De stekker naar de data

De rol van een dataplatform in het implementeren van A.I.

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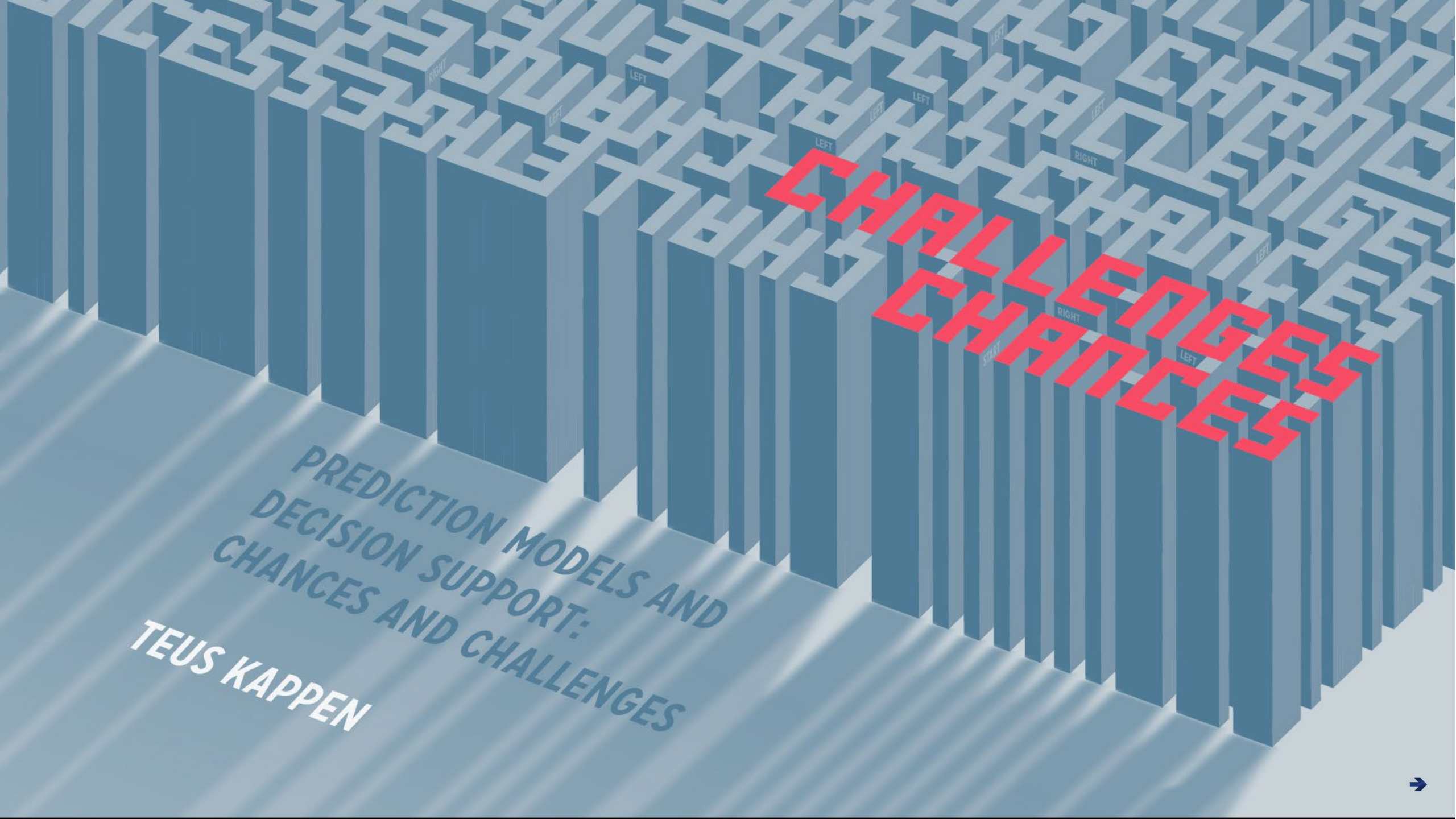
Teus Kappen
Anesthesioloog / Chief Science Information Officer

Why me?

This problem…


CHALLENGES
CHANCES
PREDICTION MODELS AND
DECISION SUPPORT:
CHANCES AND CHALLENGES
TEUS KAPPEN

Impact of Risk Assessments on Prophylactic Antiemetic Prescription and the Incidence of Postoperative Nausea and Vomiting

A Cluster-randomized Trial

Teus H. Kappen, M.D., Karel G.M. Moons, Ph.D., Leo van Wolfswinkel, M.D., Ph.D., Cornelis J. Kalkman, M.D., Ph.D., Yvonne Vergouwe, Ph.D., Wilton A. van Klei, M.D., Ph.D.

ELSEVIER

Journal of Clinical Epidemiology 70 (2016) 136–145

Barriers and facilitators perceived by physicians when using prediction models in practice

Teus H. Kappen[a,*], Kim van Loon[a], Martinus A.M. Kappen[a], Leo van Wolfswinkel[a], Yvonne Vergouwe[b,c], Wilton A. van Klei[a], Karel G.M. Moons[a,b], Cor J. Kalkman[a]

arXiv > cs > arXiv:2003.00921

Computer Science > Human-Computer Interaction

[Submitted on 2 Mar 2020]

Decision Support in the Context of a Complex Decision Situation

Teus H. Kappen, Mirko Noordegraaf, Wilton A. van Klei, Karel G.M. Moons, Cor J. Kalkman

Adaptation of Clinical Prediction Models for Application in Local Settings

Teus H. Kappen, MD, Yvonne Vergouwe, PhD, [...], and Karel G. M. Moons, PhD (+3) View all authors and affiliations

Volume 32, Issue 3 | https://doi.org/10.1177/0272989X12439755

British Journal of Anaesthesia Page 1 of 9
doi:10.1093/bja/aeu321

BJA

Impact of adding therapeutic recommendations to risk assessments from a prediction model for postoperative nausea and vomiting

T. H. Kappen[1*], Y. Vergouwe[2,3], L. van Wolfswinkel[1], C. J. Kalkman[1], K. G. M. Moons[1,2] and W. A. van Klei[1]

Kappen *et al. Diagnostic and Prognostic Research* (2018) 2:11
https://doi.org/10.1186/s41512-018-0033-6

Diagnostic and Prognostic Research

METHODOLOGY Open Access

Evaluating the impact of prediction models: lessons learned, challenges, and recommendations

Teus H. Kappen[1*], Wilton A. van Klei[1], Leo van Wolfswinkel[1], Cor J. Kalkman[1], Yvonne Vergouwe[2,3] and Karel G. M. Moons[1,3,4]


THE DOCTOR WILL SEE YOU NOW
HOW AI IS GOING TO CURE OUR SICK HEALTH CARE SYSTEM

Healthcare is ready for A.I. and machine learning

…healthcare is uniquely primed for machine learning due to the exponential increase in the volume of patient data over the past two decades. Today, around 30% of the world's data is generated by the healthcare industry.

- big data

standardization -

…the standardization of medical concepts dramatically eases communication between software…

…the global Artificial Intelligence (AI) in healthcare market is projected to grow from $13.82 billion in 2022 to $164.10 billion by 2029…

- investments

complexity -

…more complex neural networks and the ability to learn from high dimensional data allow models to learn and extract as much knowledge as possible from the various kinds of medical data…

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Really?

…is Healthcare ready for A.I.?

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Doctors about to be replaced by hospital AI systems offering better diagnosis and less arrogance

09/12/2017 / By Jhoanna Robinson

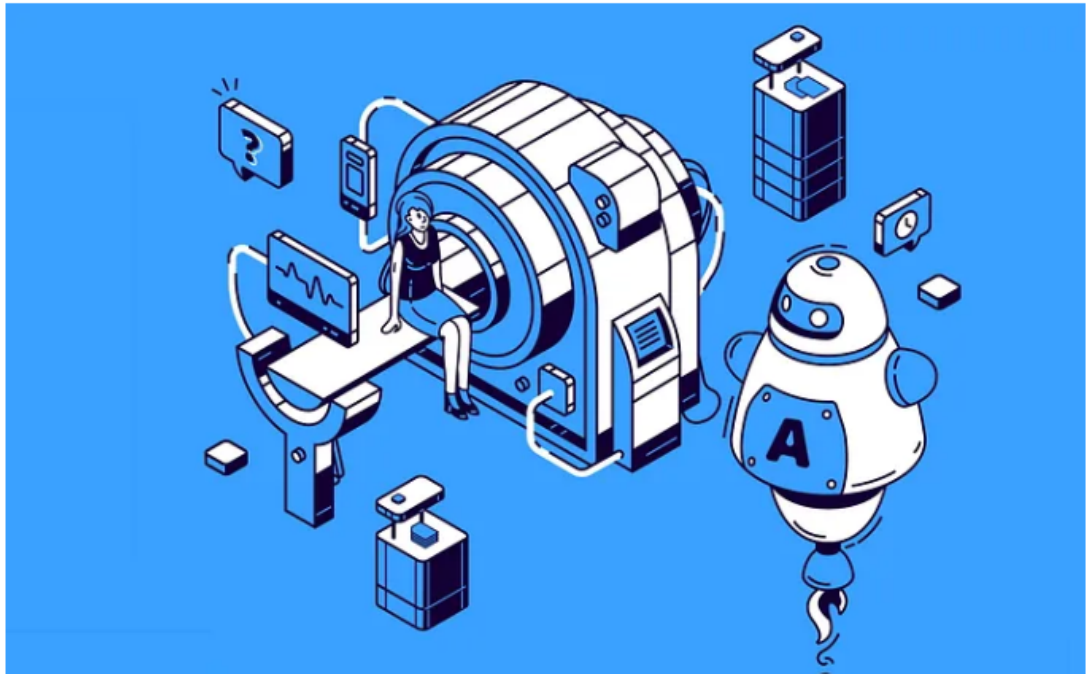
Framingham, Massachusetts-based market intelligence provider IDC Health Insights, in its recently published report on artificial intelligence and cognitive computing adoption in the Asia/Pacific titled *IDC Peerscape: Cognitive/AI Practices for Healthcare in Asia/Pacific (Excluding Japan)*, stated the best possible healthcare solutions that hospitals and health insurance companies all around the Asia-Pacific countries should adopt.

David Leibowitz

Sep 29, 2020 · 7 min read ·

AI Now Diagnoses Disease Better Than Your Doctor, Study Finds

Peer-reviewed study says you'll soon consult Dr. Bot for a second opinion



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2020

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2024

NEWS | 12 January 2024

Google AI has better bedside manner than human doctors — and makes better diagnoses

Researchers say their artificial-intelligence system could help to democratize medicine.

By Mariana Lenharo

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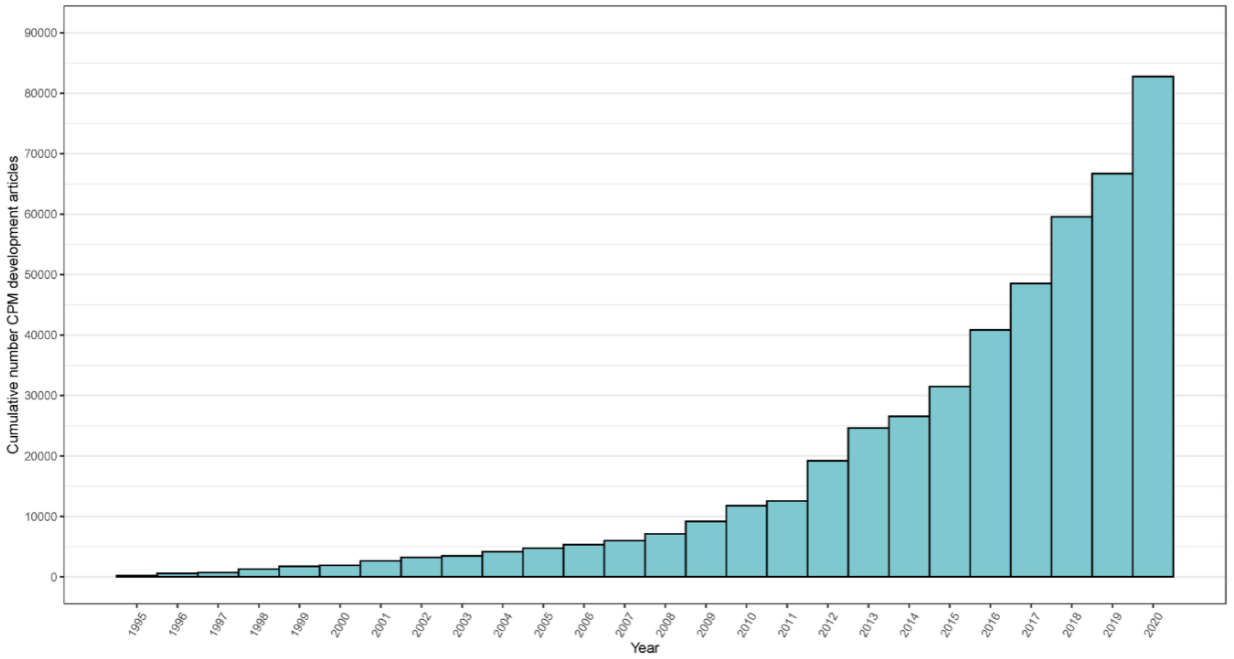
Artificial Intelligence

Figure 1. Cumulative estimated number of regression-based CPM development articles



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Artificial Intelligence

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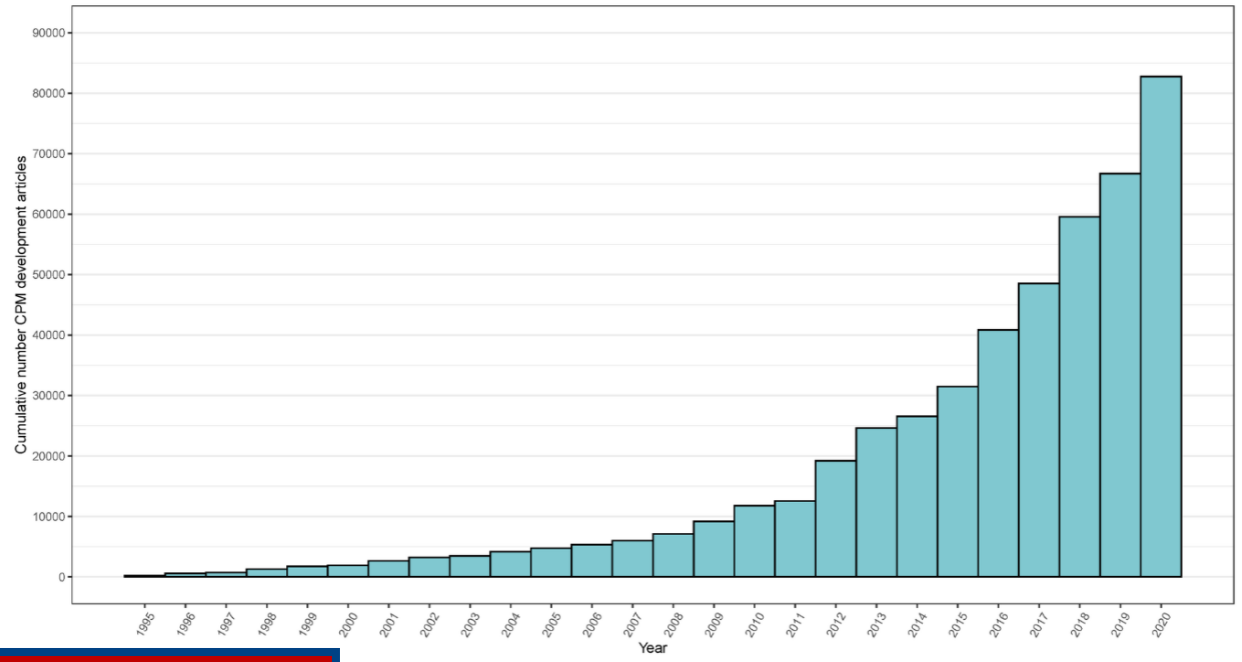
Number of publications on new clinical prediction models: a systematic literature search

AUTHORS
Banafsheh Arshi, Luc J. Smits, Laure Wynants, Laura Elizabeth Cowley, Kelly Reeve, and Eline Rijnhart

Figure 1. Cumulative estimated number of regression-based CPM development articles



for 2020 that is every 6-10 minutes

Artificial Intelligence

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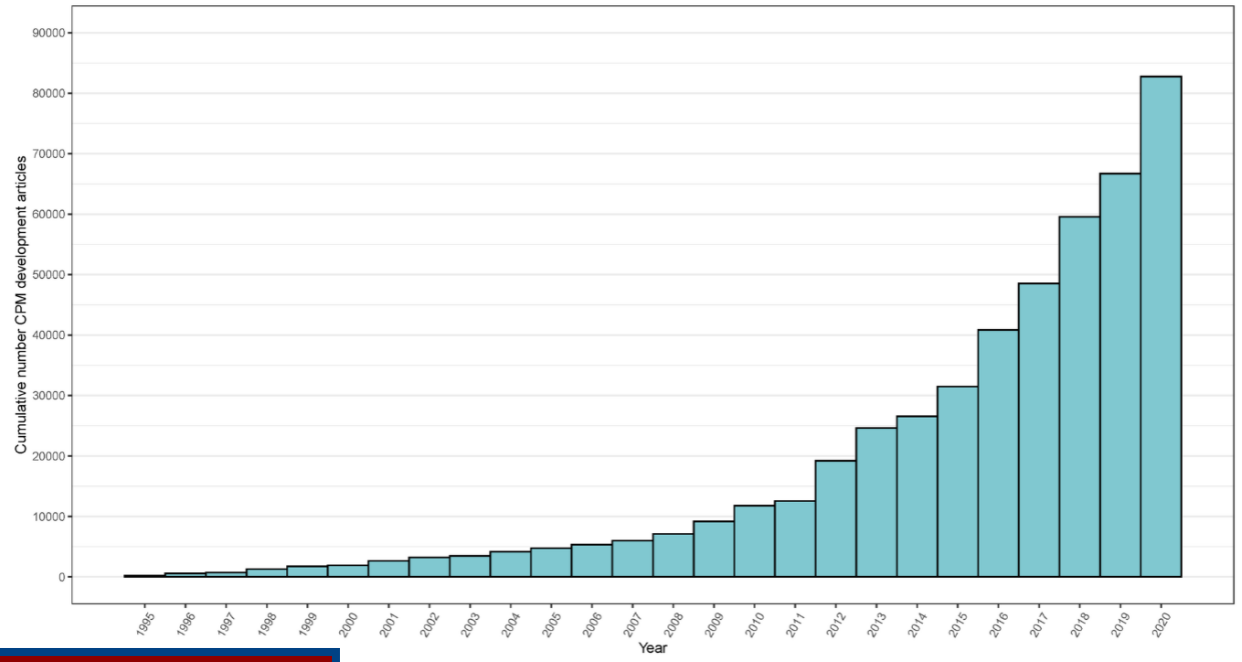

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and that is regression-based models only

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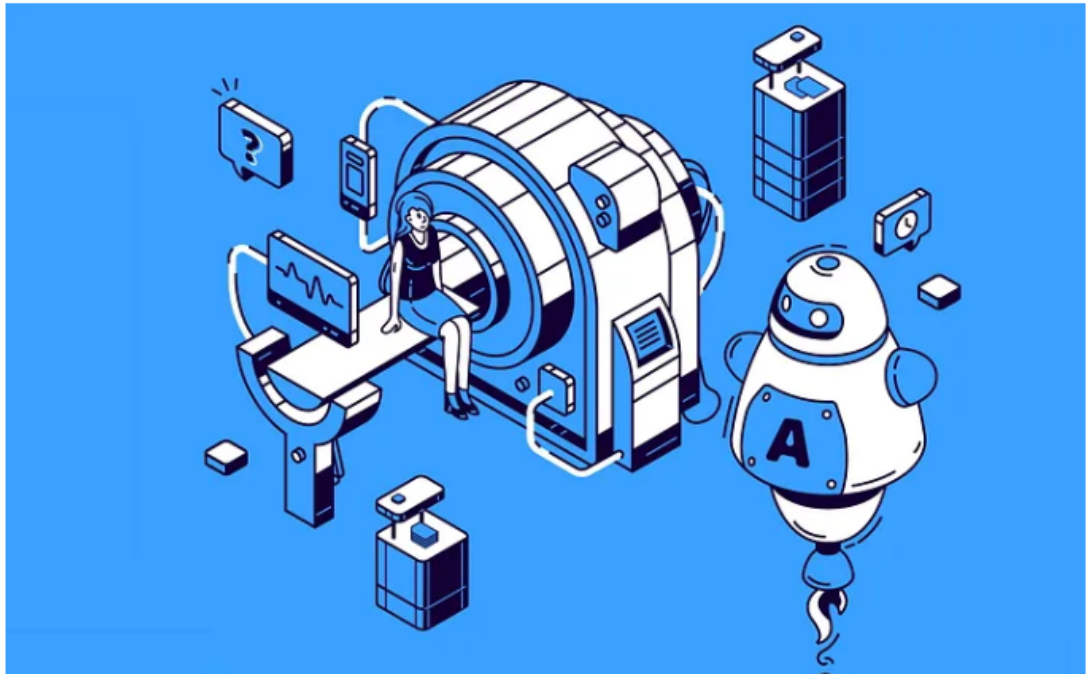

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Google AI has better bedside manner than human doctors — and makes better diagnoses

Researchers say their artificial-intelligence system could help to democratize medicine.

