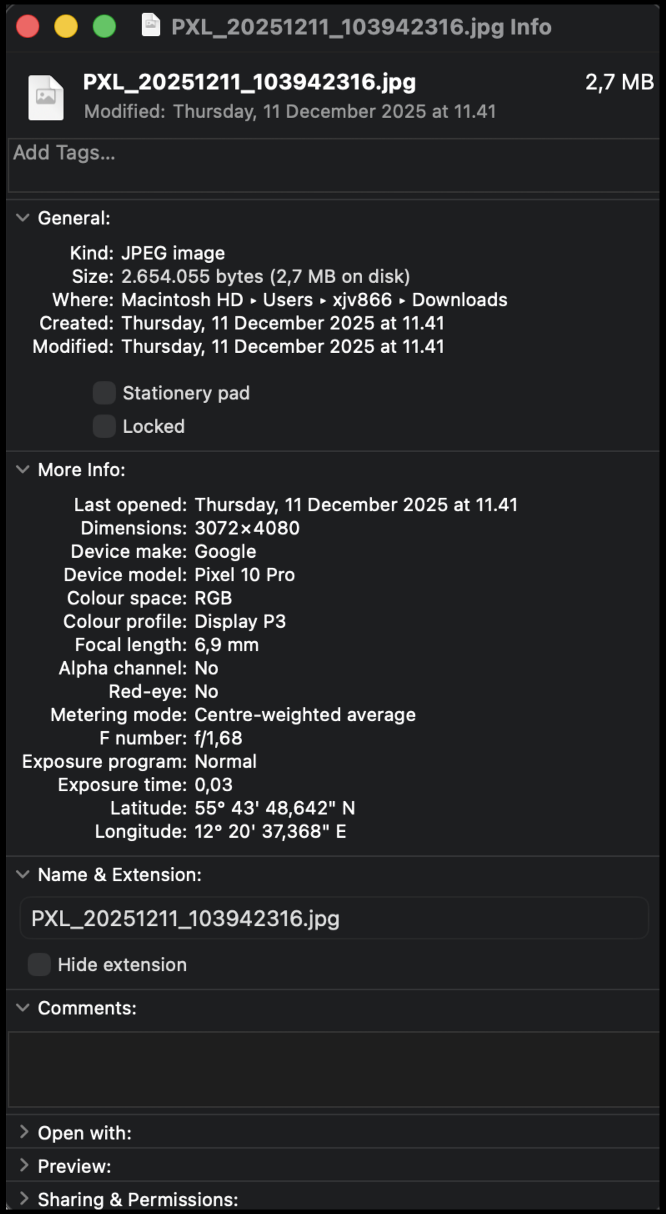
Any examples?

Metadata

Data about data. It gives context and helps you understand the data.

WhatsApp metadata (potentially shared with Meta), your profile picture, status, group names, IP address, device information, location (based on IP), and interaction logs (who you talk to, when, and for how long).

https://faq.whatsapp.com/1303762270462331 US only



Healthcare metadata, example DICOM

Data

x-ray.jpg

Metadata

BitsPerSample	8
ColorComponents	1
EncodingProcess	Baseline DCT, Huffman coding
FileAccessDate	2026-02-03 21:43:21 +0100
FileInodeChangeDate	2026-02-03 21:43:21 +0100
FileModifyDate	2026-02-03 21:43:21 +0100
FilePermissions	prw-------
FileSize	0 bytes
FileType	JPEG
FileTypeExtension	jpg
ImageHeight	1464
ImageSize	1280x1464
ImageWidth	1280
MIMEType	image/jpeg
Megapixels	1.9

Healthcare metadata, example DICOM

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MIMEType	image/jpeg
Megapixels	1.9

x-ray.dcm

.dcm = DICOM

Source DICOM tag	Destination column	Required
(0020,000D)	[studyInstanceUid]	Yes
(0010,0010)	[patientName]	No
(0010,0040)	[patientSex]	No
(0010,0020)	[patientId]	Yes
(0010,0030)	[patientBirthDate]	No
(0008,0050)	[accessionNumber]	Yes
(0008,0090)	[referringPhysicianName]	Yes
(0008,0020)	[studyDate]	Yes
(0008,1030)	[studyDescription]	Yes
(0020,000E)	[seriesInstanceUid]	Yes
(0008,0060)	[modality]	Yes
(0008,0061)	[modalitiesInStudy]	Yes
(0040,0244)	[performedProcedureStepStartDate]	No
(0008,1090)	[manufacturerModelName]	No
(0008,0018)	[sopInstanceUid]	Yes
(0008,0030)	[studyTime]	Yes
(0008,0201)	[timezoneOffsetFromUtc]	Yes
(0020,1206)	[numberOfStudyRelatedSeries]	Yes
(0020,1208)	[numberOfStudyRelatedInstances]	Yes
(0020,0011)	[seriesNumber]	Yes
(0008,103E)	[seriesDescription]	Yes
(0020,1209)	[numberOfSeriesRelatedInstances]	Yes
(0018,0015)	[bodyPartExamined]	Yes
(0020,0060)	[laterality]	Yes
(0008,0021)	[seriesDate]	Yes
(0008,0031)	[seriesTime]	Yes
(0008,0016)	[sopClassUid]	Yes
(0020,0013)	[instanceNumber]	Yes
(0042,0010)	[documentTitle]	Yes

+ 5000 attributes more…

https://dicom.nema.org/medical/dicom/current/output/chtml/part06/chapter_6.html

Healthcare metadata

More relevant when dealing with complex/unstructured data
Less so when dealing with structured data

Why?

DICOM

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(0020,000D)	[studyInstanceUid]	Yes
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(0020,0013)	[instanceNumber]	Yes
(0042,0010)	[documentTitle]	Yes

https://dicom.nema.org/medical/dicom/current/output/chtml/part06/chapter_6.html

Required / Recommended / Optional attributes in EEG

Those fields MUST be present:

Key name	Requirement Level	Data type	Description
EEGReference	REQUIRED	string	General description of the reference scheme used and (when applicable) of location of the reference electrode in the raw recordings (for example, "left mastoid", "Cz", "CMS"). If different channels have a different reference, this field should have a general description and the channel specific reference should be defined in the channels.tsv file.
SamplingFrequency	REQUIRED	number	Sampling frequency (in Hz) of all the data in the recording, regardless of their type (for example, 2400). The sampling frequency of data channels that deviate from the main sampling frequency SHOULD be specified in the channels.tsv file.
PowerLineFrequency	REQUIRED	number or "n/a"	Frequency (in Hz) of the power grid at the geographical location of the instrument (for example, 50 or 60).
SoftwareFilters	REQUIRED	object of objects or "n/a"	Object of temporal software filters applied, or "n/a" if the data is not available. Each key-value pair in the JSON object is a name of the filter and an object in which its parameters are defined as key-value pairs (for example, {"Anti-aliasing filter": {"half-amplitude cutoff (Hz)": 500, "Roll-off": "6dB/Octave"}}).