By Mariana Lenharo

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Why is it taking so long?

…if Healthcare is ready for A.I.

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The data is not really there

The problem

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Using data from

an Electronic

Medical Record

is like squeezing

water from an

only moist sponge

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What does that mean for A.I. implementation?

The problem

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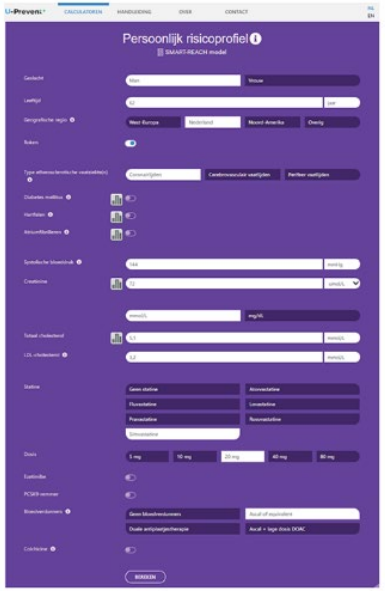
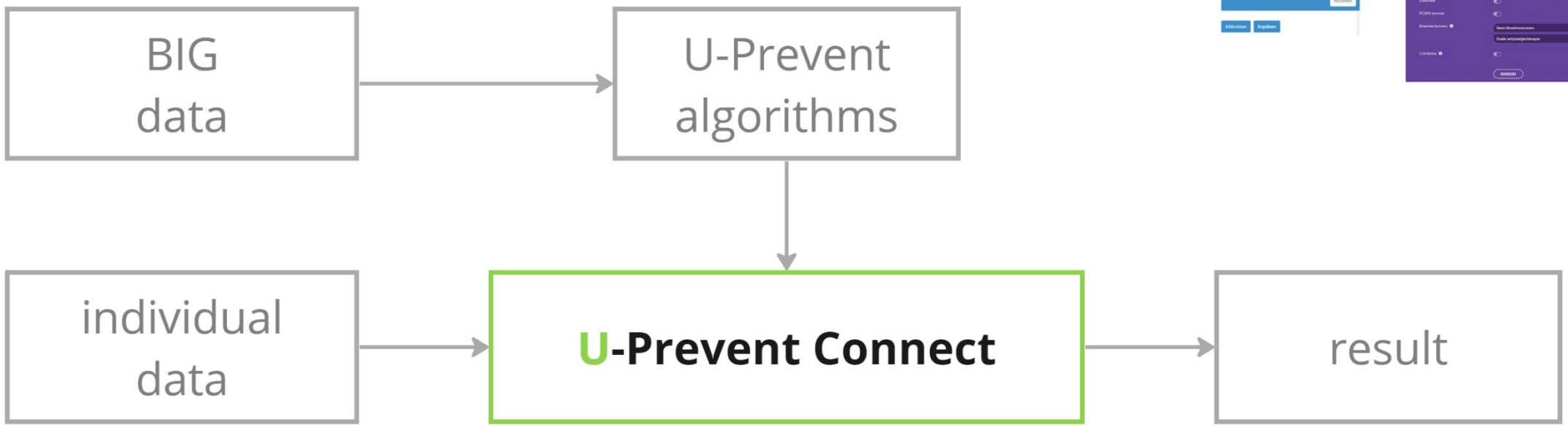
A.I. Algorithms – U-Prevent





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U-Prevent Algoritmes

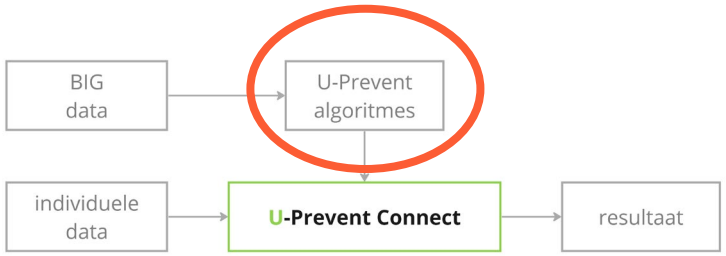

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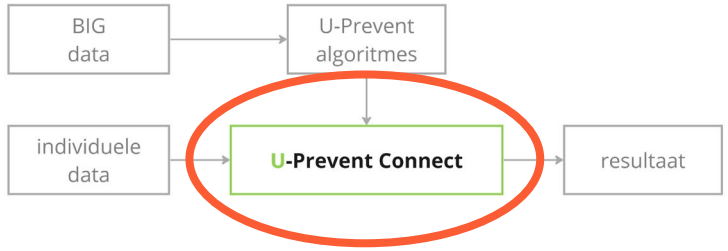
Table 2 Model coefficients and HRs

	Model coefficient	LRT statistic	p Value	HR (95% CI)
Model A, SMART risk score				
Age in years	−0.0850	62.8*	<0.01*	1.86 (1.59 to 2.19)*
Age in years squared	0.0011			
Male sex	0.1561	2.2	0.14	1.19 (0.94 to 1.51)
Diabetes mellitus	0.2232	5.3	0.02	1.30 (1.05 to 1.63)
Current smoking	0.2617	7.6	<0.01	1.33 (1.09 to 1.62)
Systolic blood pressure (per 10 mm Hg)	0.0043	4.1	0.04	1.04 (1.00 to 1.09)
Total cholesterol (mmol/l)	0.0959	5.6	0.02	1.11 (1.02 to 1.20)
HDL-cholesterol (mmol/l)	−0.4256	9.8	<0.01	0.63 (0.47 to 0.85)
hs-CRP (mg/dl) log transformed	0.1394	9.8	<0.01	1.24 (1.08 to 1.41)*
eGFR (ml/min/1.73 m²)	−0.0532	21.0*	<0.01	0.87 (0.76 to 0.98)*
eGFR squared	0.0003			
Years since first vascular event	0.0229	7.4	<0.01	1.02 (1.01 to 1.03)
History of cerebrovascular disease	0.4058	17.4	<0.01	1.65 (1.31 to 2.08)
History of coronary artery disease	0.1401	3.9	0.05	1.28 (1.00 to 1.62)
History of abdominal aortic aneurysm	0.5578	21.2	<0.01	1.93 (1.48 to 2.51)
History of peripheral arterial disease	0.2832	9.0	<0.01	1.44 (1.14 to 1.81)
Model B, carotid ultrasound				
Age in years	−0.1243	77.7*	<0.01*	1.84 (1.59 to 2.13)*
Age in years squared	0.0014			
Male sex	0.2051	4.9	0.03	1.27 (1.02 to 1.58)
Carotid intima-media thickness (mm)	0.8398	26.9	<0.01	2.49 (1.79 to 3.47)
Carotid artery stenosis >50%	0.4063	16.2	<0.01	1.53 (1.25 to 1.88)
Model C, SMART risk score PLUS				
Age in years	−0.1031	40.7*	<0.01*	1.64 (1.38 to 1.94)*
Age in years squared	0.0011			
Male sex	0.1194	1.3	0.26	1.14 (0.90 to 1.45)
Diabetes mellitus	0.1991	4.4	0.04	1.27 (1.02 to 1.59)
Current smoking	0.2213	5.5	0.02	1.27 (1.04 to 1.56)
Systolic blood pressure (per 10 mm Hg)	0.0026	1.3	0.25	1.03 (0.98 to 1.07)
Total cholesterol (mmol/l)	0.0898	4.9	0.03	1.10 (1.01 to 1.20)
HDL-cholesterol (mmol/l)	−0.4002	8.5	<0.01	0.65 (0.48 to 0.87)
hs-CRP (mg/dl) log transformed	0.1272	7.9	<0.01	1.21 (1.06 to 1.39)*
eGFR (ml/min/1.73 m²)	−0.0509	18.9*	<0.01*	0.87 (0.77 to 0.99)*
eGFR squared	0.0003			
Years since first vascular event	0.0228	7.2	<0.01	1.02 (1.01 to 1.03)
History of cerebrovascular disease	0.2618	7.5	<0.01	1.42 (1.11 to 1.82)
History of coronary artery disease	0.1235	3.4	0.07	1.25 (0.99 to 1.59)
History of abdominal aortic aneurysm	0.5953	23.7	<0.01	2.01 (1.54 to 2.63)
History of peripheral arterial disease	0.2607	7.9	<0.01	1.40 (1.11 to 1.77)
Carotid intima-media thickness (mm)	0.6482	16.4	<0.01	2.05 (1.46 to 2.86)
Carotid artery stenosis >50%	0.2615	5.4	0.02	1.31 (1.05 to 1.64)

Penalised coefficients of models A, B and C and accompanying χ^2 values, p values and (unpenalised) HRs.
*Risk models contain linear and squared terms for age and eGFR and natural log-transformed terms for hs-CRP. Therefore, the likelihood ratio test statistic and p value of age and eGFR are computed for both terms together. Furthermore, HRs were computed for the difference between the study population's 75th and the 25th percentile of age (ie, 69 vs 55 years), hs-CRP (ie, 4.7 mg/dl vs 1.0 mg/dl) and eGFR (ie, 72 vs 58 ml/min/173m^2).
eGFR, glomerular filtration rate as estimated by the modification of diet in renal disease equation; HDL, high-density lipoprotein, hs-CRP, high-sensitivity C-reactive protein; LRT, likelihood ratio test.

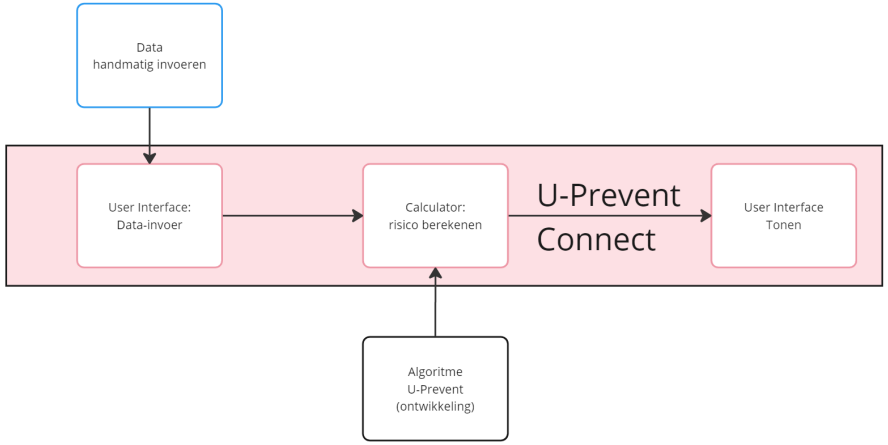
U-Prevent Website



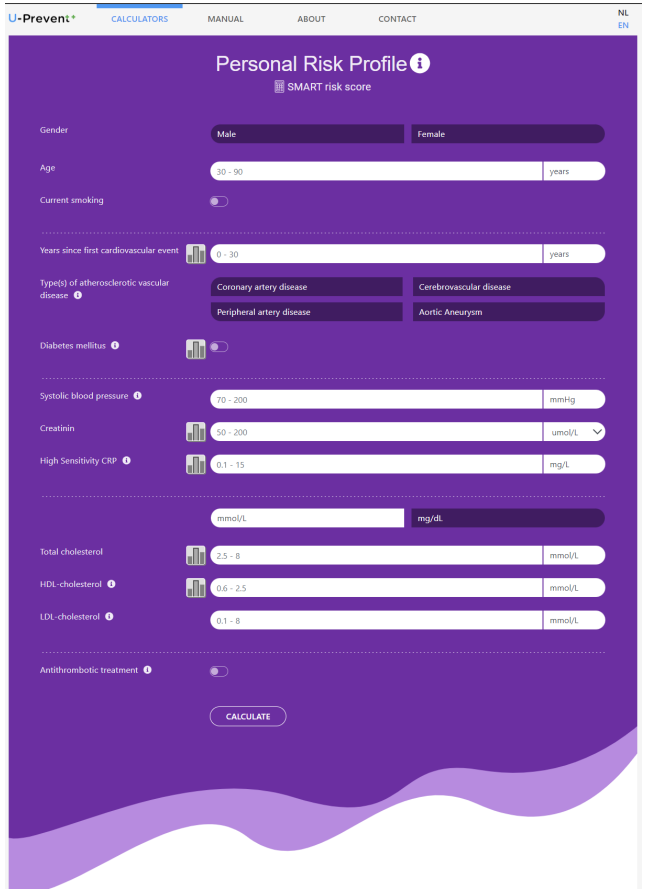
Gebruiker:
zorgverlener / patiënt

Technisch / Applicatie

Onderzoeker / A.I.
developer
Algemene kennis



Ortec



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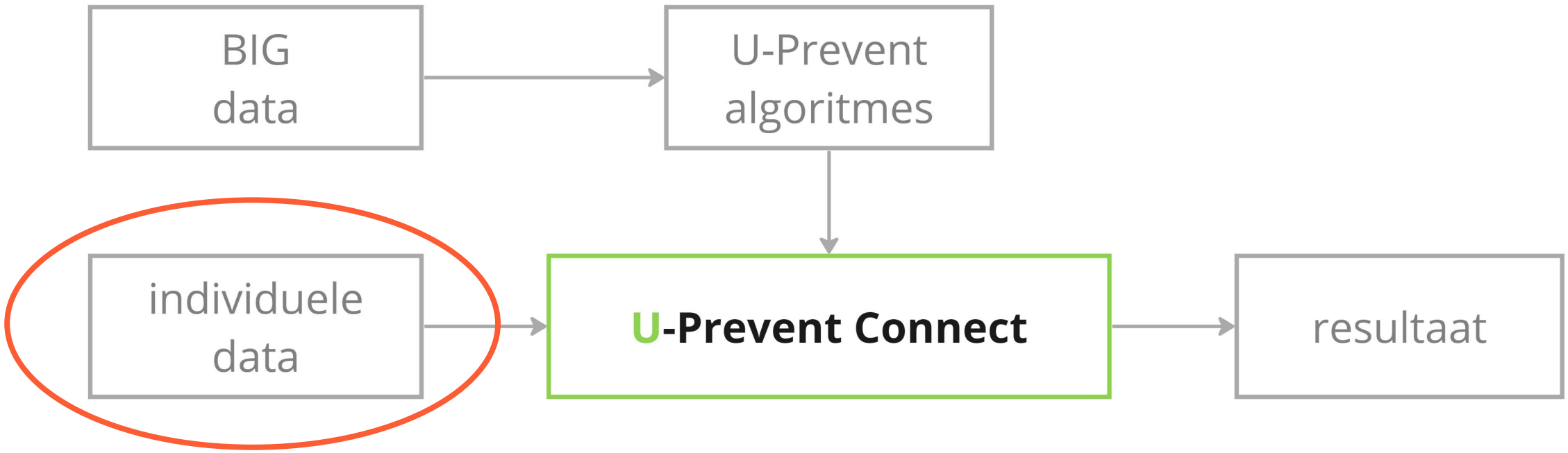
U-Prevent: en toen de stekker naar de data…



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U-Prevent Website

Gebruiker:
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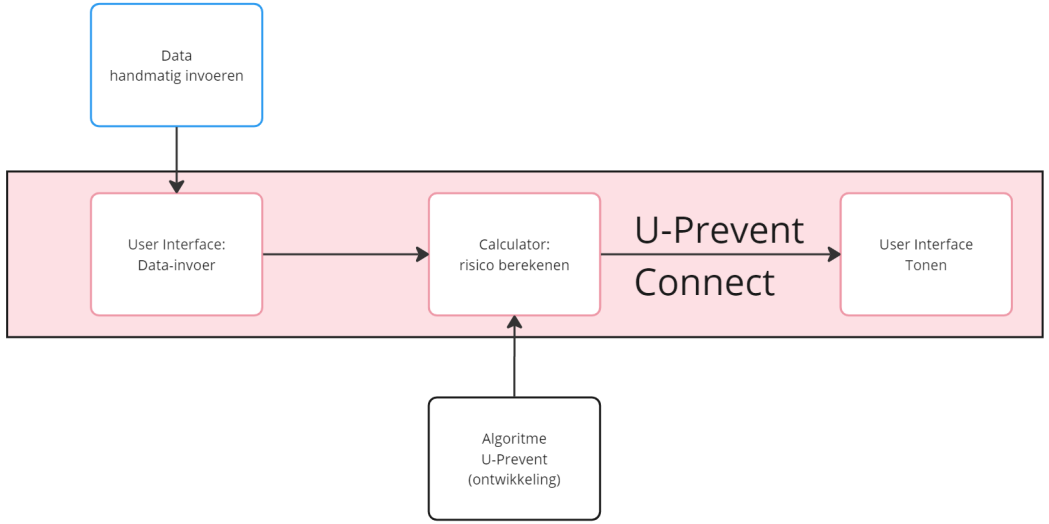