Those fields SHOULD be present:

Key name	Requirement Level	Data type	Description
CapManufacturer	RECOMMENDED	string	Name of the cap manufacturer (for example, "EasyCap").

https://bids-specification.readthedocs.io/en/stable/modality-specific-files/electroencephalography.html

Genome data

In genomics or transcriptomics, metadata describe the sample that the DNA/RNA sequence was obtained from, e.g. the organism, the cell line, and the library-preparation method.

Why are metadata important?

Metadata allow you to make better use of your data. With Life Science Data, for example, metadata are essential to correctly interpret the data and carry out meaningful comparisons with data from other samples or studies.

There is almost never a good reason not to save metadata – there are minimal storage requirements compared to the data they describe, and they offer several advantages.

Data reusability and reproducibility

You need metadata to reproduce your data correctly. For example, if you want to decode a picture with colors as they were intended, you need to use the right color profile (e.g. sRGB). If you want to reproduce DNA/RNA sequencing data or compare it with data from experiments in other studies, you need to know what cell line and experimental conditions were used, what treatments the cells or tissues were subjected to, etc.

https://genestack.com/resources/library/what-are-metadata-and-why-are-they-important/

eConsults

ConferMED
Connecting Primary Care to the Future

eConsult Example
Pediatric Dermatology Specialist

PEDIATRIC DERMATOLOGY eConsult Request — **Current Status:** Submitted

Referral Information

eConsult ID:
Status: Submitted
Dialog Status:
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Auth Number:
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Appointment:

Diagnosis: **ICD Code:**
Procedure(s): **Qty:**
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Continue to observe or recommend additional treatment?

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Treatment: Removal of a lymphangioma can be done if desired by the patient for cosmetic reasons. There are a variety of options including electrodessication, cryosurgery, or excision.

Clinical Course: These growths do not resolve but are usually clinically stable with minimal symptoms. They can increase in size or change color as noted above, but significant changes in any lesion warrant further evaluation as an unrelated skin cancer can grow incidentally under or adjacent to a benign lesion.

For additional information, I found the following resource helpful.

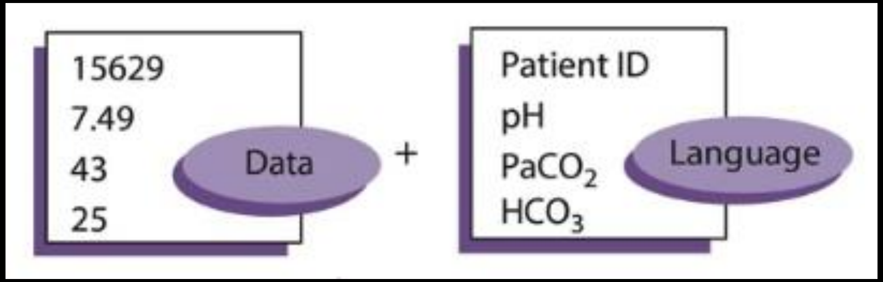
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4371681/

Thank you for your consultation. Please do not hesitate to contact me with further questions.

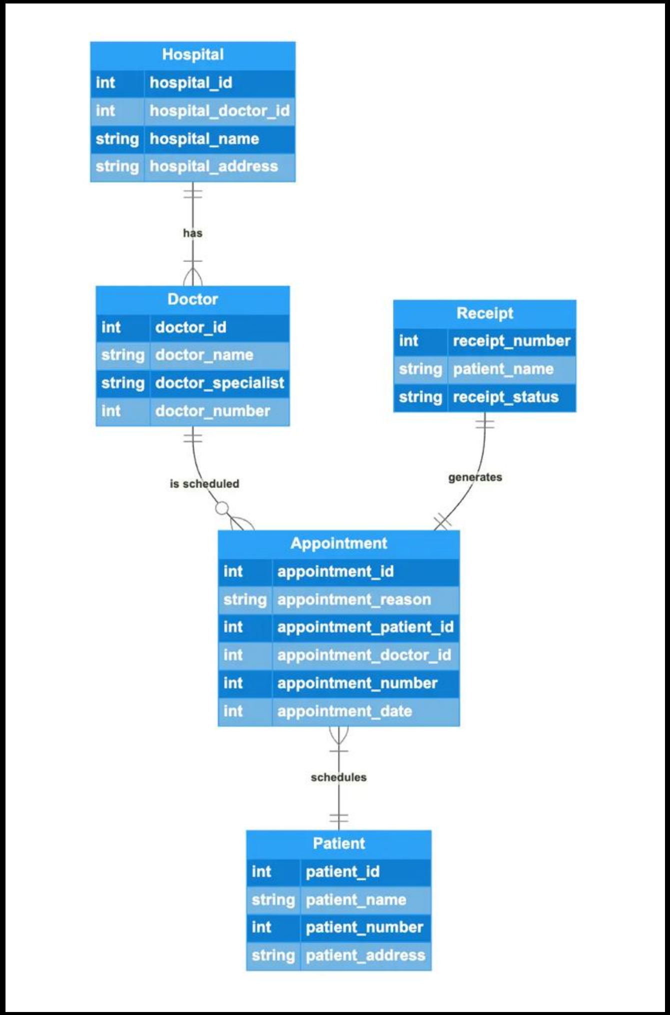
Information such as patient/provider information, demographics, timestamps, signatures, etc.

Healthcare metadata

More relevant when dealing with complex/unstructured data
Less so when dealing with structured data

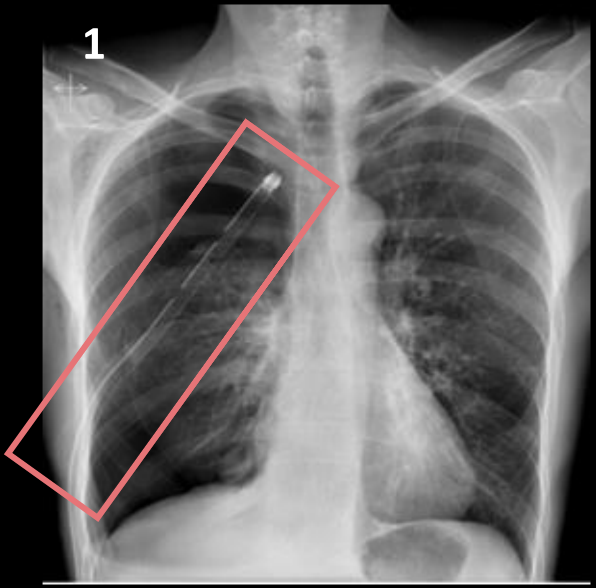


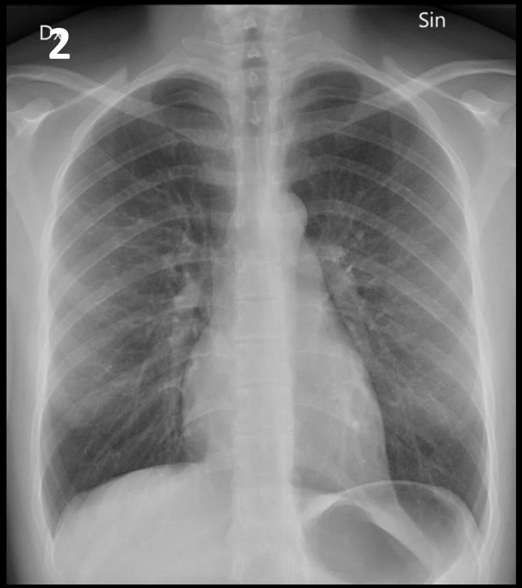
Example structured data



Example entity relationship diagram (structured data)

Healthcare metadata
Example DICOM

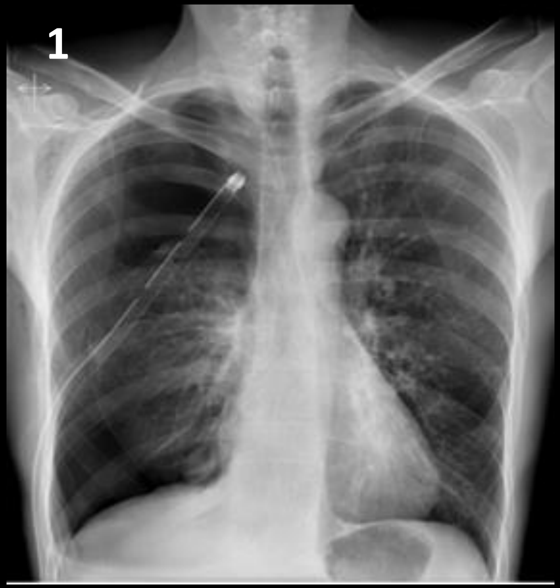


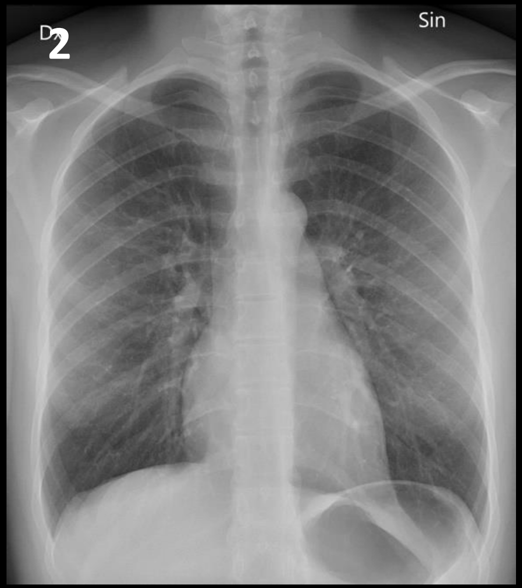


Would AI be better at detecting the tube or predicting which hospital the X-ray is from?

Image	Finding	Hospital
1	Chest tube present	Hospital A
2	No chest tube	Hospital B

Healthcare metadata
Example DICOM





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Healthcare metadata
Example DICOM

As small as 8 x 8 pixels
0.996 accuracy

Image	Hospital
1	Hospital A
2	Hospital B

Compton, R., Zhang, L., Puli, A. & Ranganath, R.. (2023). When More is Less: Incorporating Additional Datasets Can Hurt Performance By Introducing Spurious Correlations. Proceedings of the 8th Machine Learning for Healthcare Conference in Proceedings of Machine Learning Research 219:110-127 Available from https://proceedings.mlr.press/v219/compton23a.html.

Healthcare metadata
Example DICOM

As small as 8 x 8 pixels
0.996 accuracy

Image	Hospital
1	Hospital A
2	Hospital B

Location (derived from the type of scanner used) is part of the metadata.

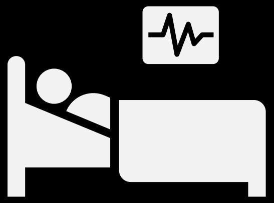
This metadata is crucial because it captures details such as field strength, acquisition parameters, and vendor-specific variations. Factors known to significantly influence the generalisability of deep learning models.

Metadata such as demographics, location, or equipment used is essential for evaluating the robustness and fairness of AI models.

What can we use this data for?

Hubert D. Zając | hdz@di.ku.dk

Using healthcare data



Primary use: Patient care

Primary use is the use of health data to directly deliver healthcare to a person.

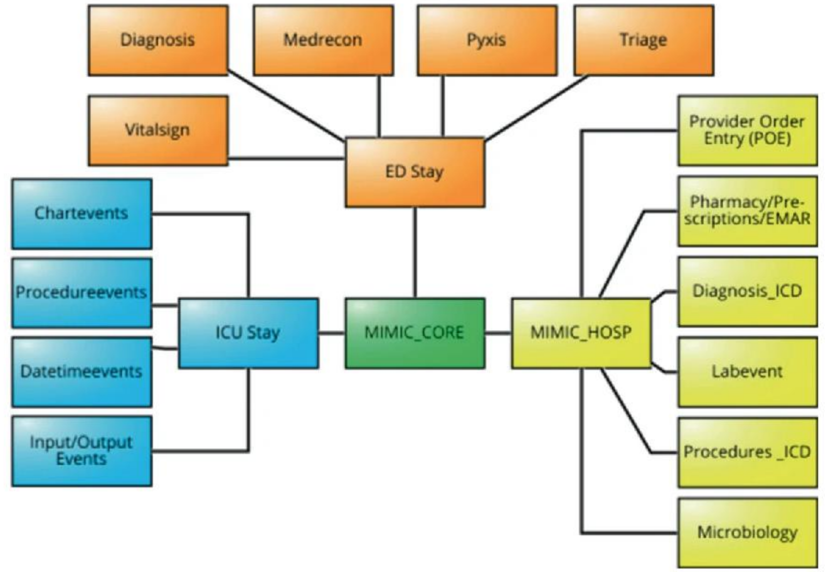
Secondary use: Knowledge creation

Secondary use is the use of health data for purposes outside of direct patient care