Ortec

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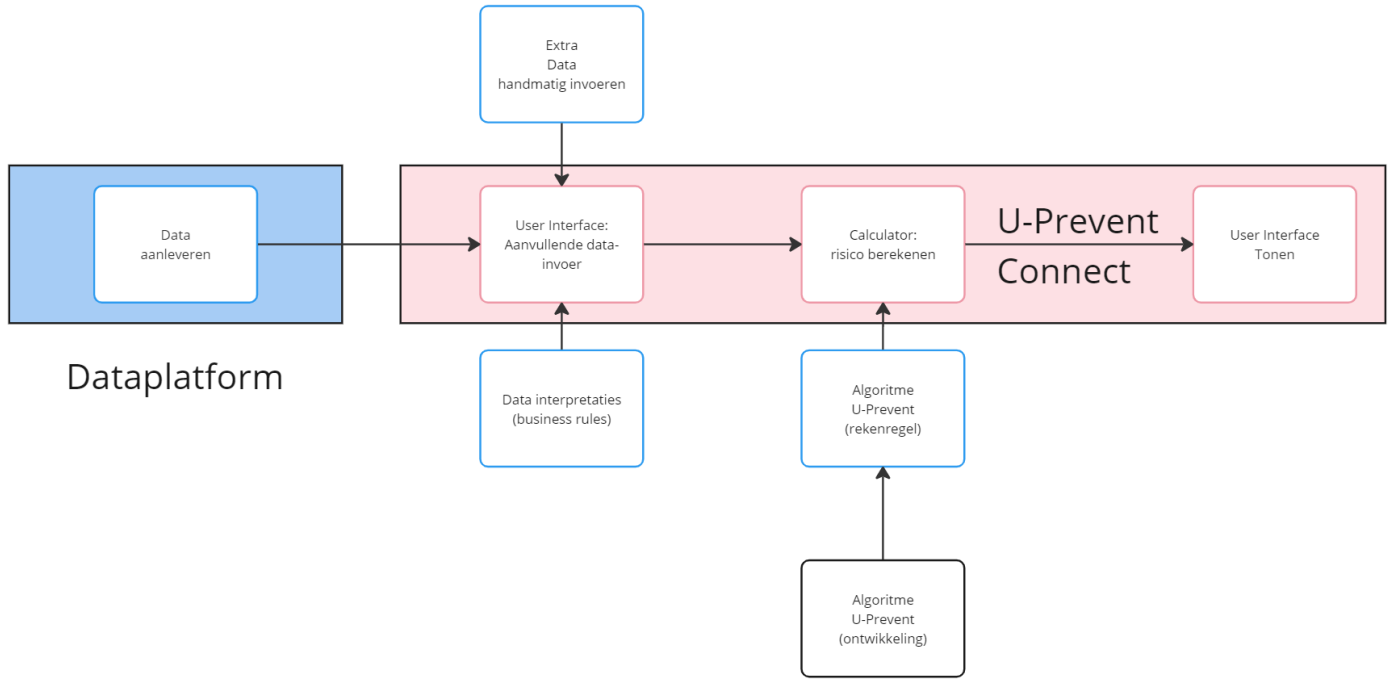
U-Prevent Connect: onze eerste gedachte

Gebruiker:
zorgverlener / patiënt

Technisch / Applicatie

Proceseigenaar (verantwoordelijke zv)
Toegepaste kennis

Onderzoeker / A.I.
developer
Algemene kennis



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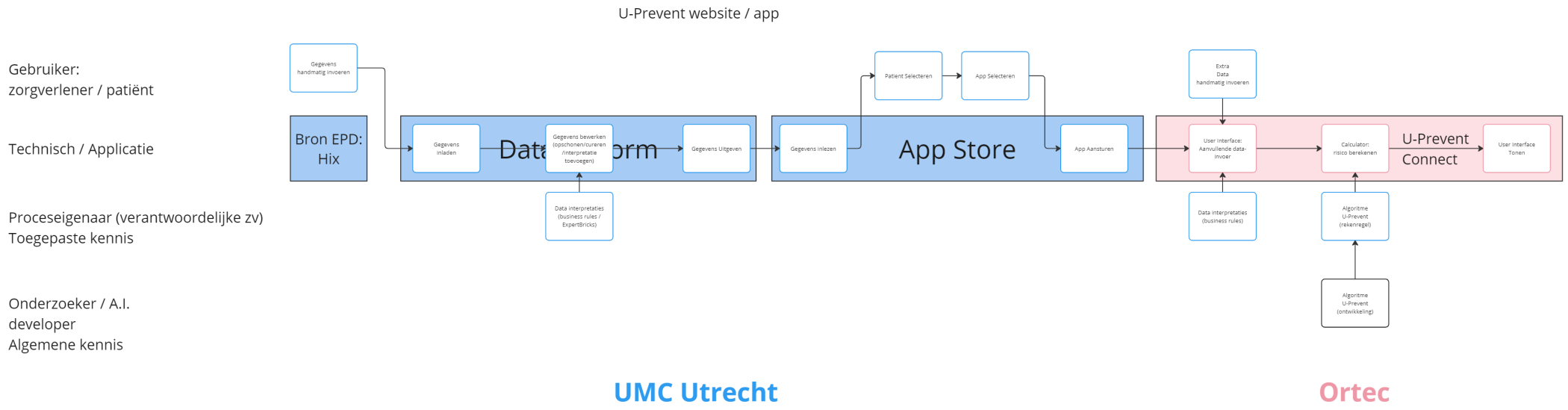
U-Prevent Connect: de werkelijkheid



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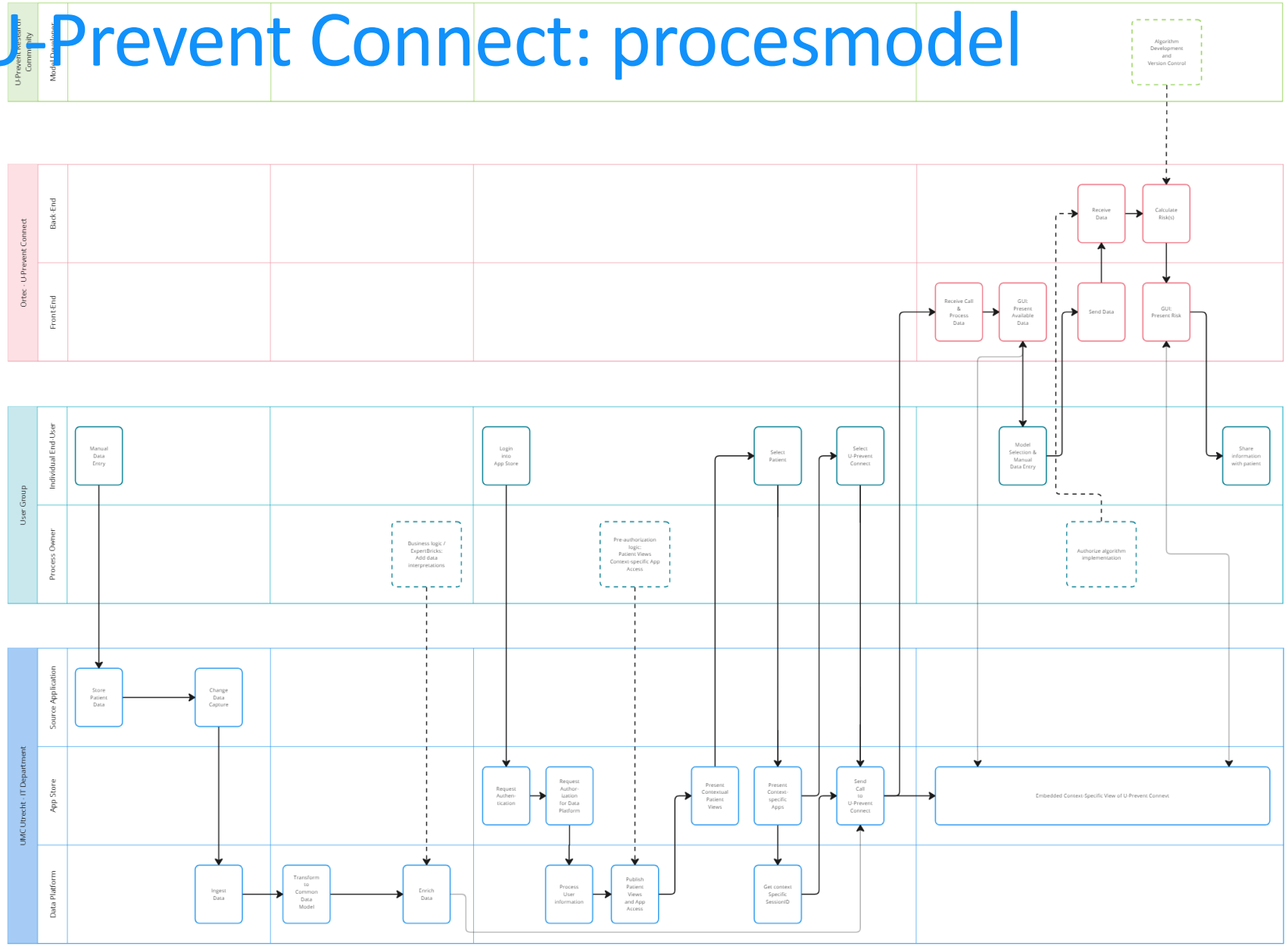
U-Prevent Connect: procesmodel



Three big problems

Getting the data
Getting the data right
Modular User Interfaces (& Authorization)

Three big problems

Getting the data

Getting the data right

Modular User Interfaces (& Authorization)

Het Dataplatform

Basisontwerp

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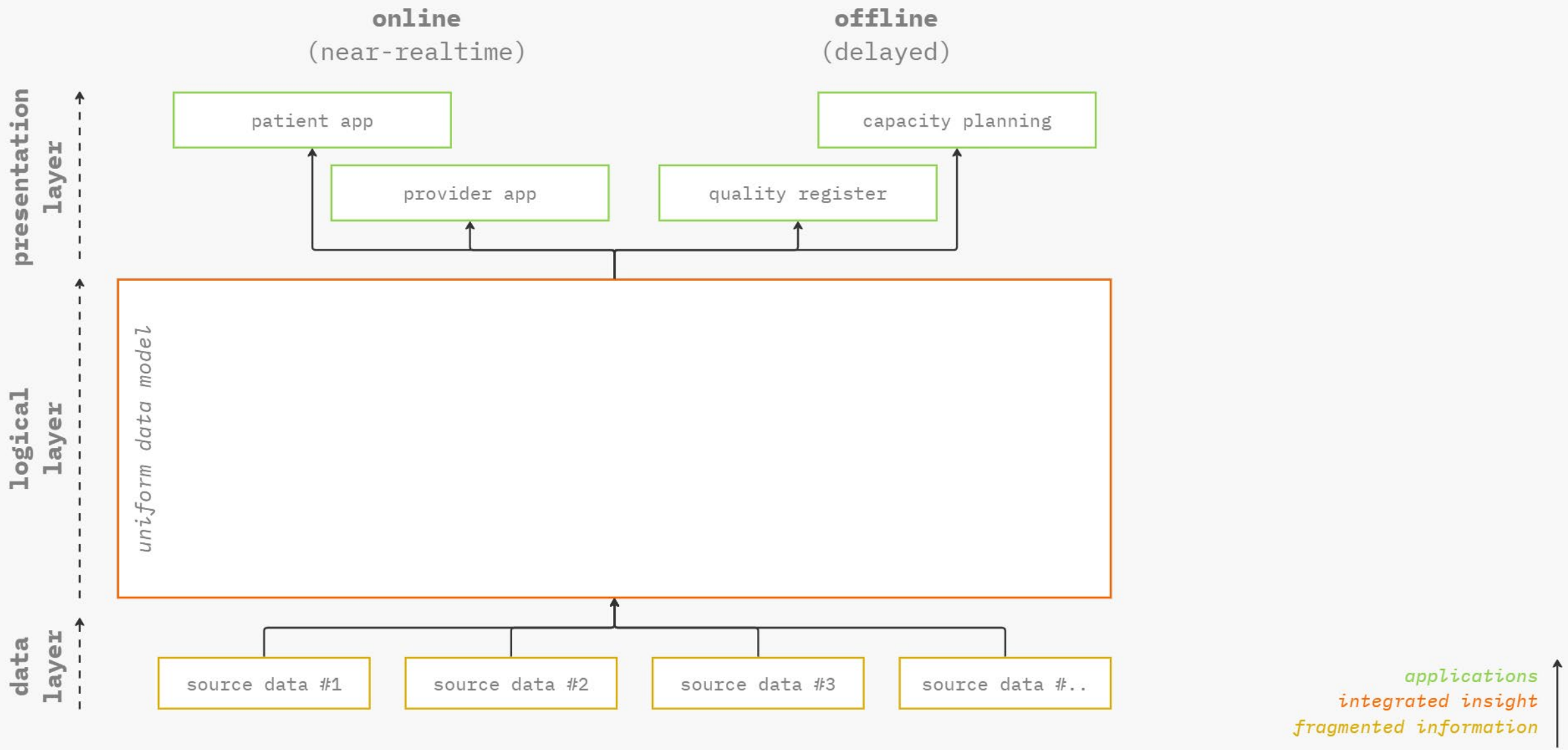
A. Blueprint of a General Modular Healthcare Application Landscape



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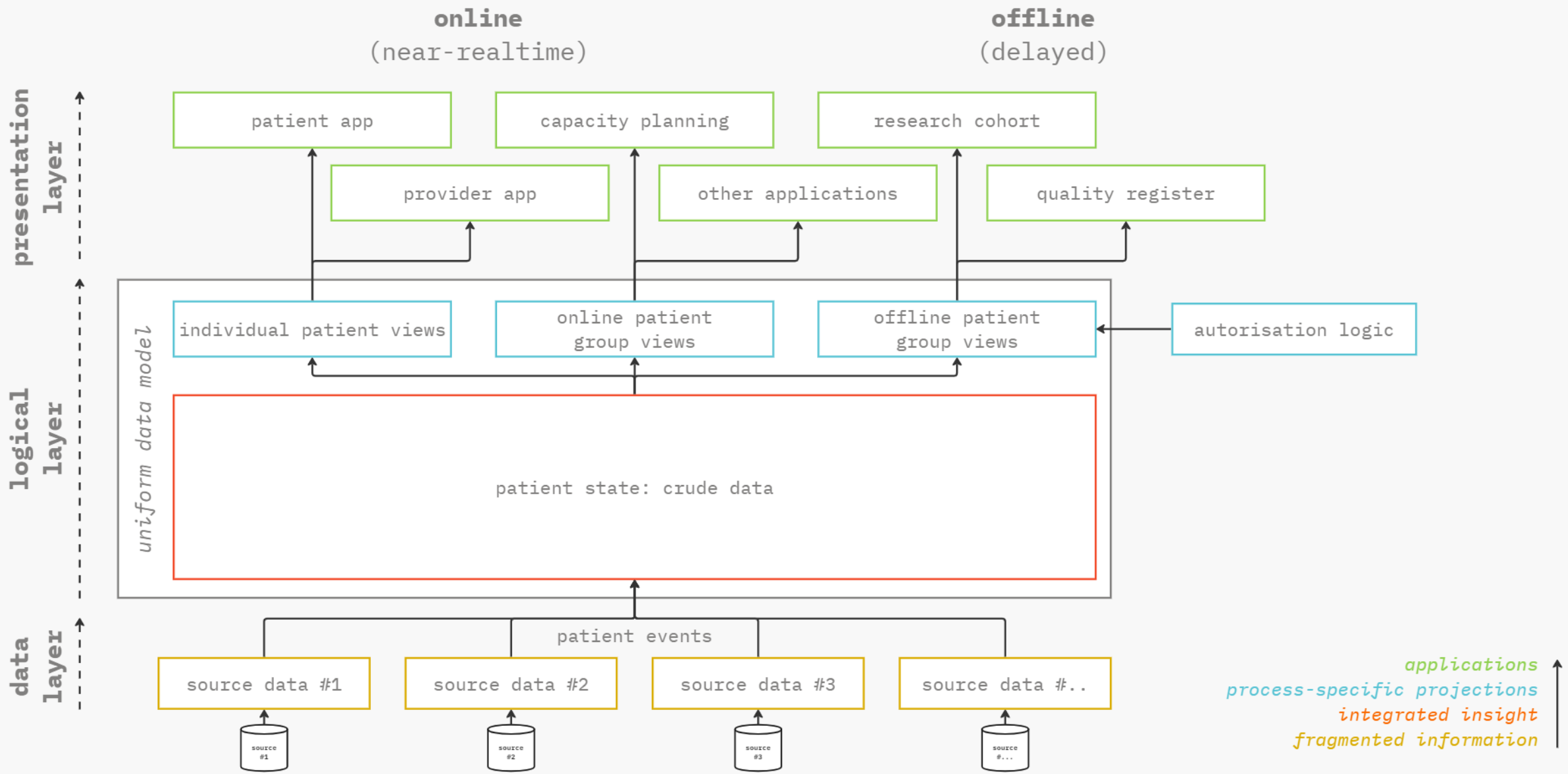

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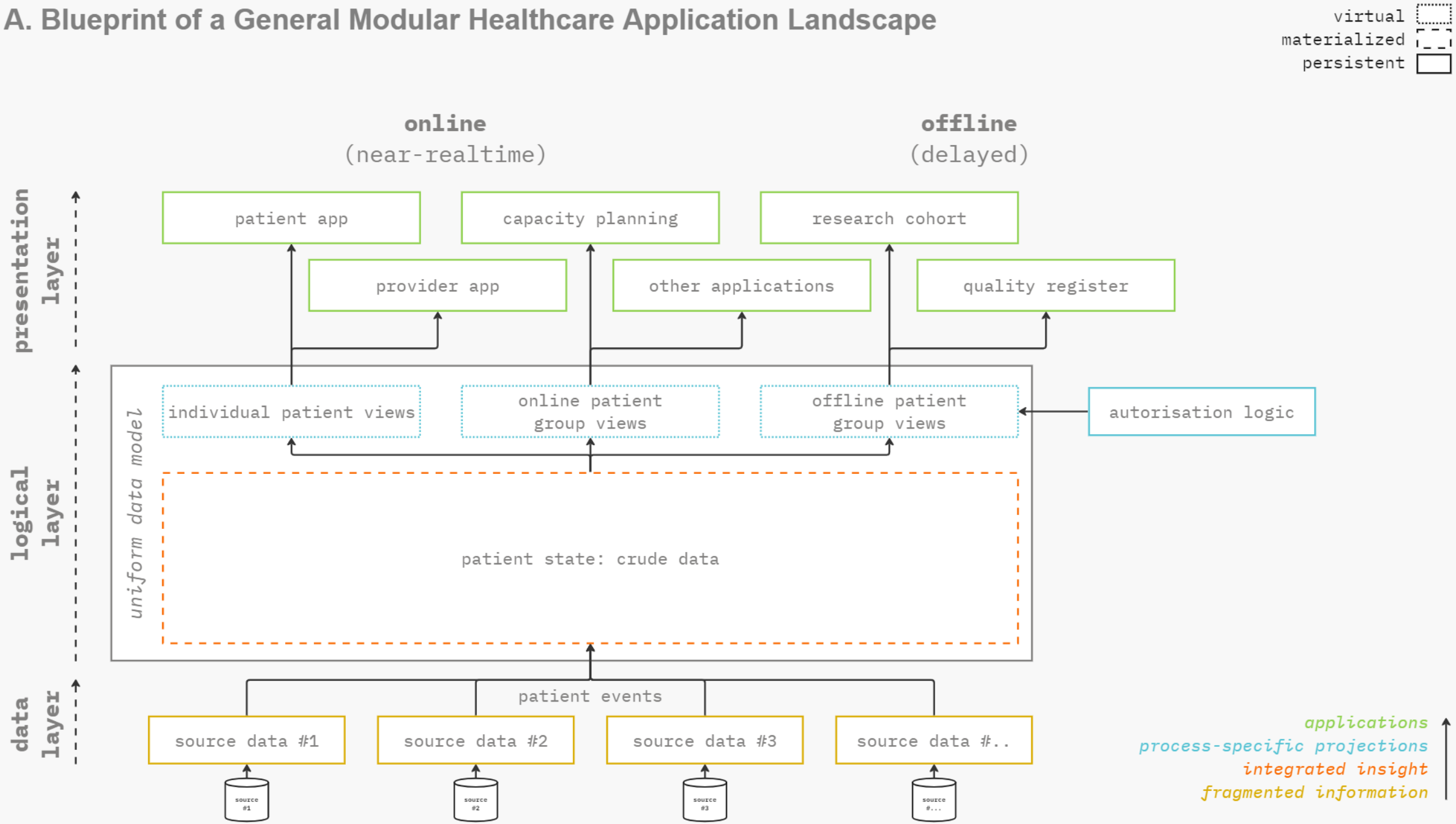