Primary use: Patient care

Using healthcare data

In Electronic Healthcare Records data is stored in DBs

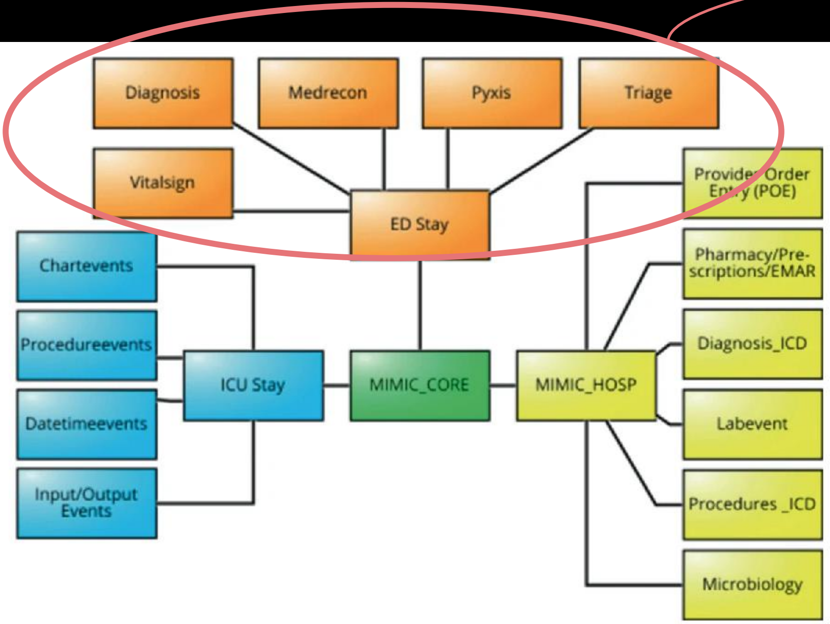


MIMIC-IV 1.0 simplified data model. The colours represent the respective modules: Green: Core, Yellow: Hosp, Blue: ICU, Orange: ED (Color figure online)

Primary use: Patient care

Using healthcare data

In Electronic Healthcare Records data is stored in DBs



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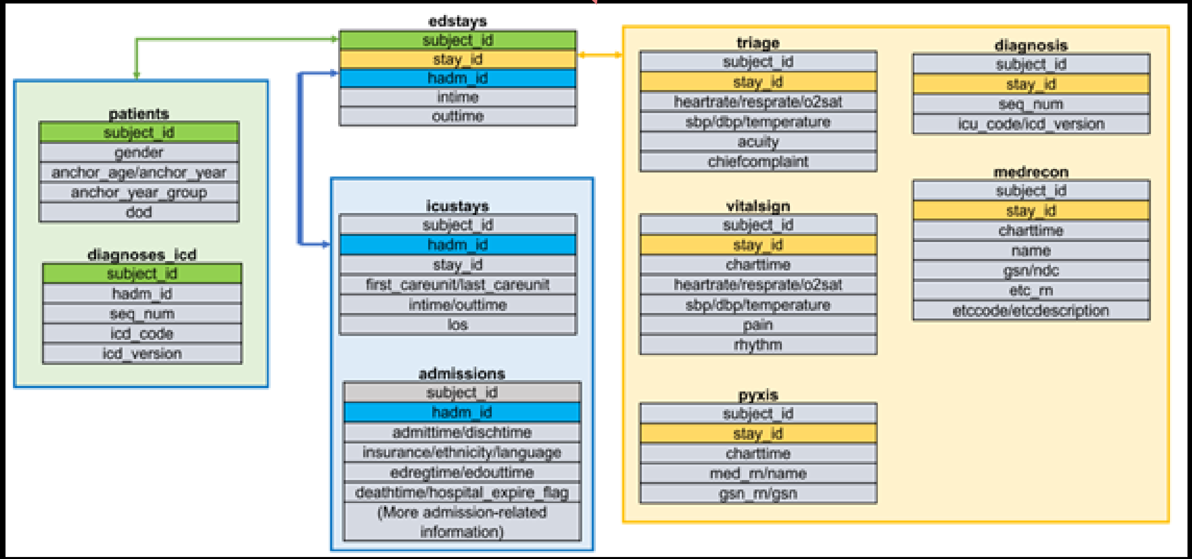

Primary use: Patient care

Using healthcare data

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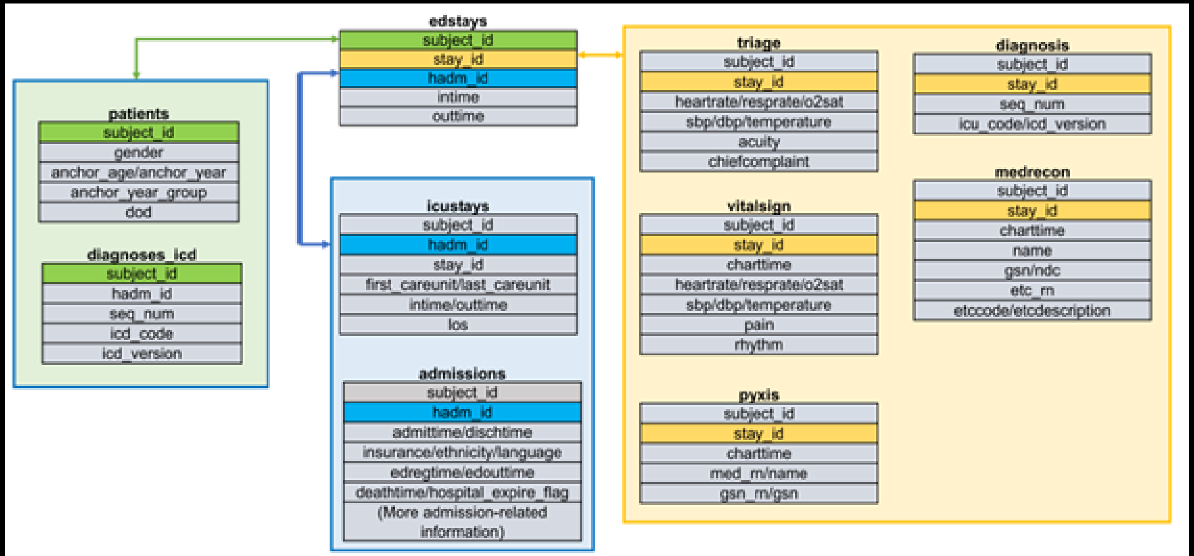
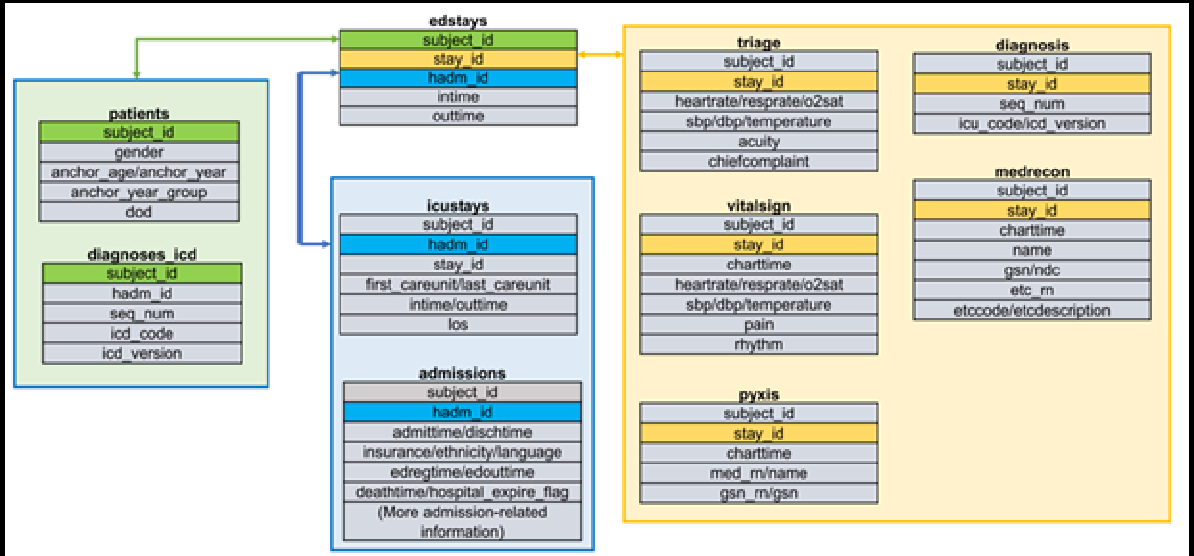