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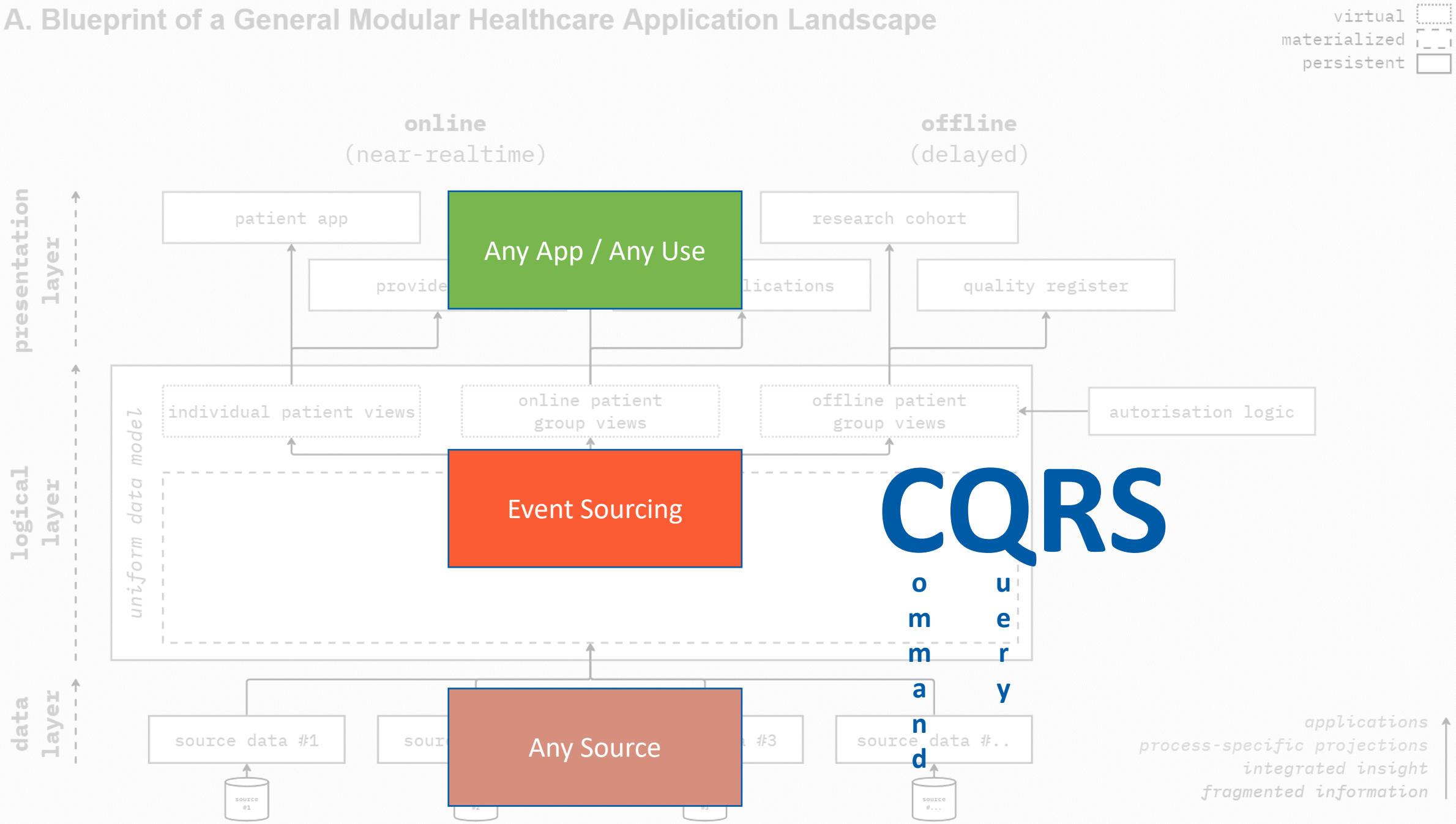

Three big problems

Getting the data

Getting the data right

Modular User Interfaces (& Authorization)

U-Prevent: this data does not exist in the EMR

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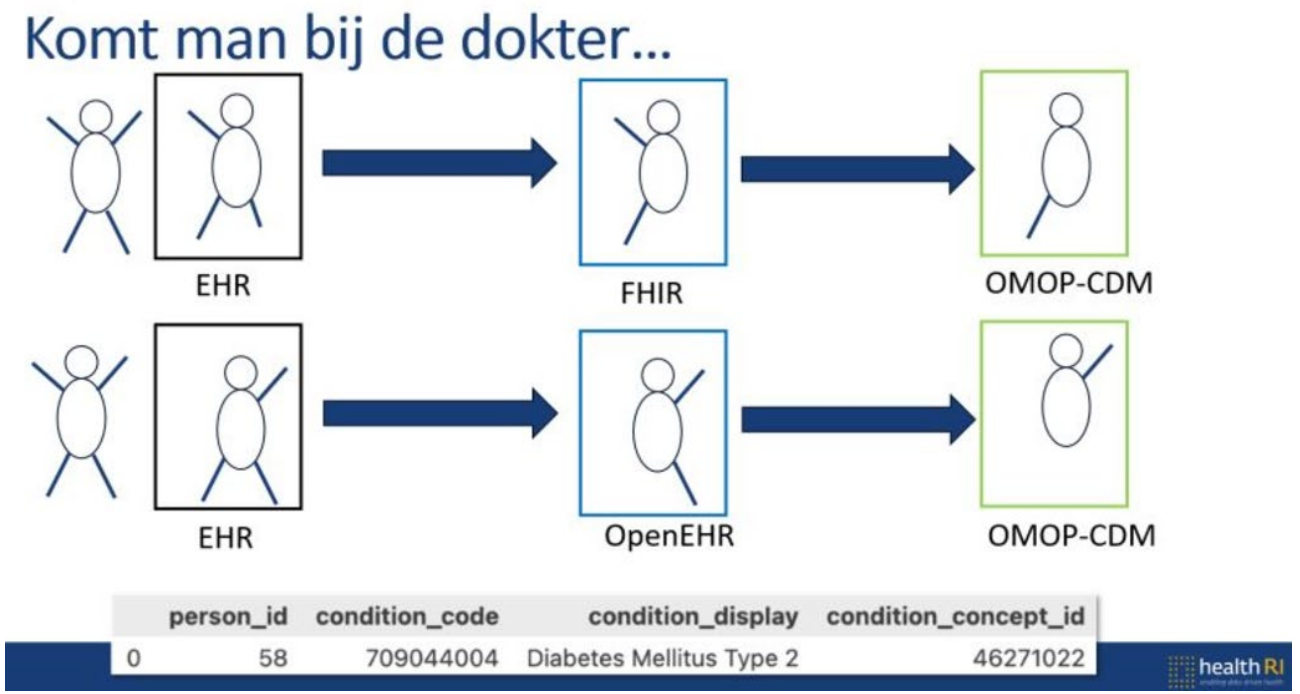
Loss of data

Pim Volkert • 1st
Coördinator Clinical Data Architecture
1w • Edited •

Komt man bij de dokter...
Tijdens de Health-RI Mini-Hackathon hebben we patiëntgegevens uit een #EPD via twee verschillende pipelines getransformeerd naar #OMOP-CDM, wat dezelfde waarde (Diabetes Mellitus Type 2) opleverde. Dit vergde echter de nodige moeite.
We merkten dat tijdens het proces van patiëntcontact tot OMOP-CDM dataset veel informatie verloren gaat. Bij elke stap verlies je zo maar een 'ledemaat'.
Het grootste probleem ligt aan het begin van de keten: als de data bij de bron niet goed wordt opgeslagen in het EPD, vermindert de waarde verderop aanzienlijk.
Daarnaast bleek dat werken met standaarden zoals #zibs, #BgZ en #FHIR-profielen nog steeds tot grote variatie in output leidt. En dat niet alle EPD leveranciers FHIR output kunnen genereren.
Tenslotte zagen we dat de concrete samenwerking tussen ziekenhuizen, regio en bedrijven erg goed werkt. Dank aan alle betrokkenen, Stichting HL7 Nederland voor de organisatie, Ruud Bongers, Wouter Zanen en Marieke Pierik voor hun gastoptredens.



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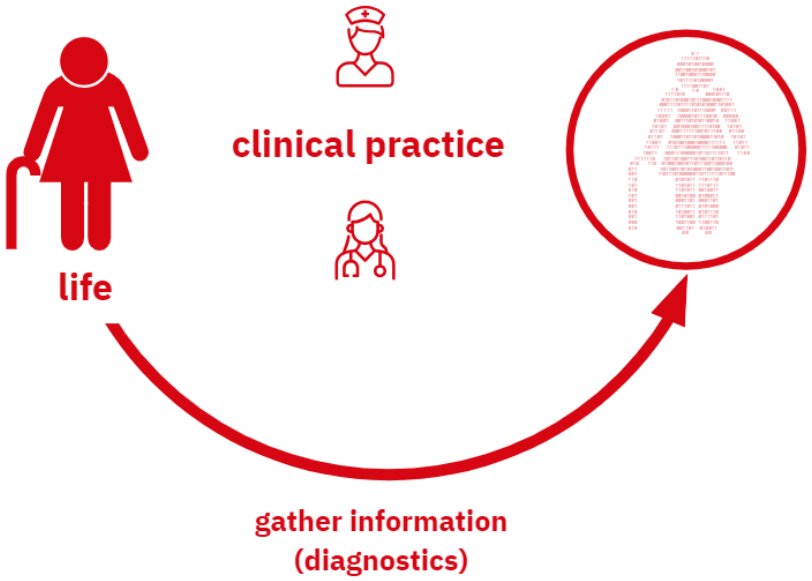
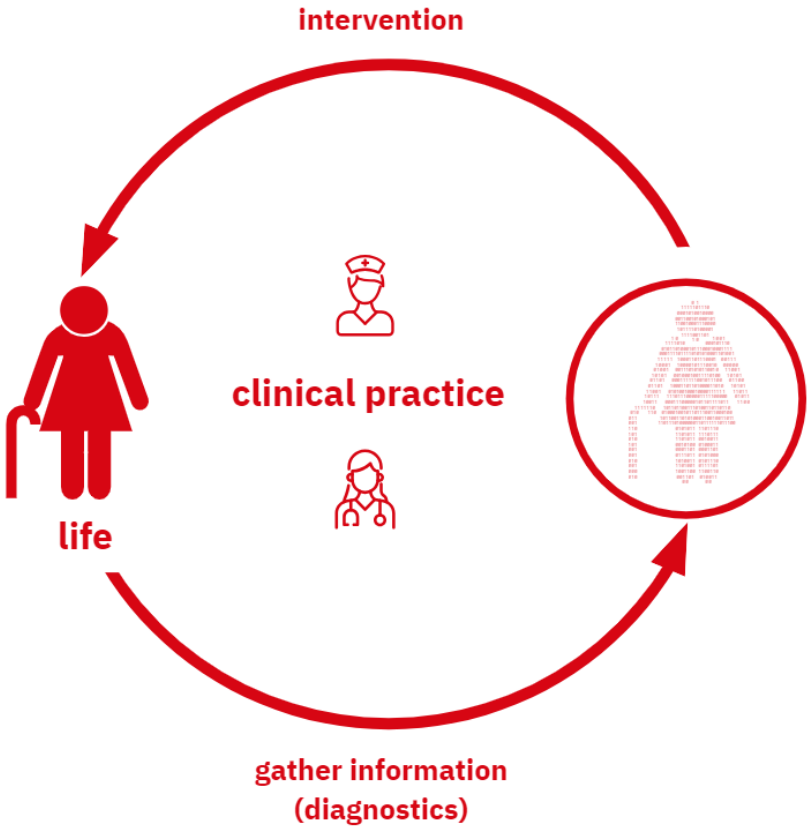
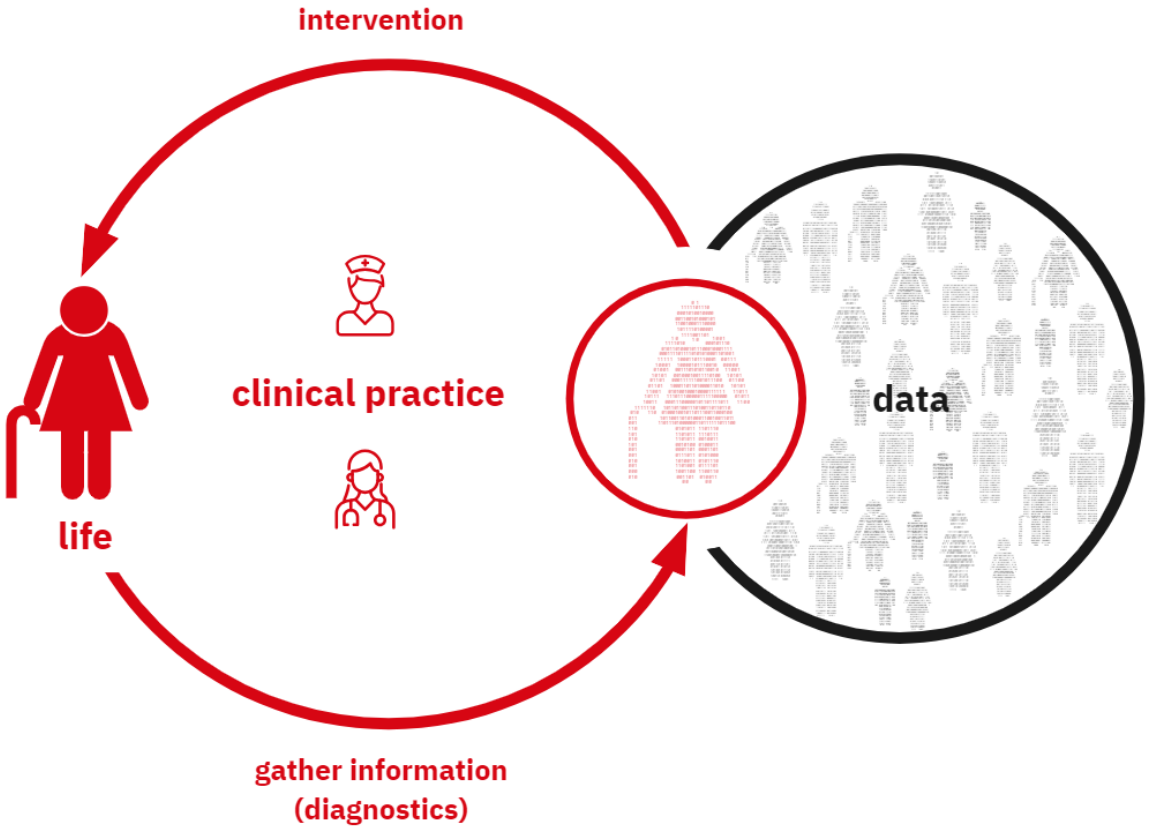
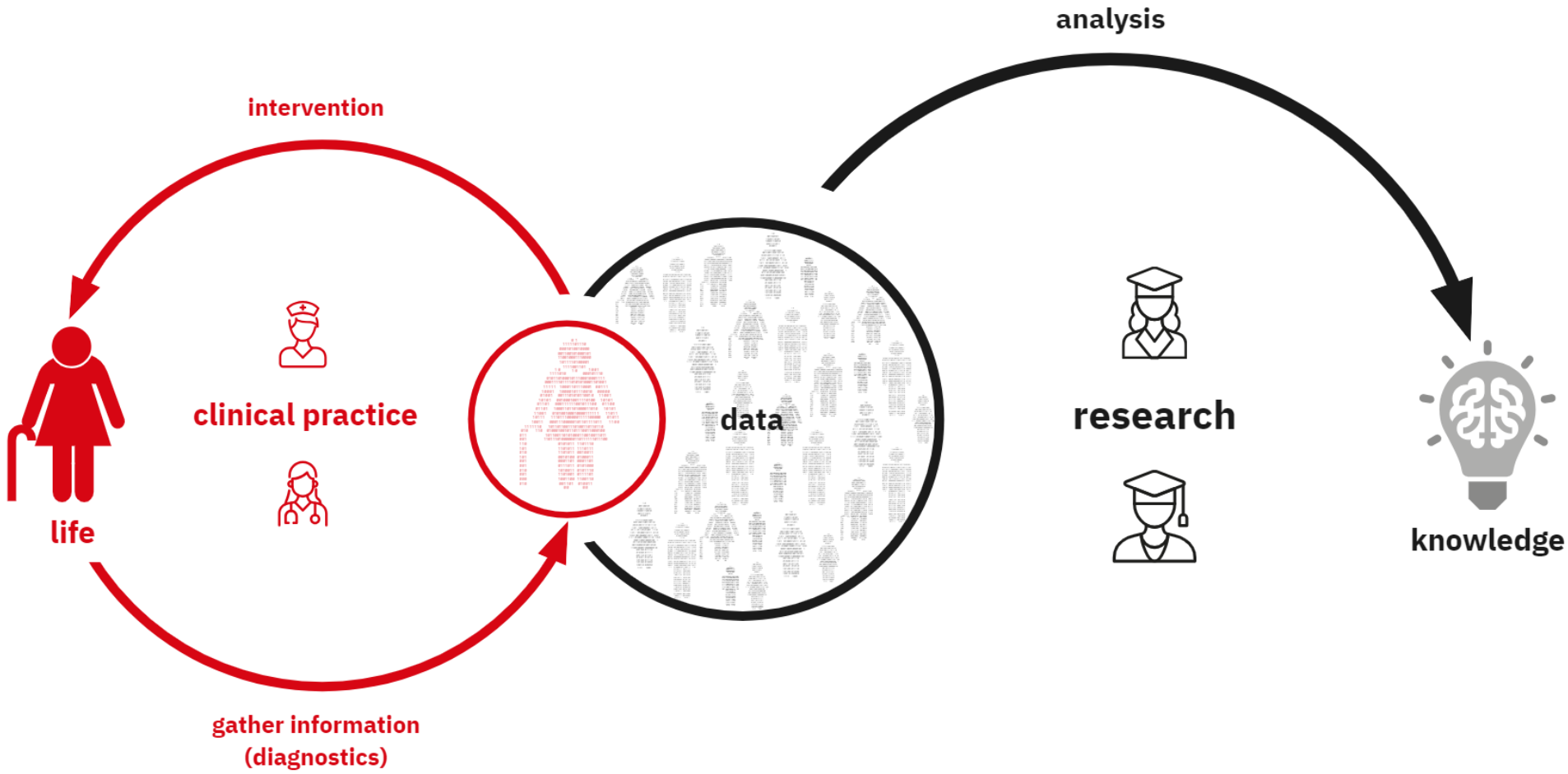
clinical practice
life