Great format for storing,
Not so great for using

Primary use: Patient care

Using healthcare data

In Electronic Healthcare Records data is stored in DBs



Four orientations for clinical data presentation

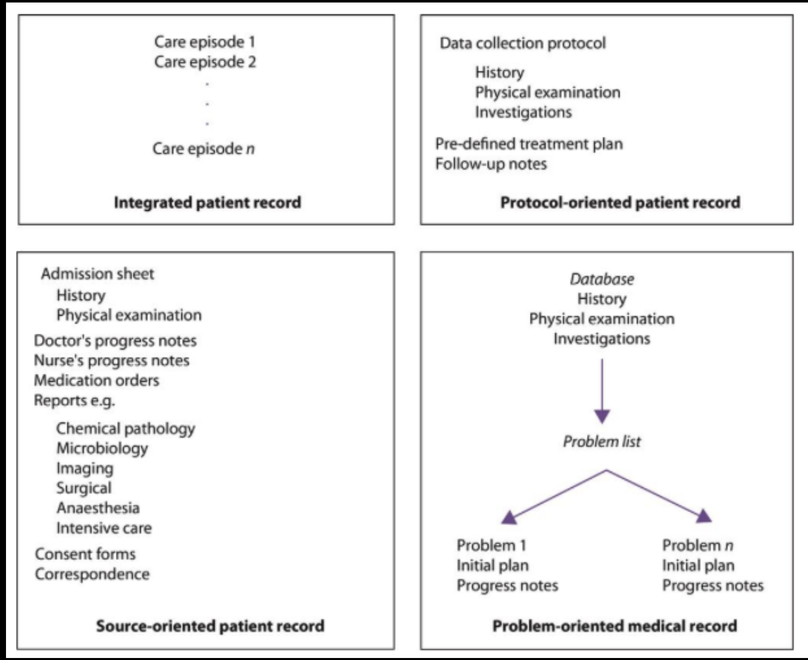


Figure 5.2

Primary use: Patient care

Using healthcare data

Integrated patient record

Def.

Data are presented in a strictly chronological way, identifying each episode of care by time and date. Data arriving from an investigation such as radiology may be followed by progress notes written by a clinician, followed by a change in medication orders. A variation of this is the time-oriented medical record, developed for chronically ill patients, in which data are arranged in two dimensions, according to axes of time and data type

Primary use: Patient care

Using healthcare data

Source-oriented patient record

Admission sheet
- History
- Physical examination

Doctor's progress notes
Nurse's progress notes
Medication orders
Reports e.g.
- Chemical pathology
- Microbiology
- Imaging
- Surgical
- Anaesthesia
- Intensive care

Consent forms
Correspondence

Source-oriented patient record

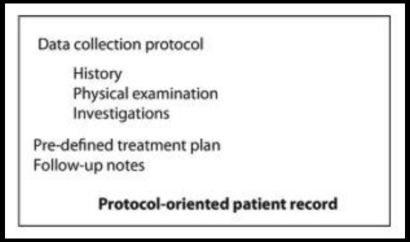
Def.

The SOPR is organised according to the source that generated the data, typically different hospital departments. There are separate sections for medical notes, nursing notes, laboratory data, radiological results and so forth. Within each source section, data are sometimes further subdivided, for example, according to the different types of test, and then arranged chronologically.

Primary use: Patient care

Using healthcare data

Protocol-oriented patient record



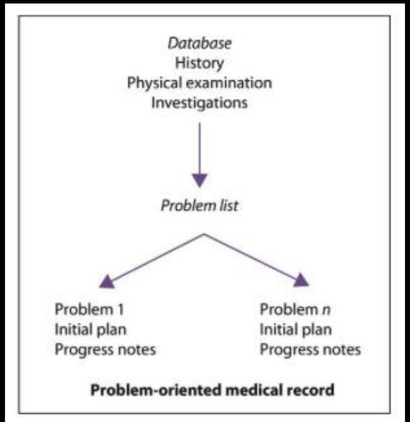
Def.

When a patient is being given a standard treatment for a well-understood condition such as asthma or diabetes, a standard template can be used to guide the construction of the medical record. The template or protocol is captured in a pre-structured form that dictates what specific data are to be obtained and recorded by the clinician and what the treatment plan for the patient will be.

Primary use: Patient care

Using healthcare data

Problem-oriented patient record



Def.

The POMR has four components – a problem list, an initial plan, a database containing all patient data and progress notes (Weed, 1968). The POMR organises data according to the list of the patient's problems, which may be anything from symptoms through to well-defined diagnoses. The problem list is dynamic and is used to name, number and date each problem, and it acts as an index to the whole record. The plan describes what will be done for each problem. All progress notes, laboratory tests, treatment notes and medications are numbered according to the problem to which they relate. Progress notes are often written according to the SOAP (subjective, objective, assessment, plan) template

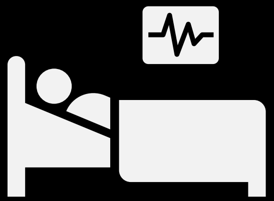
Data views in practice

Go to this url: hdzajac.com -> Teaching Prototypes -> Patient Records Viewer

⚠ It’s a prototype, medical data, adherence to the rules may be inaccurate

In groups/pairs – inspect the different views, see if they adhere to the definitions, discuss the benefits and disadvantages of each of them (for patients, clinicians, system developers, people maintaining them). What about the amount of data, maintainability, and different clinical settings?

Using healthcare data



Primary use: Patient care

Primary use is the use of health data to directly deliver healthcare to a person.

Secondary use: Knowledge creation

Secondary use is the use of health data for purposes outside of direct patient care

Secondary use: Knowledge creation

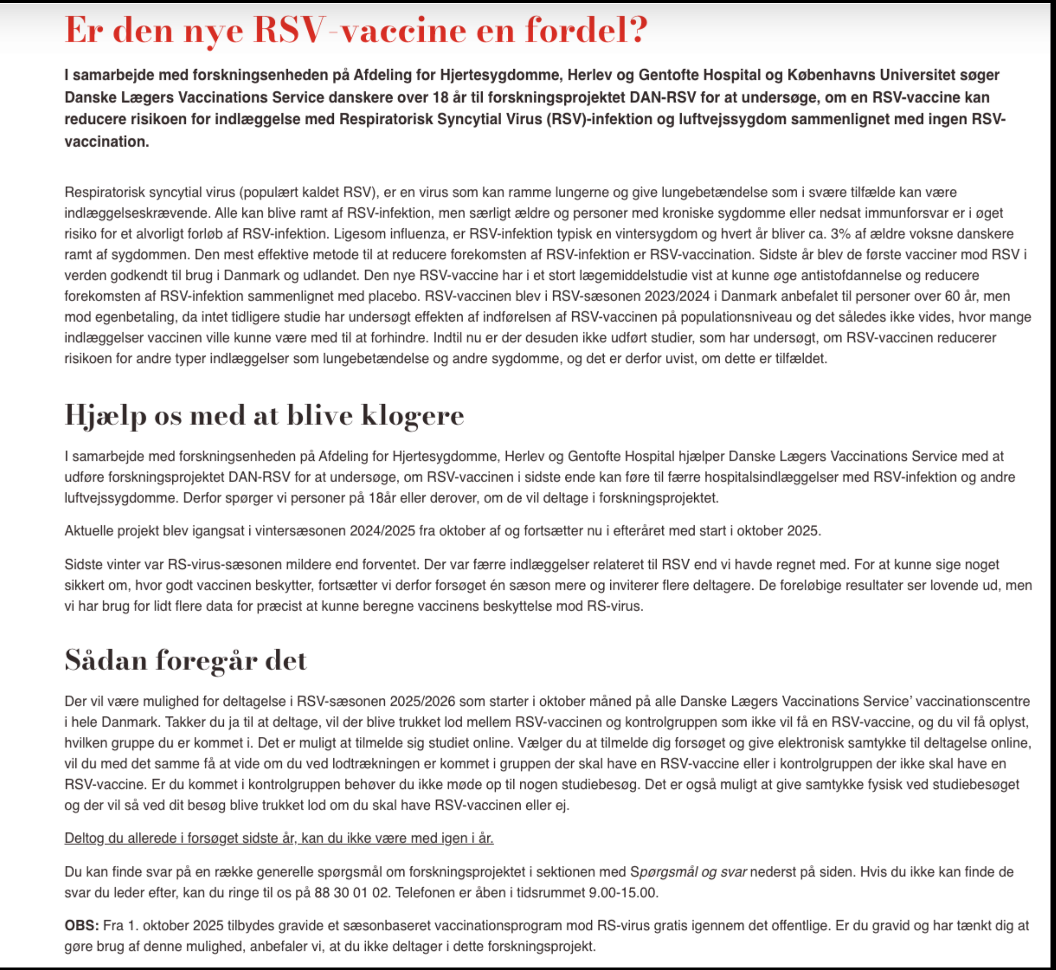
Using healthcare data for any other purpose than directly engaging in patient care is considered secondary use.

Secondary use: Knowledge creation

Using healthcare data

Research & Development

- Vaccine trials
- Studying disease progression



Er den nye RSV-vaccine en fordel?

I samarbejde med forskningsenheden på Afdeling for Hjertesygdomme, Herlev og Gentofte Hospital og Københavns Universitet søger Danske Lægers Vaccinations Service danskere over 18 år til forskningsprojektet DAN-RSV for at undersøge, om en RSV-vaccine kan reducere risikoen for indlæggelse med Respiratorisk Syncytial Virus (RSV)-infektion og luftvejssygdom sammenlignet med ingen RSV-vaccination.

Respiratorisk syncytial virus (populært kaldet RSV), er en virus som kan ramme lungerne og give lungebetændelse som i svære tilfælde kan være indlæggelseskrævende. Alle kan blive ramt af RSV-infektion, men særligt ældre og personer med kroniske sygdomme eller nedsat immunforsvar er i øget risiko for et alvorligt forløb af RSV-infektion. Ligesom influenza, er RSV-infektion typisk en vintersygdom og hvert år bliver ca. 3% af ældre voksne danskere ramt af sygdommen. Den mest effektive metode til at reducere forekomsten af RSV-infektion er RSV-vaccination. Sidste år blev de første vacciner mod RSV i verden godkendt til brug i Danmark og udlandet. Den nye RSV-vaccine har i et stort lægemiddelstudie vist at kunne øge antistofdannelse og reducere forekomsten af RSV-infektion sammenlignet med placebo. RSV-vaccinen blev i RSV-sæsonen 2023/2024 i Danmark anbefalet til personer over 60 år, men mod egenbetaling, da intet tidligere studie har undersøgt effekten af indførelsen af RSV-vaccinen på populationsniveau og det således ikke vides, hvor mange indlæggelser vaccinen ville kunne være med til at forhindre. Indtil nu er der desuden ikke udført studier, som har undersøgt, om RSV-vaccinen reducerer risikoen for andre typer indlæggelser som lungebetændelse og andre sygdomme, og det er derfor uvist, om dette er tilfældet.

Hjælp os med at blive klogere

I samarbejde med forskningsenheden på Afdeling for Hjertesygdomme, Herlev og Gentofte Hospital hjælper Danske Lægers Vaccinations Service med at udføre forskningsprojektet DAN-RSV for at undersøge, om RSV-vaccinen i sidste ende kan føre til færre hospitalsindlæggelser med RSV-infektion og andre luftvejssygdomme. Derfor spørger vi personer på 18år eller derover, om de vil deltage i forskningsprojektet.

Aktuelle projekt blev igangsat i vintersæsonen 2024/2025 fra oktober af og fortsætter nu i efteråret med start i oktober 2025.

Sidste vinter var RS-virus-sæsonen mildere end forventet. Der var færre indlæggelser relateret til RSV end vi havde regnet med. For at kunne sige noget sikkert om, hvor godt vaccinen beskytter, fortsætter vi derfor forsøget én sæson mere og inviterer flere deltagere. De foreløbige resultater ser lovende ud, men vi har brug for lidt flere data for præcist at kunne beregne vaccinens beskyttelse mod RS-virus.