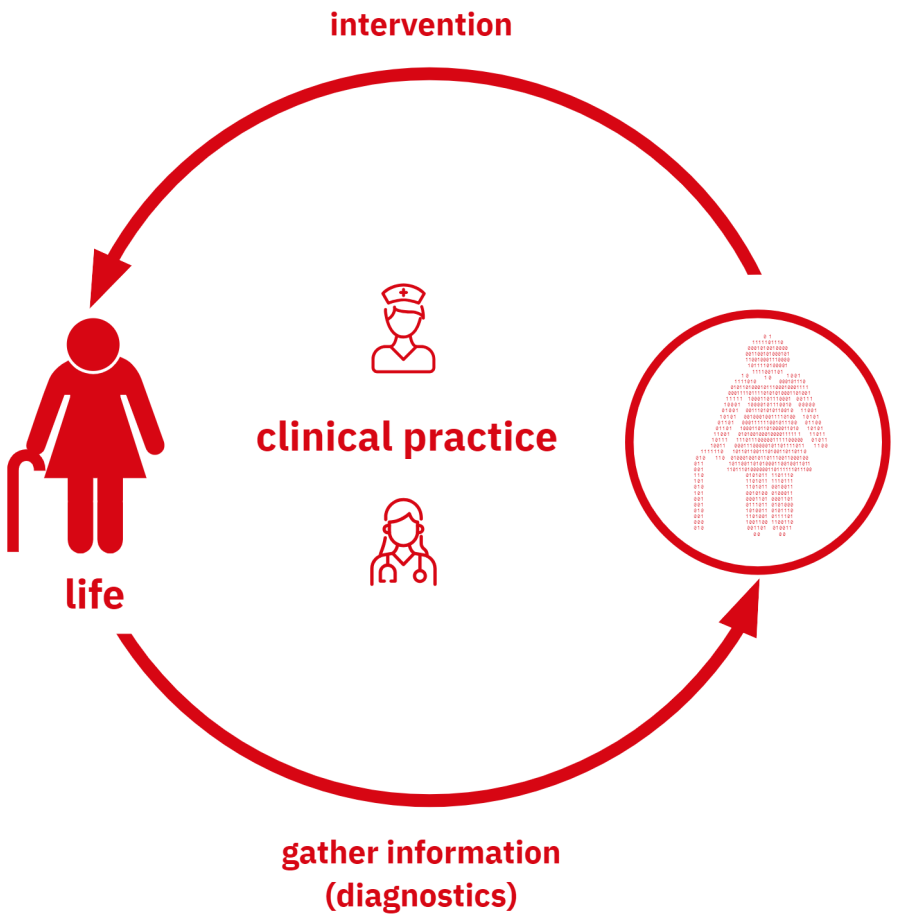

clinical practice
life
gather information
(diagnostics)


intervention
clinical practice
life
gather information
(diagnostics)

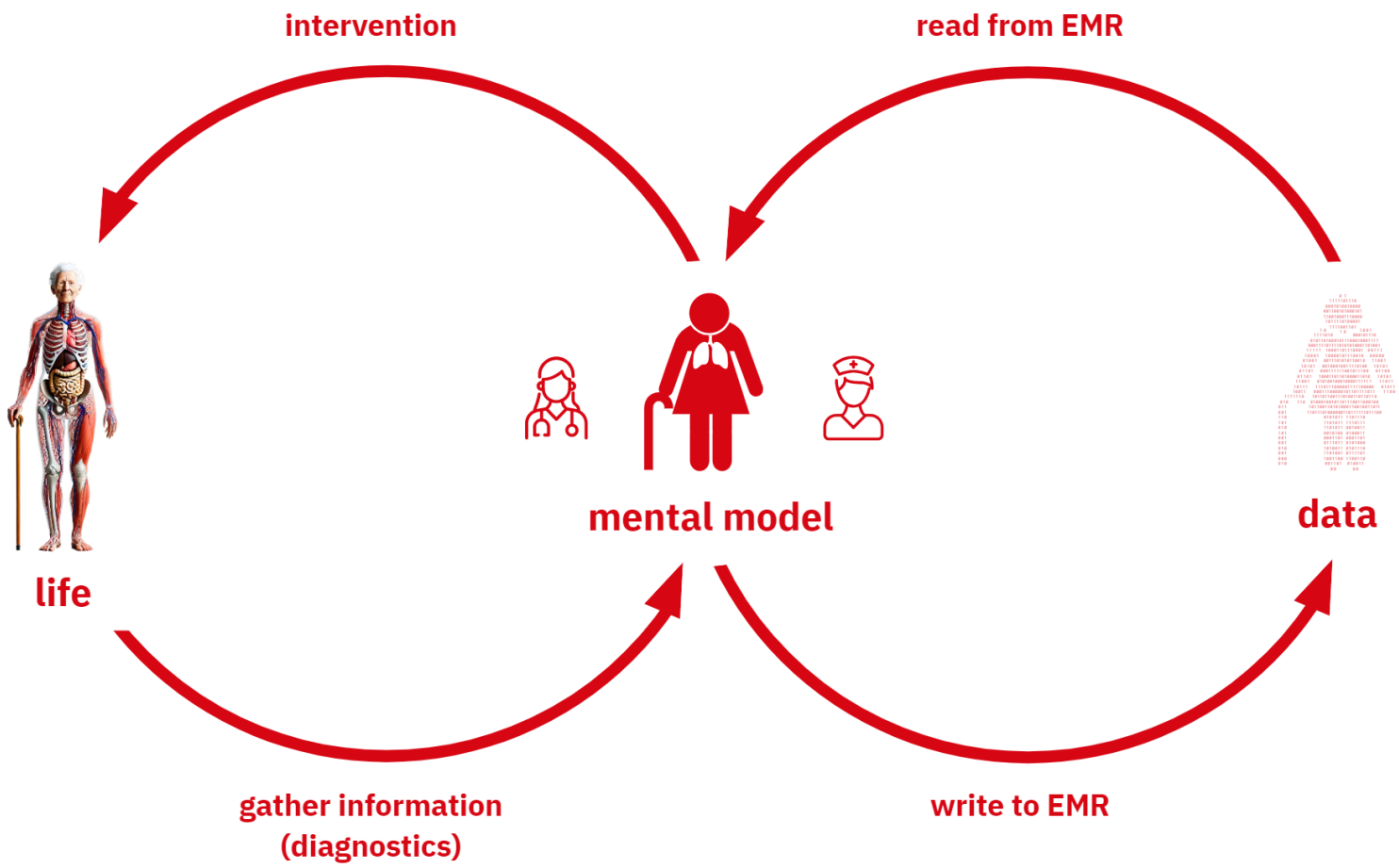

intervention
clinical practice
life
data
gather information
(diagnostics)


analysis
intervention
clinical practice
data
research
knowledge
life
gather information
(diagnostics)

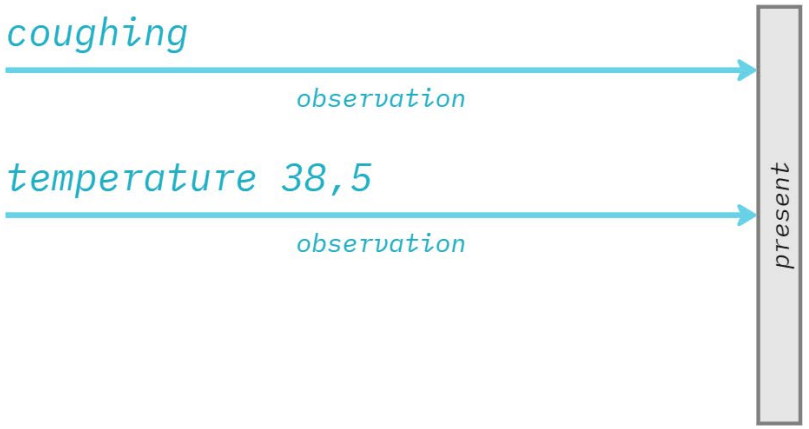
Data and Knowledge in Clinical Practice



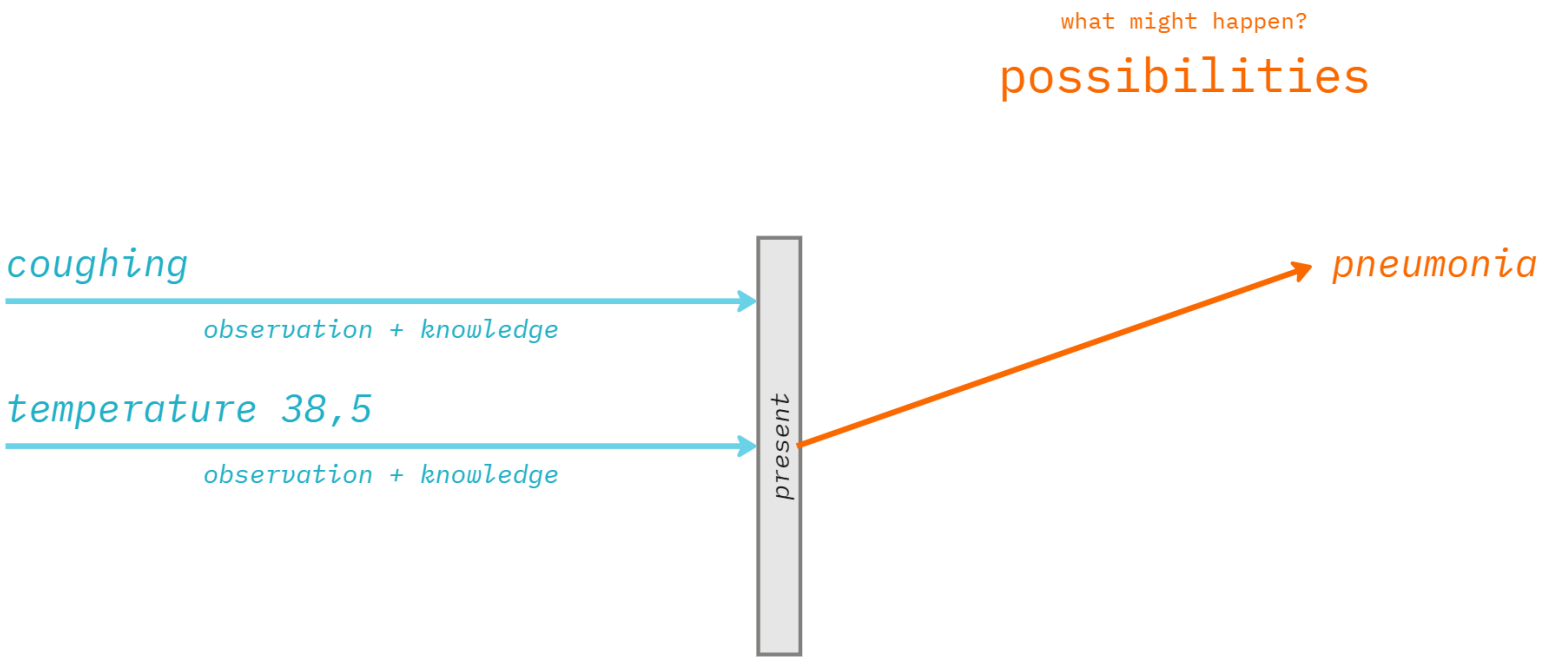
Data and Knowledge in Clinical Practice



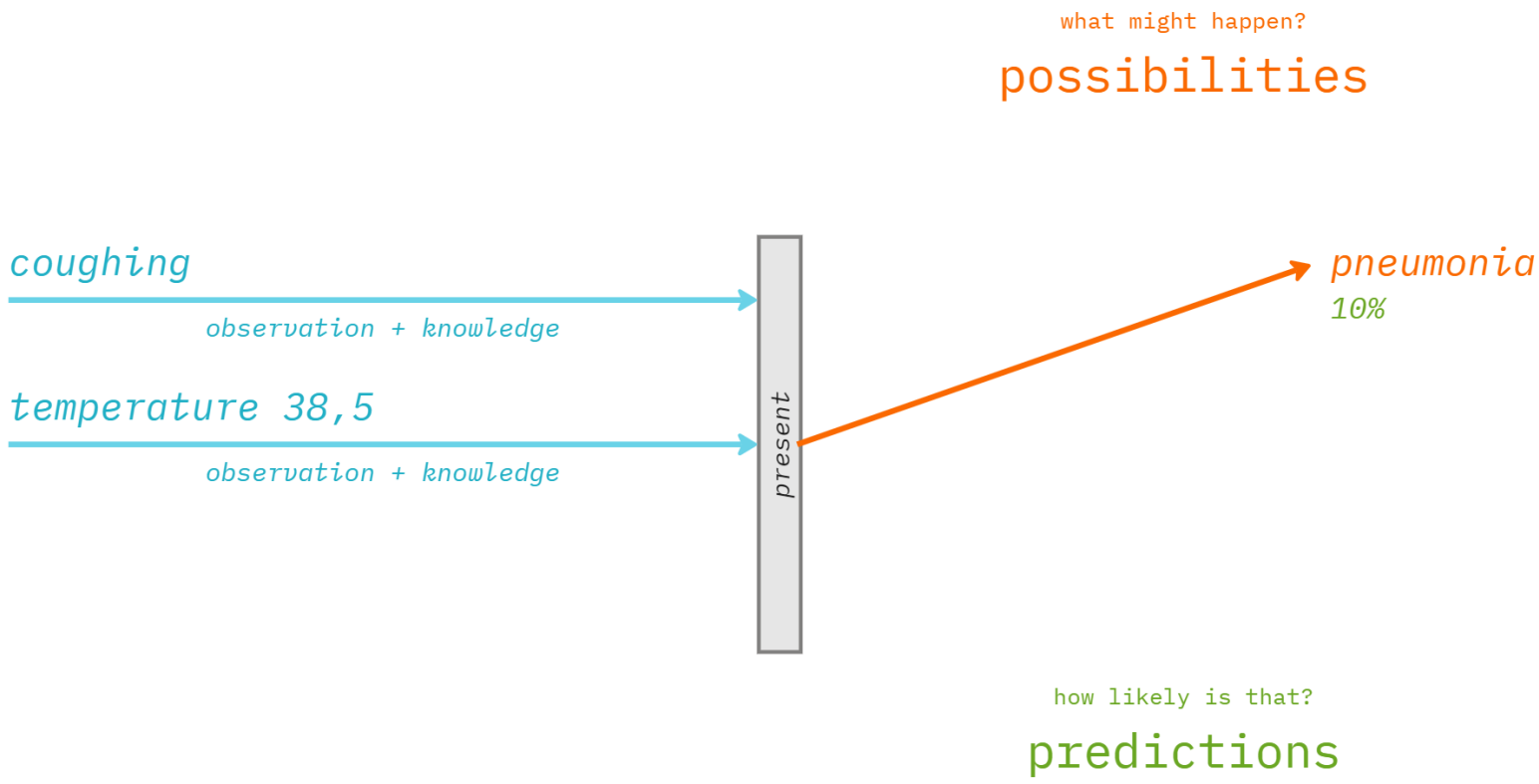
It starts with symptoms



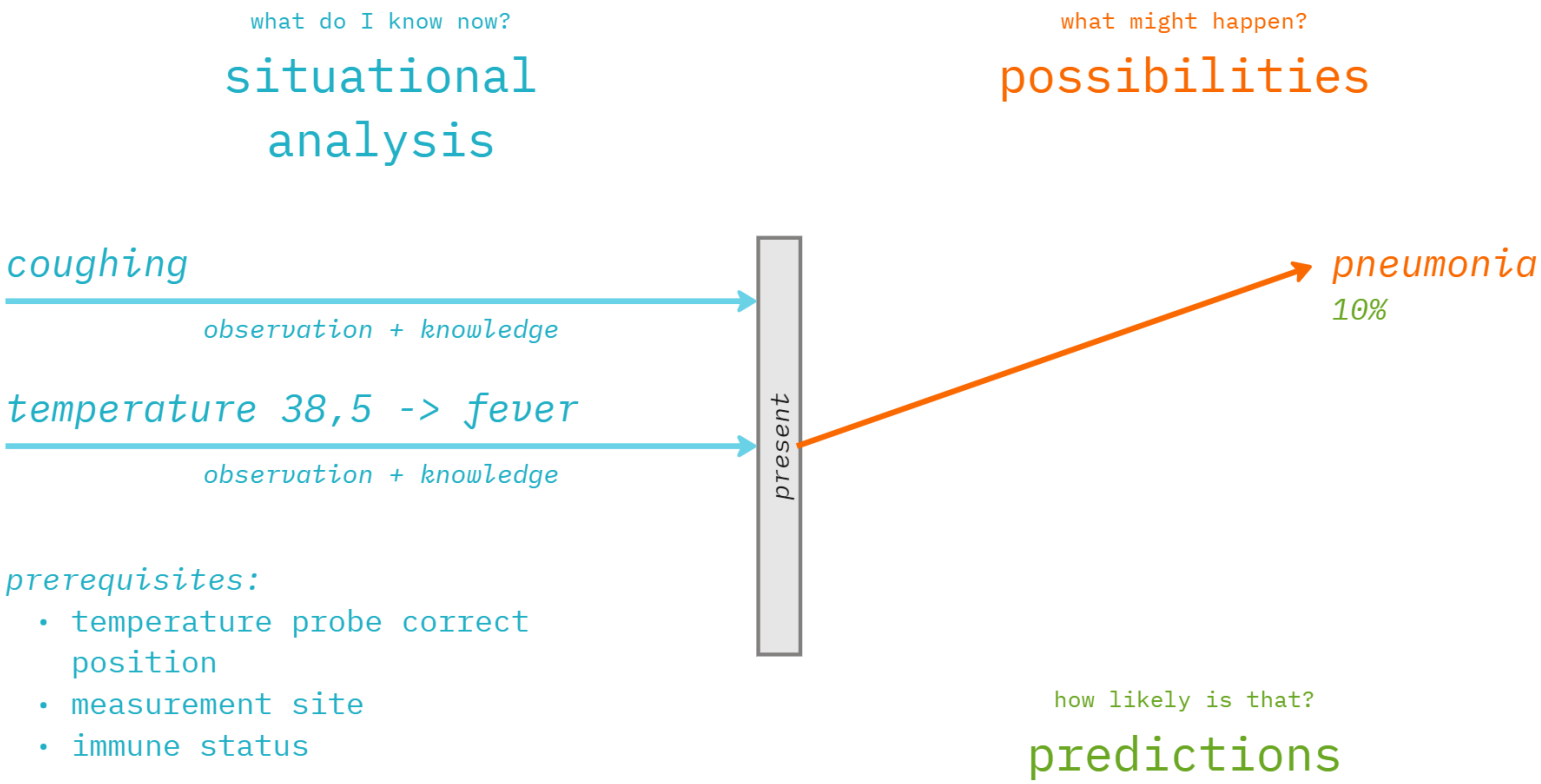
Use knowledge to think of what might be wrong…