Sådan foregår det

Der vil være mulighed for deltagelse i RSV-sæsonen 2025/2026 som starter i oktober måned på alle Danske Lægers Vaccinations Service' vaccinationscentre i hele Danmark. Takker du ja til at deltage, vil der blive trukket lod mellem RSV-vaccinen og kontrolgruppen som ikke vil få en RSV-vaccine, og du vil få oplyst, hvilken gruppe du er kommet i. Det er muligt at tilmelde sig studiet online. Vælger du at tilmelde dig forsøget og give elektronisk samtykke til deltagelse online, vil du med det samme få at vide om du ved lodtrækningen er kommet i gruppen der skal have en RSV-vaccine eller i kontrolgruppen der ikke skal have en RSV-vaccine. Er du kommet i kontrolgruppen behøver du ikke møde op til nogen studiebesøg. Det er også muligt at give samtykke fysisk ved studiebesøget og der vil så ved dit besøg blive trukket lod om du skal have RSV-vaccinen eller ej.

Deltog du allerede i forsøget sidste år, kan du ikke være med igen i år.

Du kan finde svar på en række generelle spørgsmål om forskningsprojektet i sektionen med *Spørgsmål og svar* nederst på siden. Hvis du ikke kan finde de svar du leder efter, kan du ringe til os på 88 30 01 02. Telefonen er åben i tidsrummet 9.00-15.00.

OBS: Fra 1. oktober 2025 tilbydes gravide et sæsonbaseret vaccinationsprogram mod RS-virus gratis igennem det offentlige. Er du gravid og har tænkt dig at gøre brug af denne mulighed, anbefaler vi, at du ikke deltager i dette forskningsprojekt.

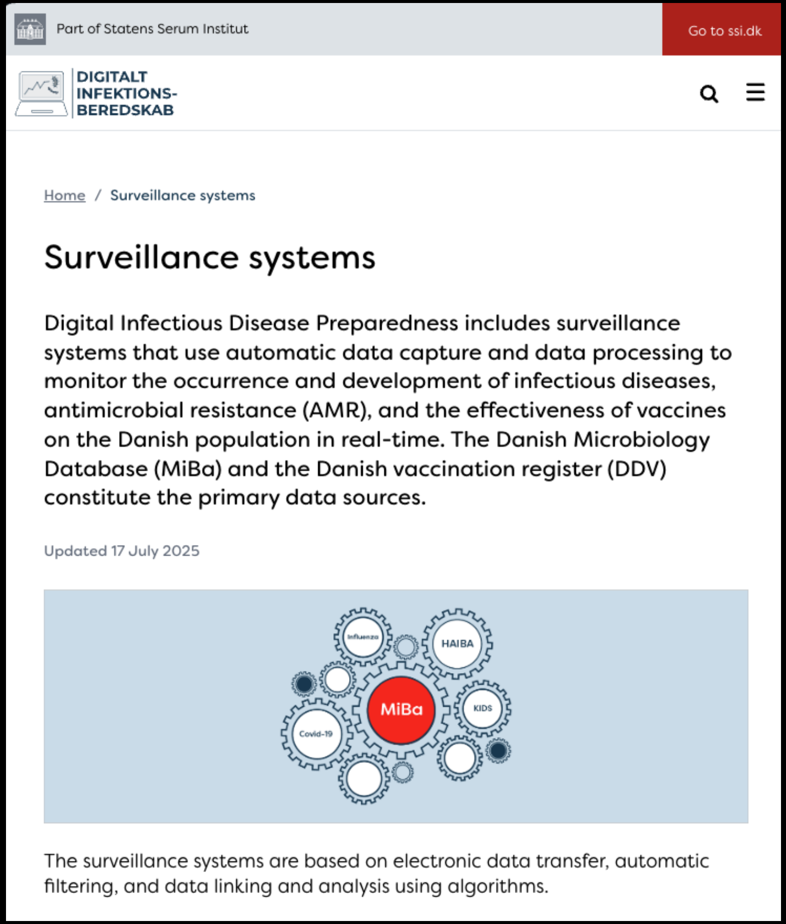
https://www.minvaccination.dk/forskningsprojekt-dan-rsv-2025

Using healthcare data

Secondary use: Knowledge creation

Research & Development
- Vaccine trials
- Studying disease progression

Public Health & Epidemiology
- Outbreak detection
- Informing healthcare policymaking



Part of Statens Serum Institut

Go to ssi.dk

DIGITALT INFEKTIONS-BEREDSKAB

Home / Surveillance systems

Surveillance systems

Digital Infectious Disease Preparedness includes surveillance systems that use automatic data capture and data processing to monitor the occurrence and development of infectious diseases, antimicrobial resistance (AMR), and the effectiveness of vaccines on the Danish population in real-time. The Danish Microbiology Database (MiBa) and the Danish vaccination register (DDV) constitute the primary data sources.

Updated 17 July 2025

The surveillance systems are based on electronic data transfer, automatic filtering, and data linking and analysis using algorithms.

https://mibaen.ssi.dk/surveillance-systems

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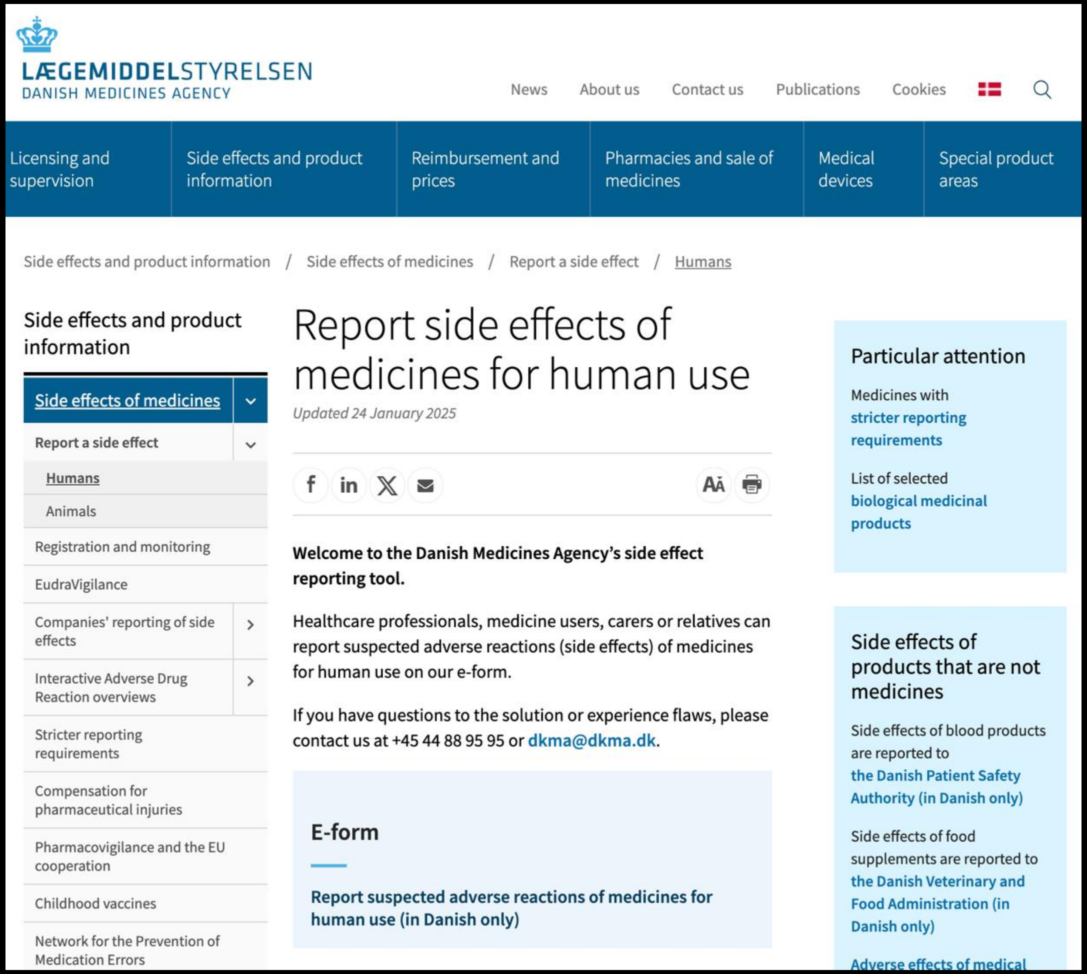
Healthcare Operations & Quality Improvement
- Clinical guideline development
- Adverse effects detection