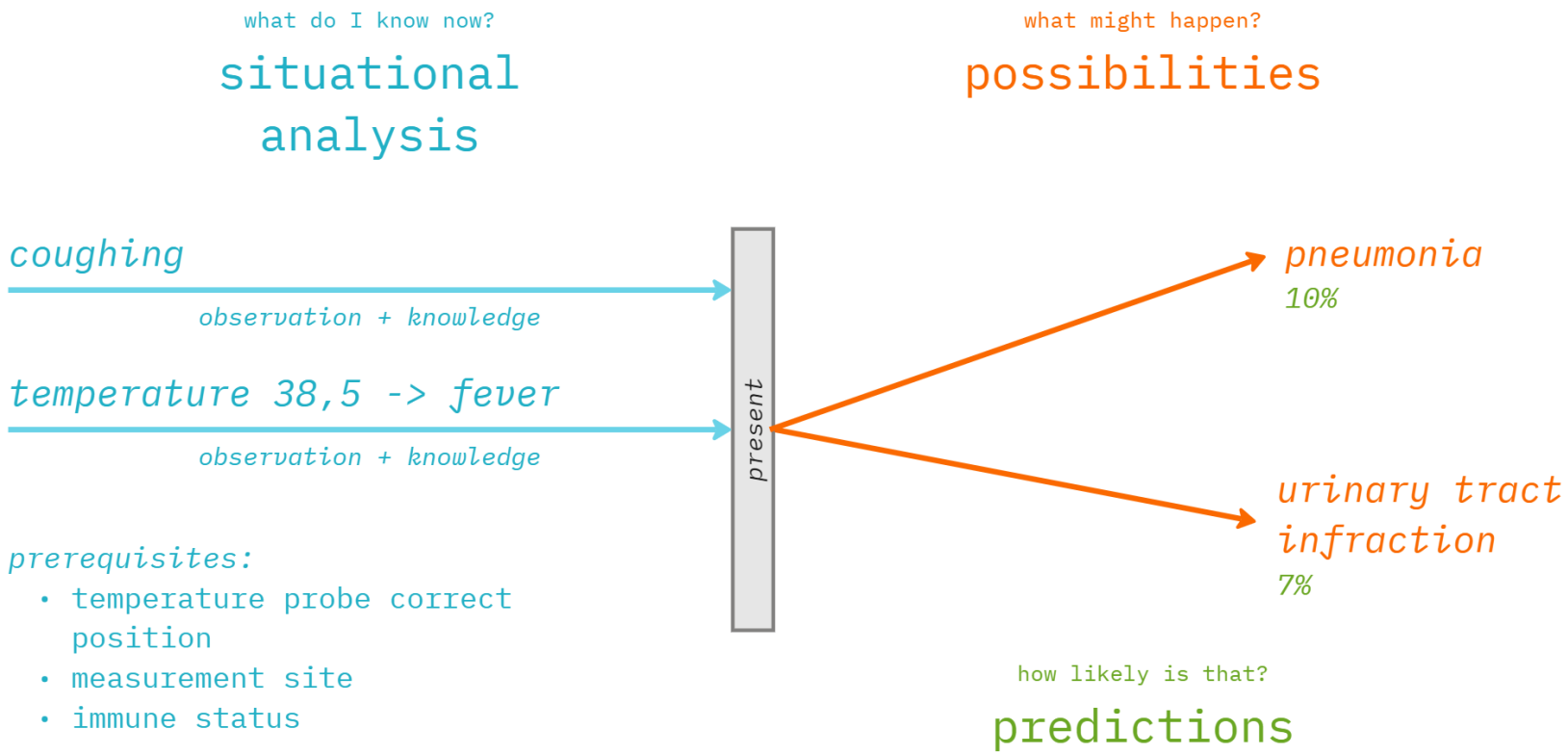
...and estimate how likely this is



...but typically it requires a lot more interpretation



...a lot of the interpretation needs to be reusable



A.I. models and their features

iScience

CellPress

Volume 26, Issue 7, 21 July 2023, 107027

Article

AI-based disease risk score for community-acquired pneumonia hospitalization

Saeed Shakibfar [1], Morten Andersen [1], Maurizio Sessa [1 2]

Study population of 620.908 individuals

735588 initial features

321 were filtered based on variance

Optimal number of features: 10

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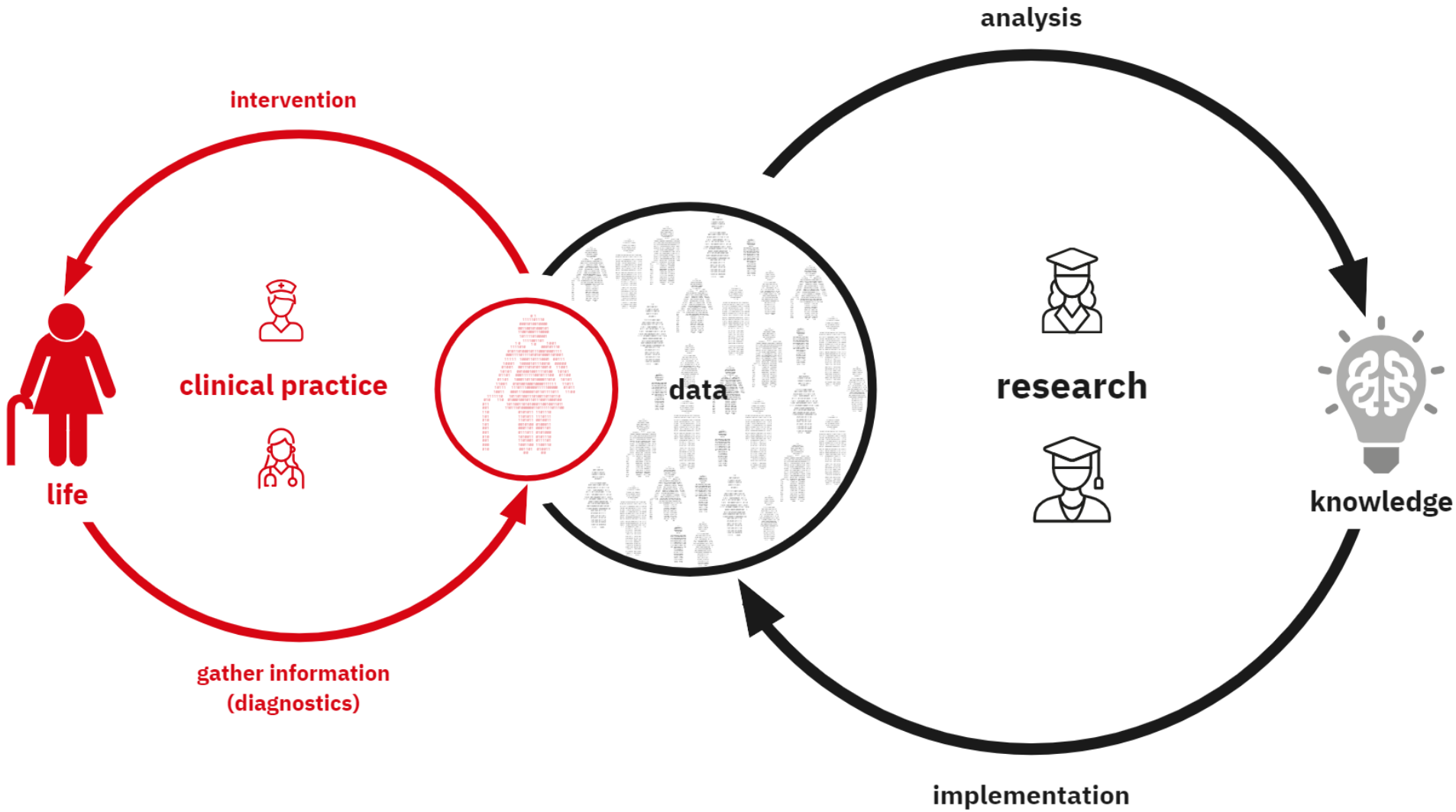
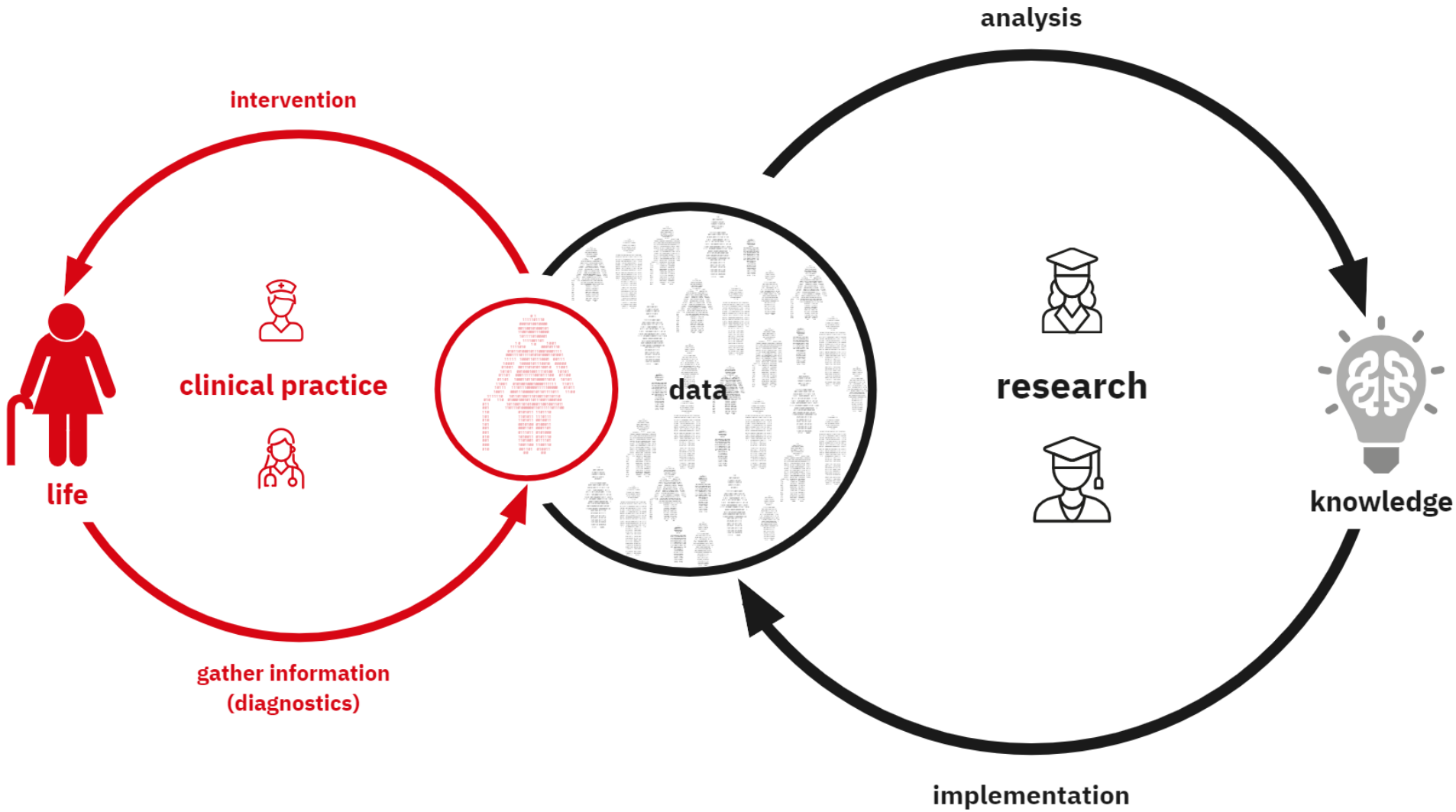
Table 3. Survey to compute the disease risk score in general practice

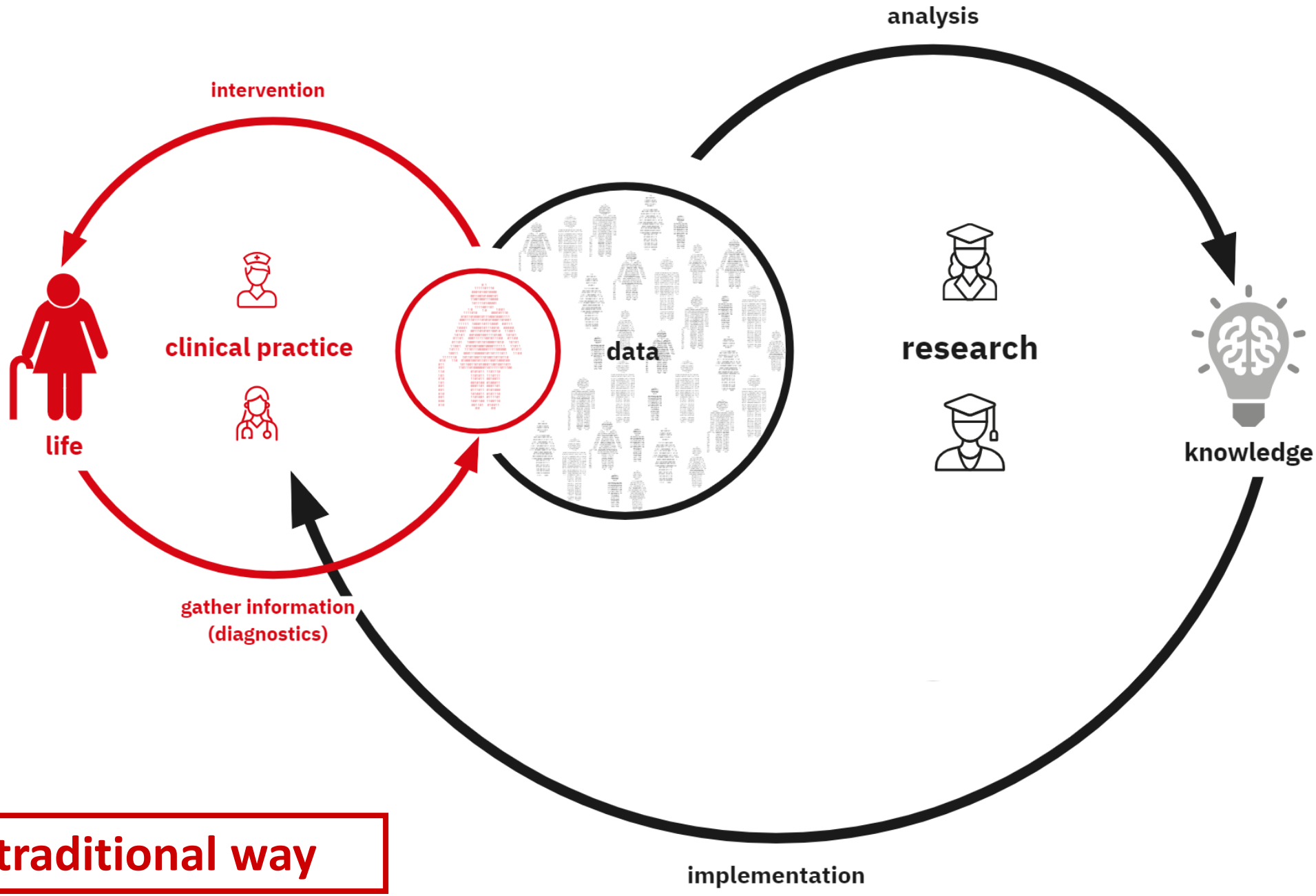
Rows	Predictors	Clinical condition to evaluate	Yes	No
1	Phenoxymethylpenicillin	Did the patient during the last 2 months require treatment with phenoxymethylpenicillin for pulmonary infection?	+4	+0
2	Prednisolone	Did the patient during the last 2 months require treatment with Prednisolone for pulmonary infection?	+3	+0
3	Furosemide	Did the patient during the last 2 months require treatment with furosemide for cardiovascular disorders?	+3	+0
4	Chronic obstructive pulmonary disease	Is the patient diagnosed with a chronic obstructive pulmonary disease?	+2	+0
5	Chronic obstructive pulmonary disease - acute exacerbation	Did the patient during the last year have a chronic obstructive pulmonary disease exacerbation?	+2	+0
6	Potassium Chloride	Did the patient during the last 2 months require treatment with potassium chloride for hypokalemia?	+2	+0
7	Paracetamol	Did the patient during the last year require recurrent treatment with paracetamol for chronic diseases?	+1	+0
8	Suspected disease or condition	Did the patient have recent hospital access for an unspecified condition of the lungs?	+1	+0
9	Roxithromycin	Did the patient during the last 2 months require treatment with roxithromycin for pulmonary infection?	+1	+0
10	Terbutaline	Did the patient during the last 2 months require treatment with terbutaline for bronchodilation?	+1	+0

Instructions: To obtain the disease risk score you should sum the value in the column "Yes" for each row where you answered yes.

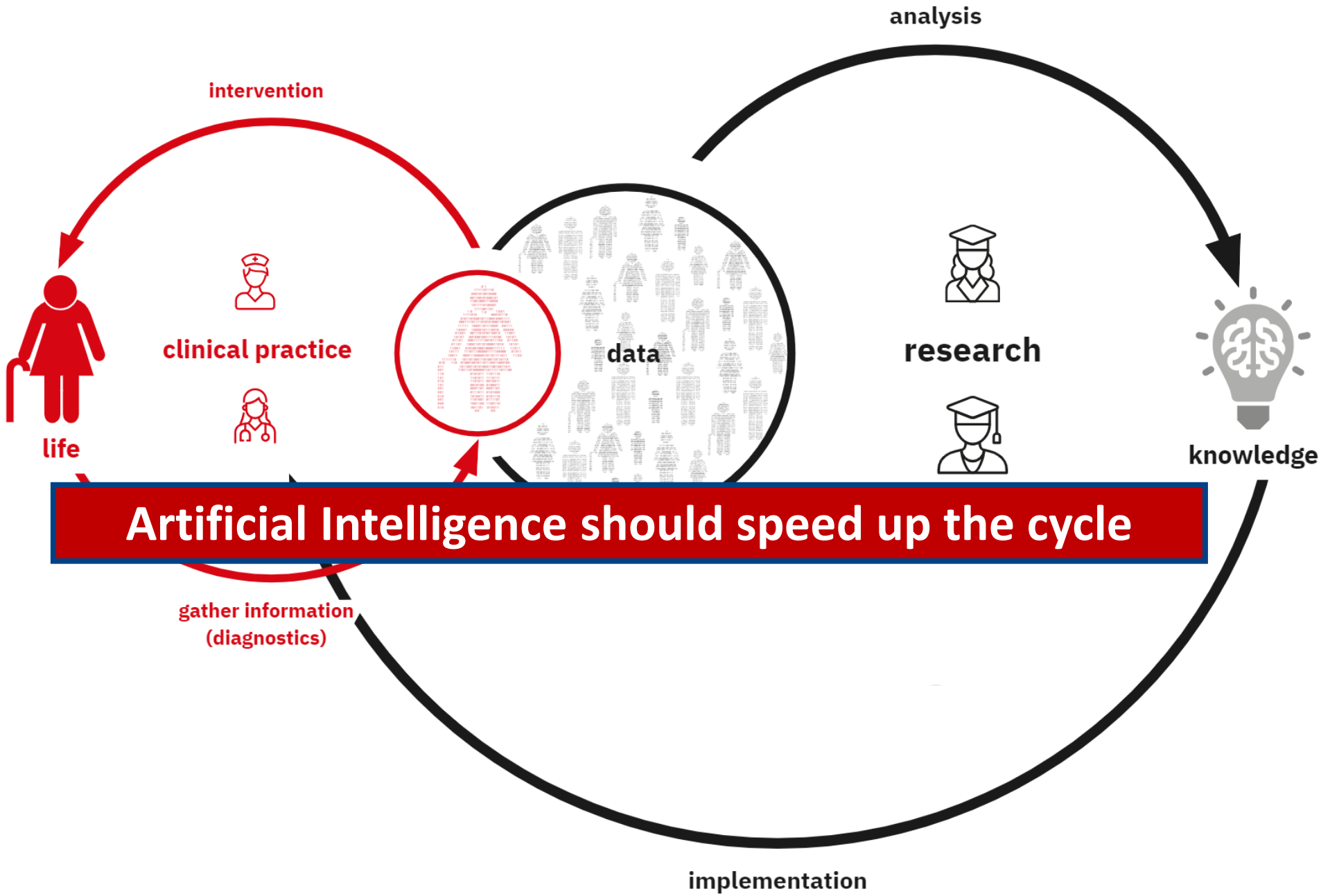

analysis
intervention
clinical practice
life
data
research
knowledge
gather information
(diagnostics)
implementation



this only seems logical:
It does not reach clinical practice



the traditional way


analysis
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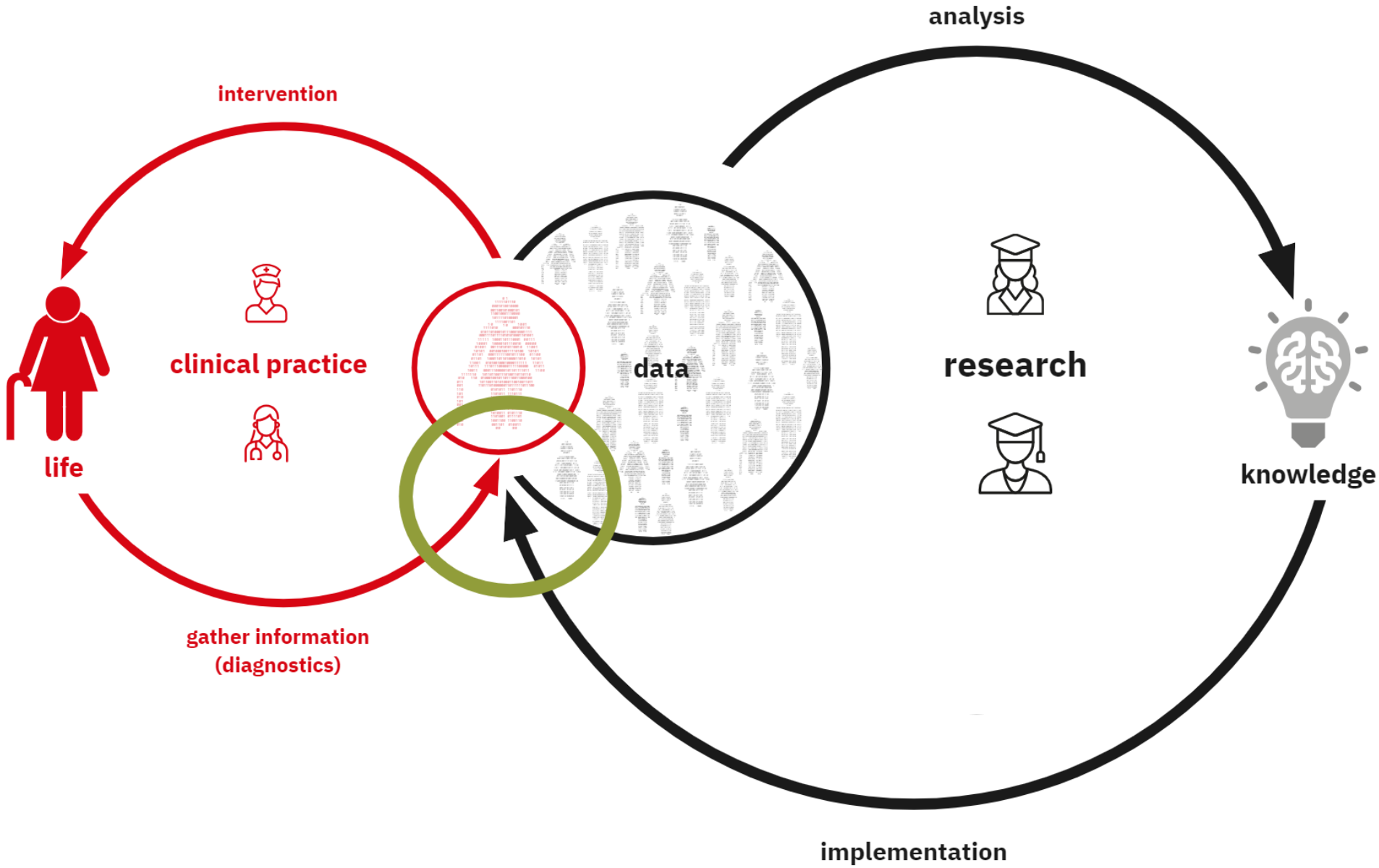
life
Artificial Intelligence should speed up the cycle
gather information
(diagnostics)
implementation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Three big problems

Getting the data

Getting the data right

Modular User Interfaces (& Authorization)

a Modular User Interface (& Authorization)

What about the front-end?

Separating the reasoning and the user interface

Link between model and user interface

Workflow: 4 levels

Role selection
Patient selection
Patient overview
Specific Modules

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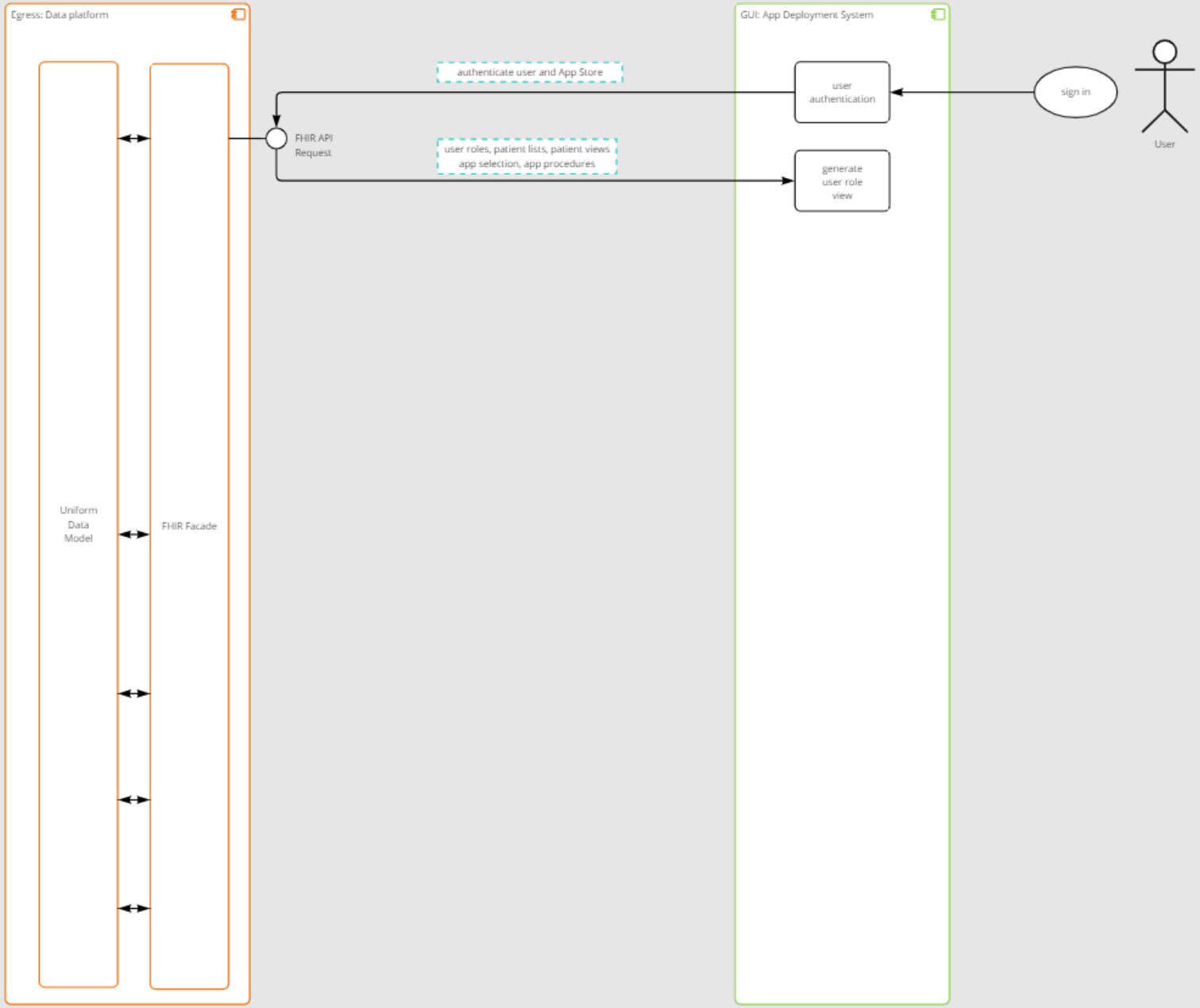
Egress: Data platform
Uniform Data Model
FHIR Facade
FHIR API Request
authenticate user and App Store
user roles, patient lists, patient views app selection, app procedures
GUI: App Deployment System
user authentication
generate user role view
sign in
User

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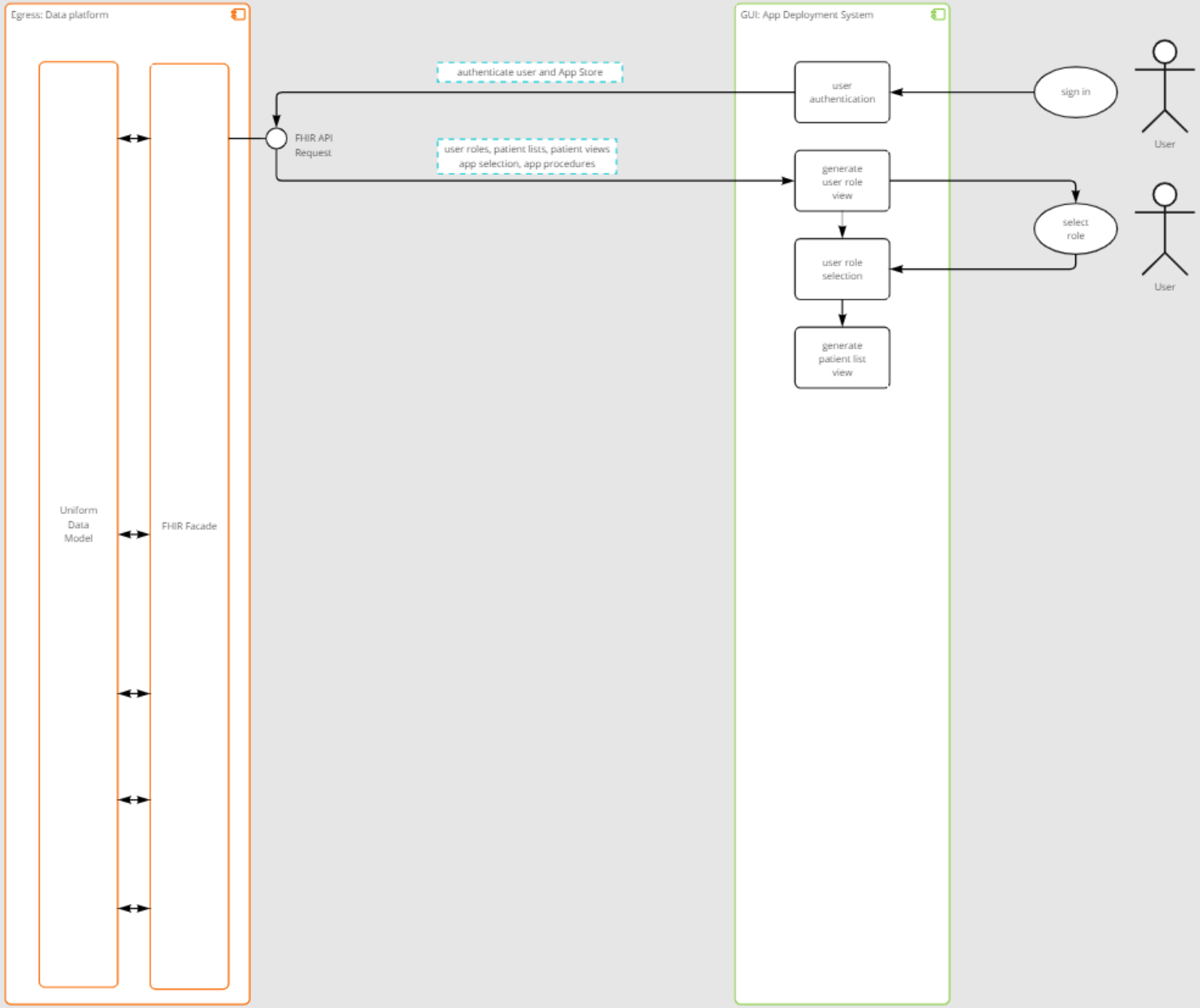
Workflow – User Interface – the Role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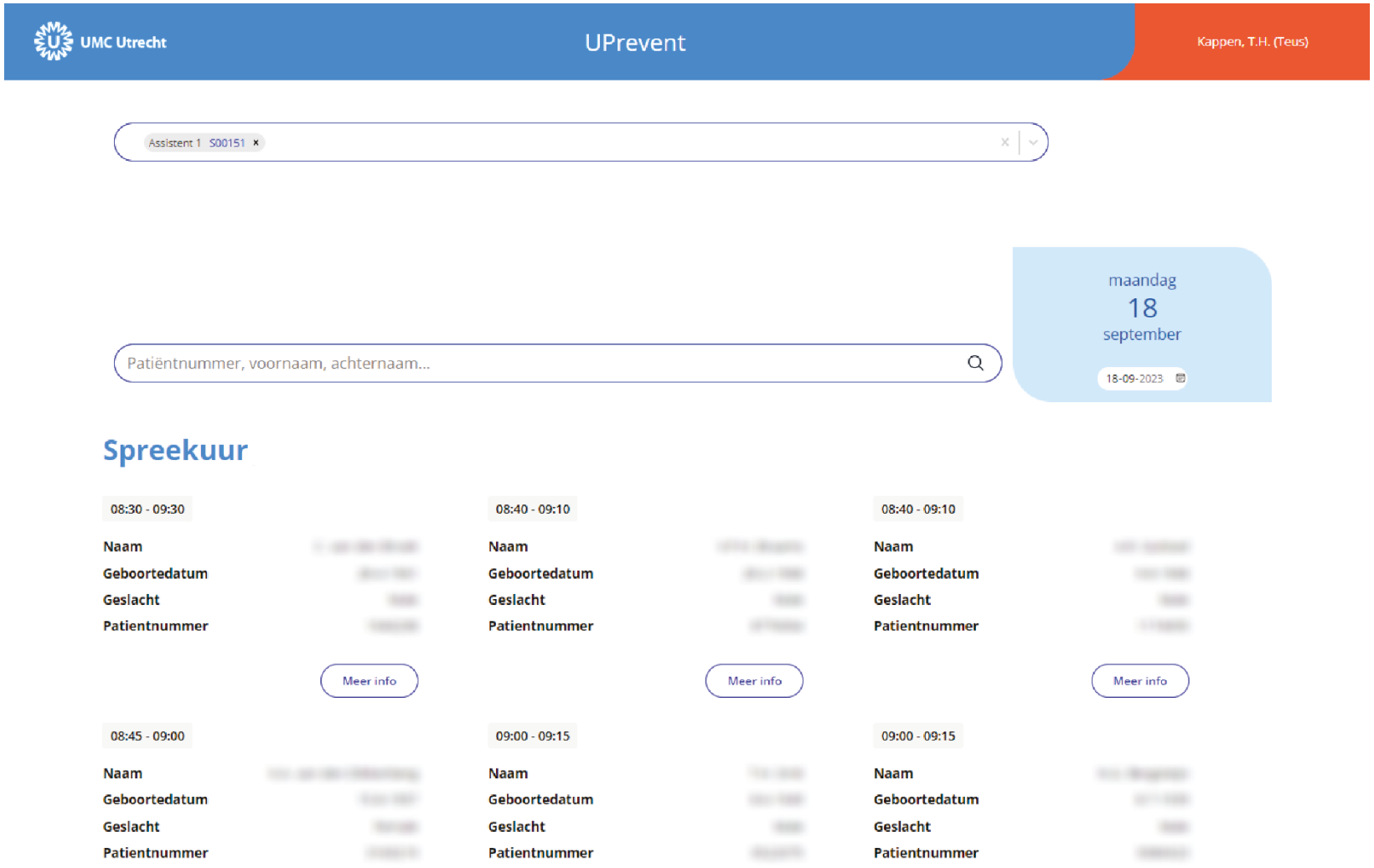
Workflow – User Interface – Patient selection



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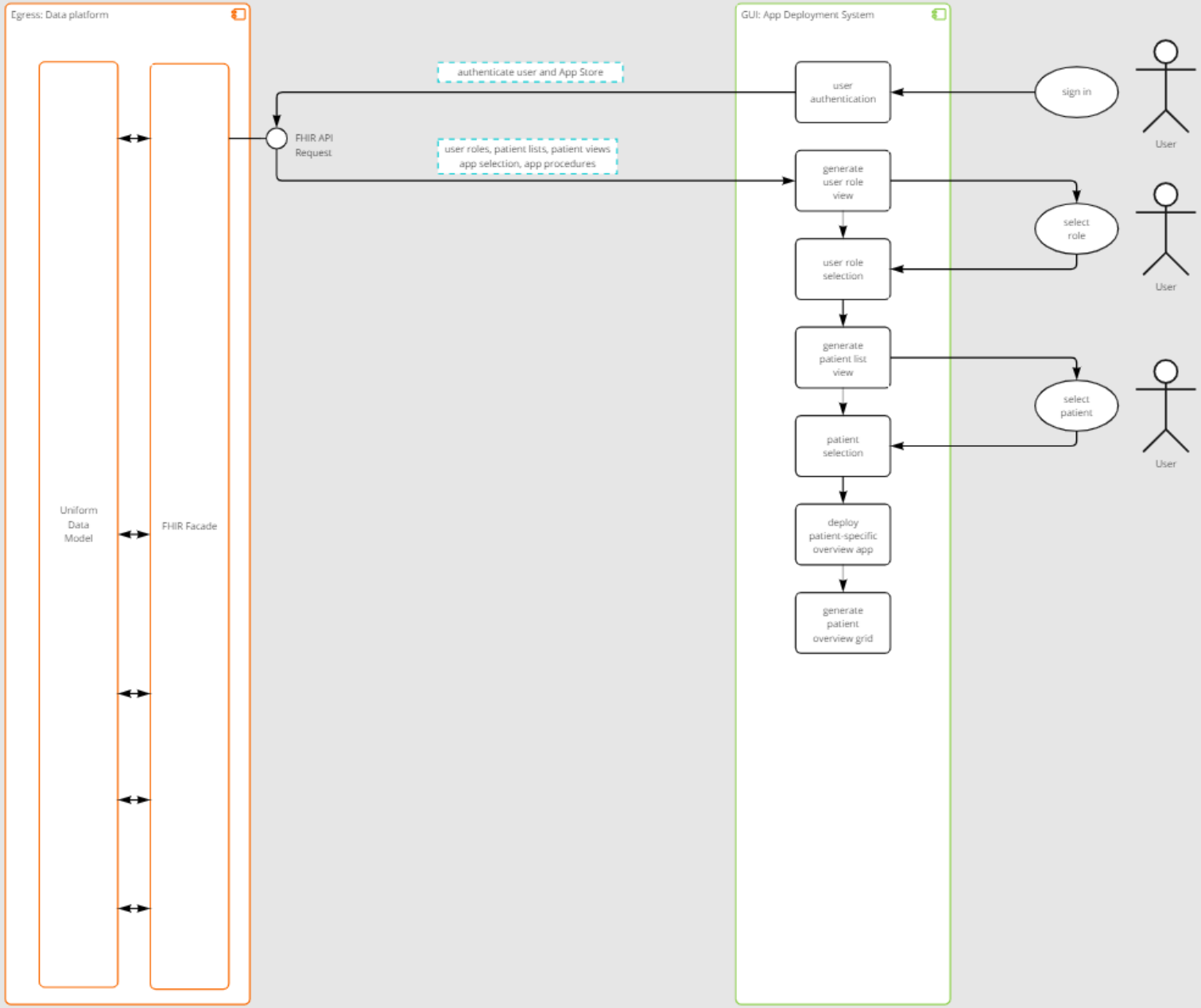
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patient selection
deploy patient-specific overview app
generate patient overview grid
sign in
select role
select patient
User
User
User

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Workflow – User Interface – Patient overview modules