https://laegemiddelstyrelsen.dk/en/sideeffects/side-effects-of-medicines/report-a-side-effect/~/link.aspx?_id=6B84AE2577A04EB29B0A47F444BD6548&_z=z

Using healthcare data

Secondary use: Knowledge creation

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- Clinical guideline development
- Adverse effects detection

Education & Training
- Case studies for medical students
- Educational materials for patients

https://www.esmo.org/for-patients/patient-guides

Using healthcare data

Secondary use: Knowledge creation

Research & Development
- Vaccine trials
- Studying disease progression

Public Health & Epidemiology
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Healthcare Operations & Quality Improvement
- Clinical guideline development
- Adverse effects detection

Education & Training
- Case studies for medical students
- Educational materials for patients

Technology & AI Training
- Decision support systems
- Precision medicine
- Digital health applications

among others…

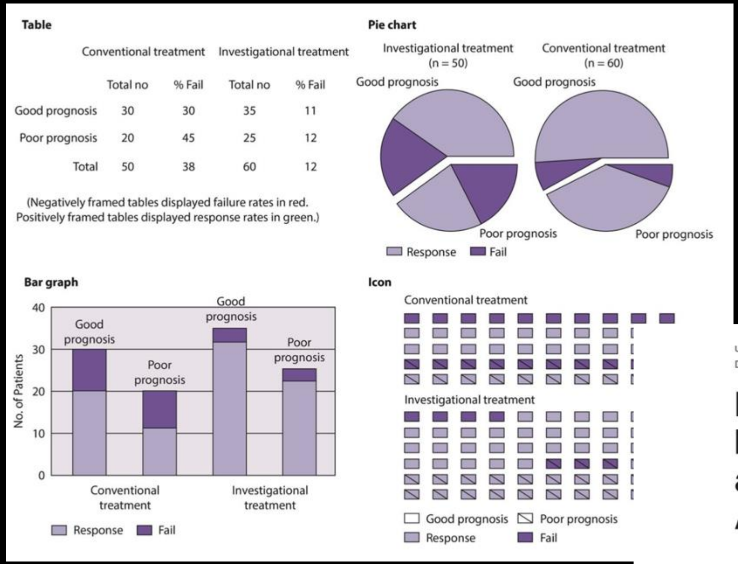
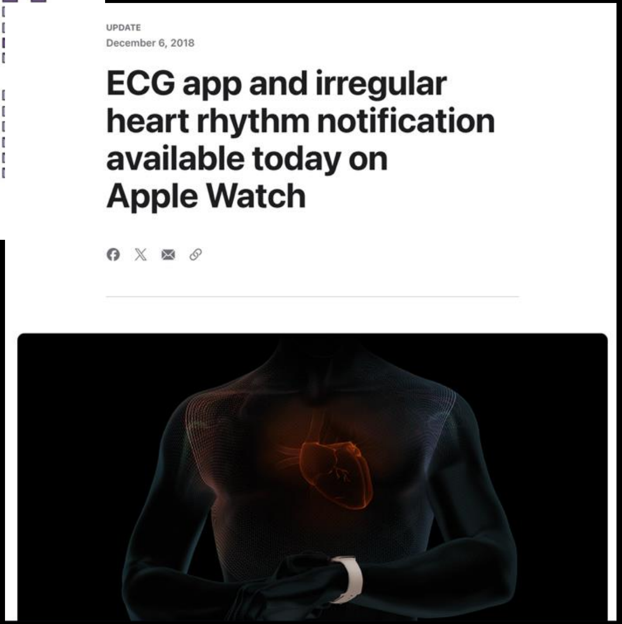
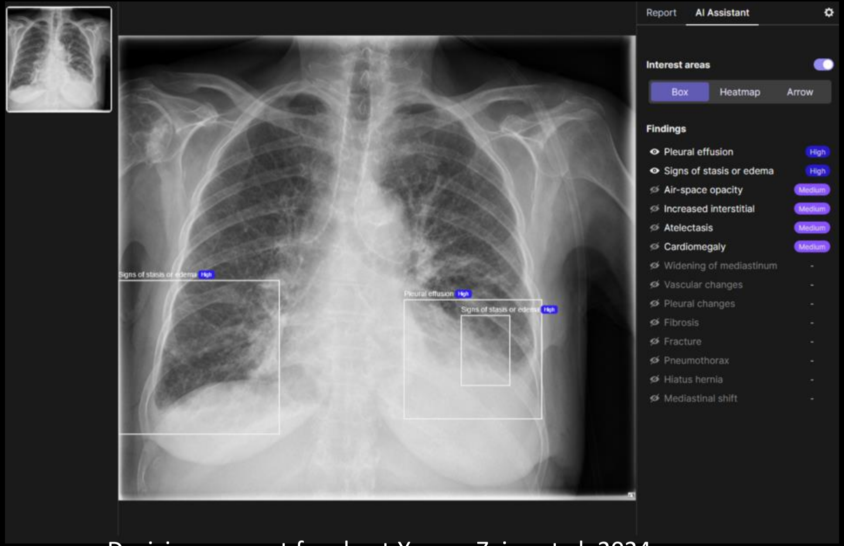


Figure 4.1



https://www.apple.com/newsroom/2018/12/ecg-app-and-irregular-heart-rhythm-notification-available-today-on-apple-watch/



Decision support for chest X-rays, Zajac et al, 2024