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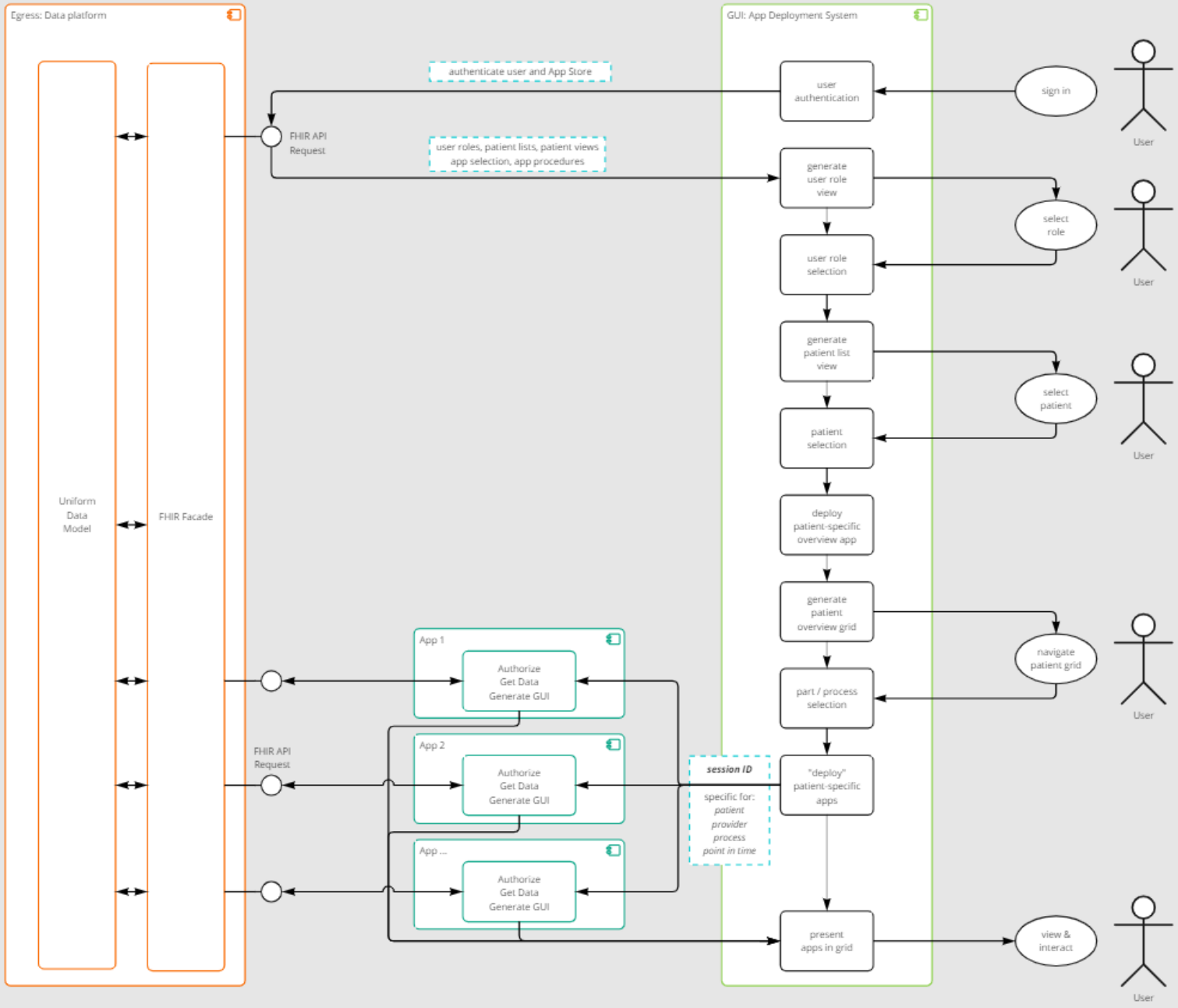
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patient selection
deploy patient-specific overview app
generate patient overview grid
navigate patient grid
part / process selection
"deploy" patient-specific apps
present apps in grid
view & interact
session ID
specific for:
patient
provider
process
point in time
App 1
Authorize
Get Data
Generate GUI
App 2
App ...

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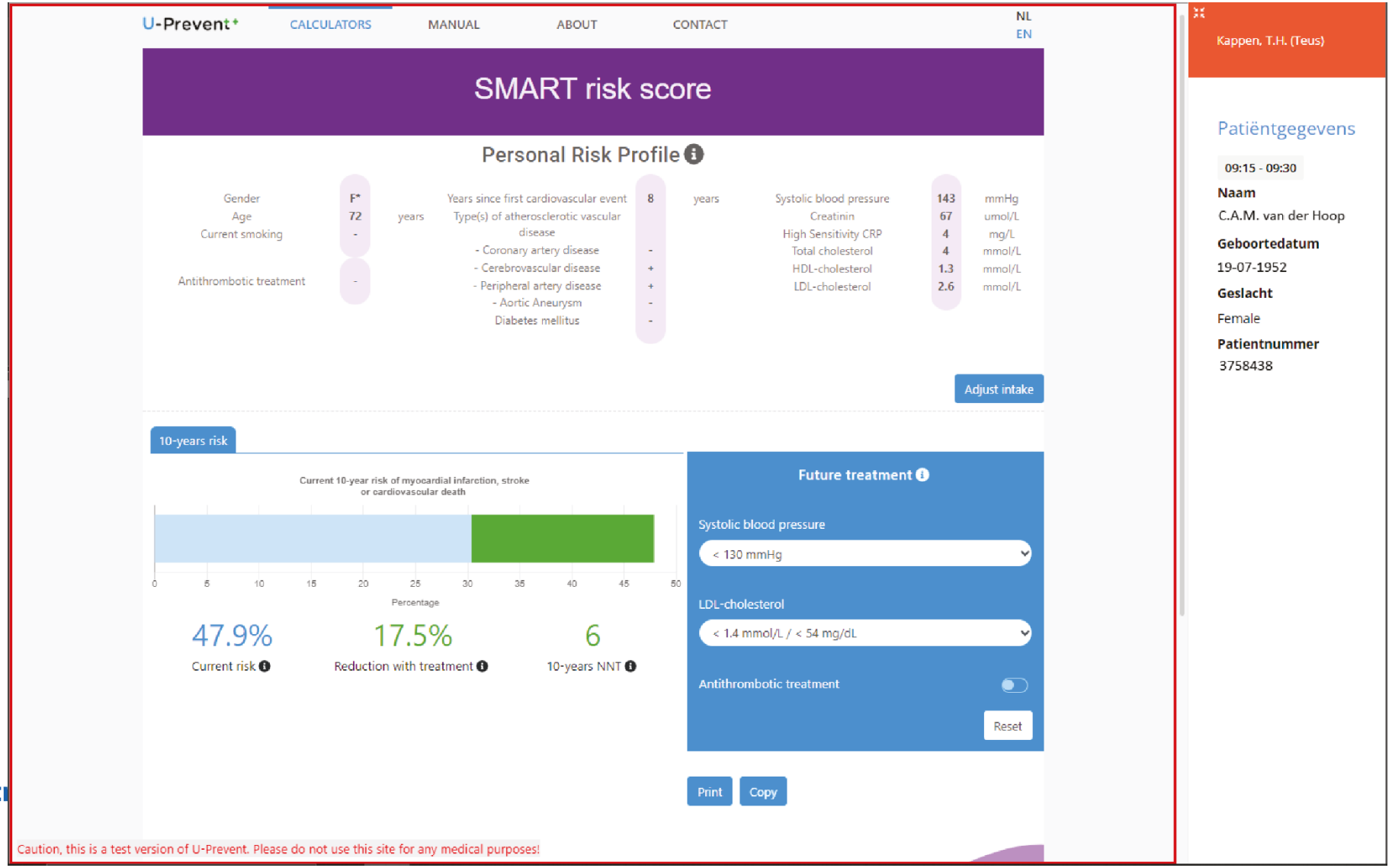
Workflow – User Interface – Specific patient modules



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Workflow: 4 levels

Role selection
Patient selection
Patient overview
Specific Modules

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Workflow: 4 levels

Role selection
Patient selection
Patient overview
Specific Modules

All levels can be modular

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Workflow: 4 levels

Role selection
Patient selection
Patient overview
Specific Modules

All levels can *should* be modular

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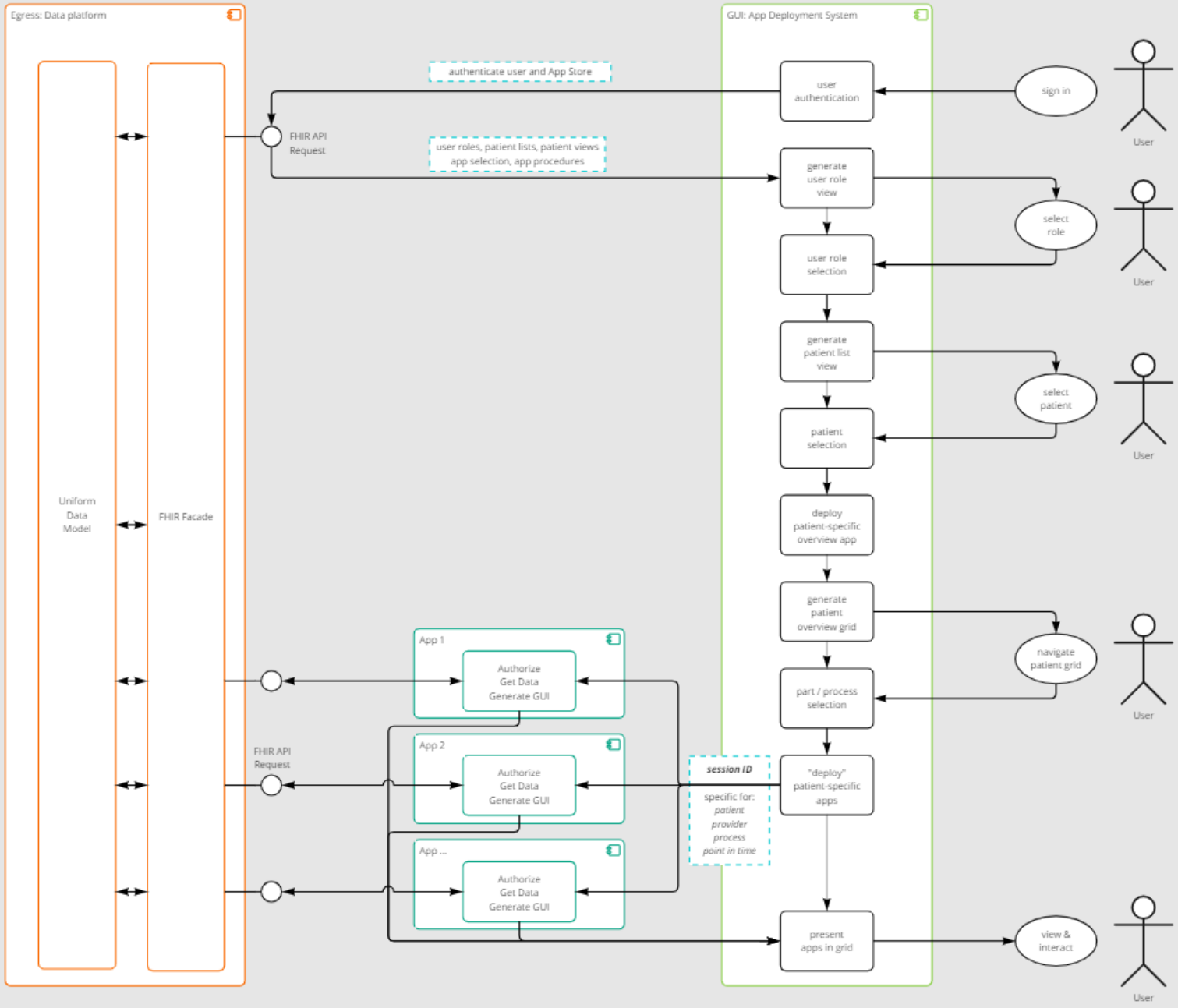
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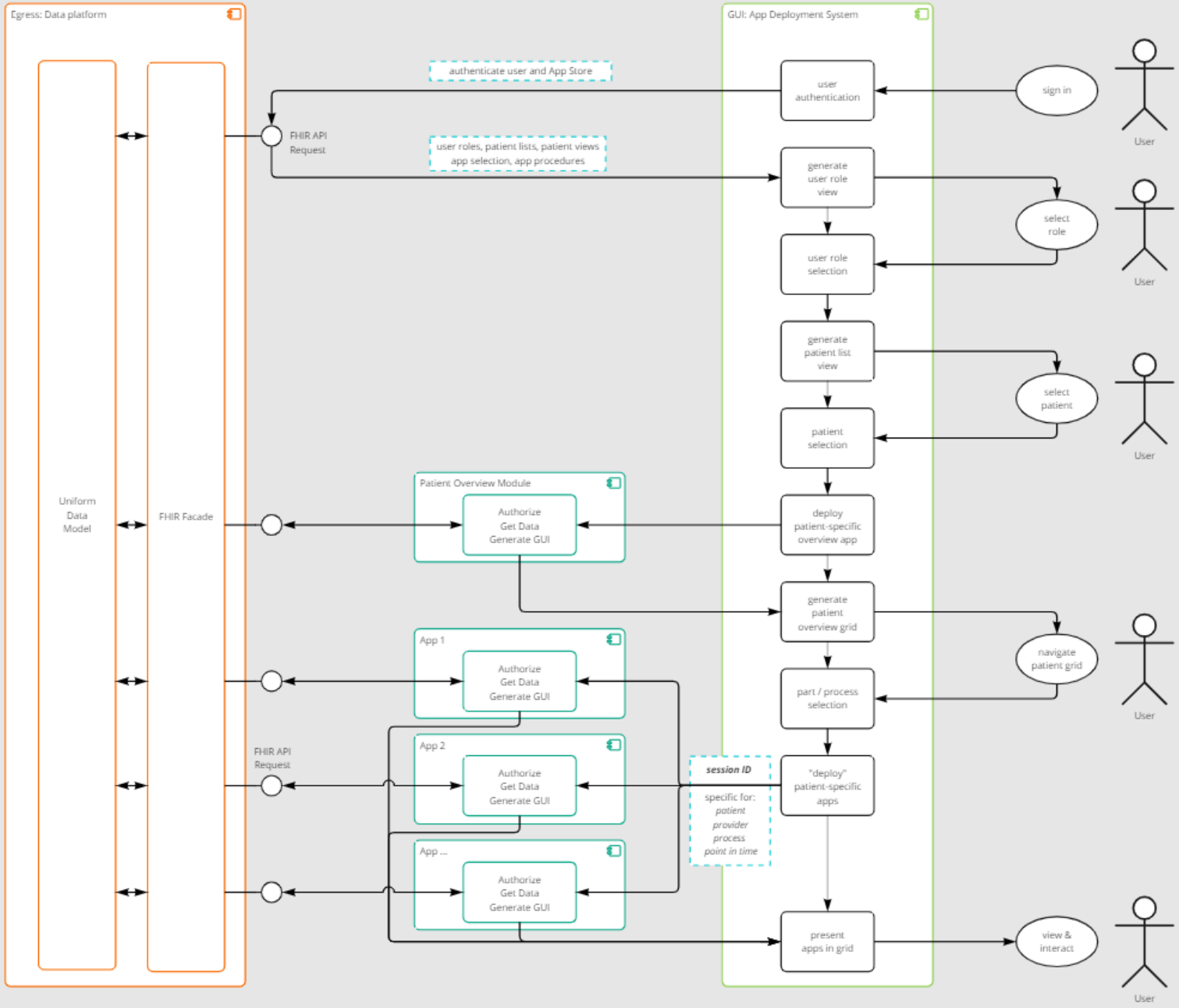
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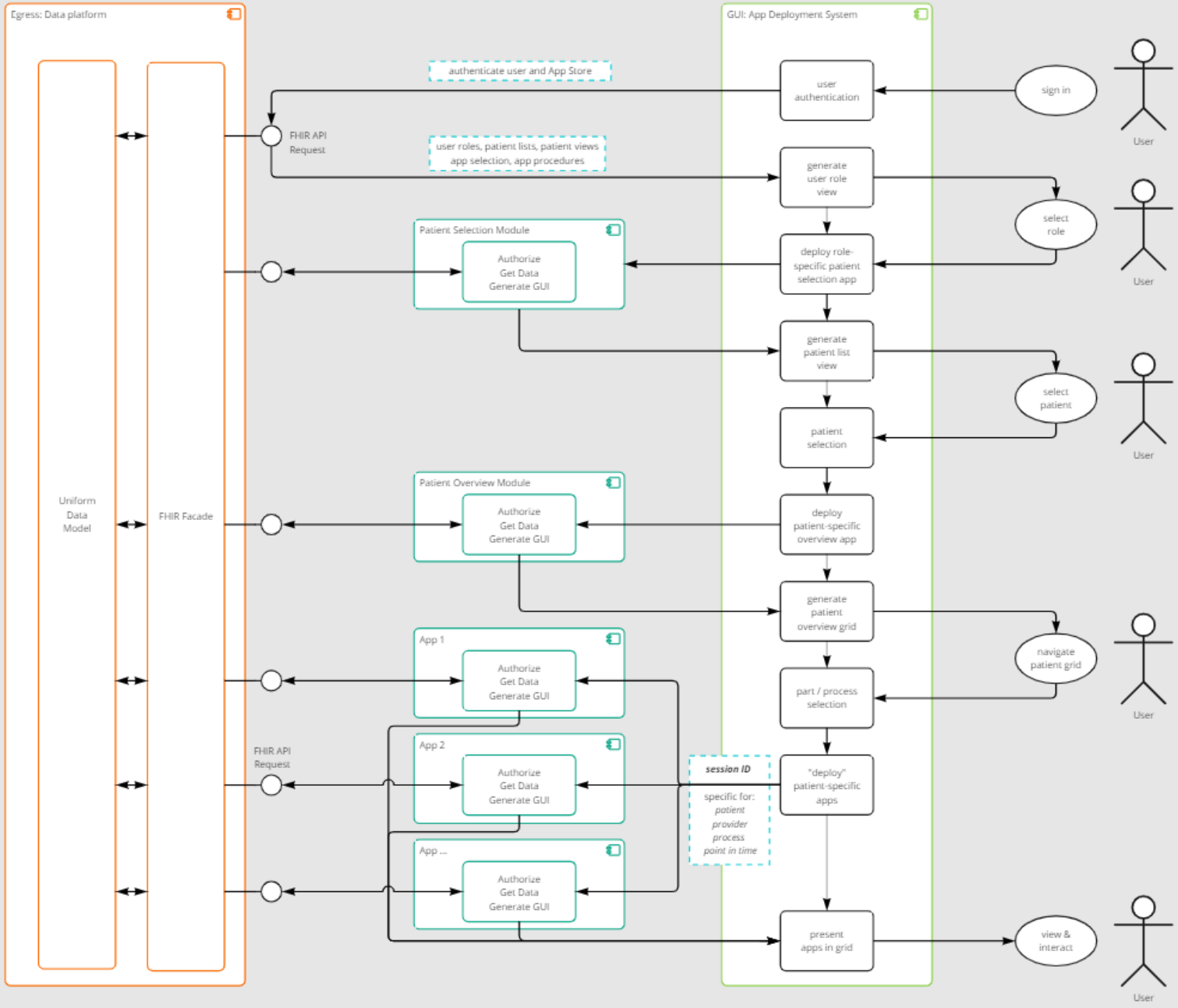
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Generate GUI
App 2
Authorize
Get Data
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App ...
Authorize
Get Data
Generate GUI
session ID
specific for:
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Het Dataplatform

Wat betekent dat voor het dataplatform?

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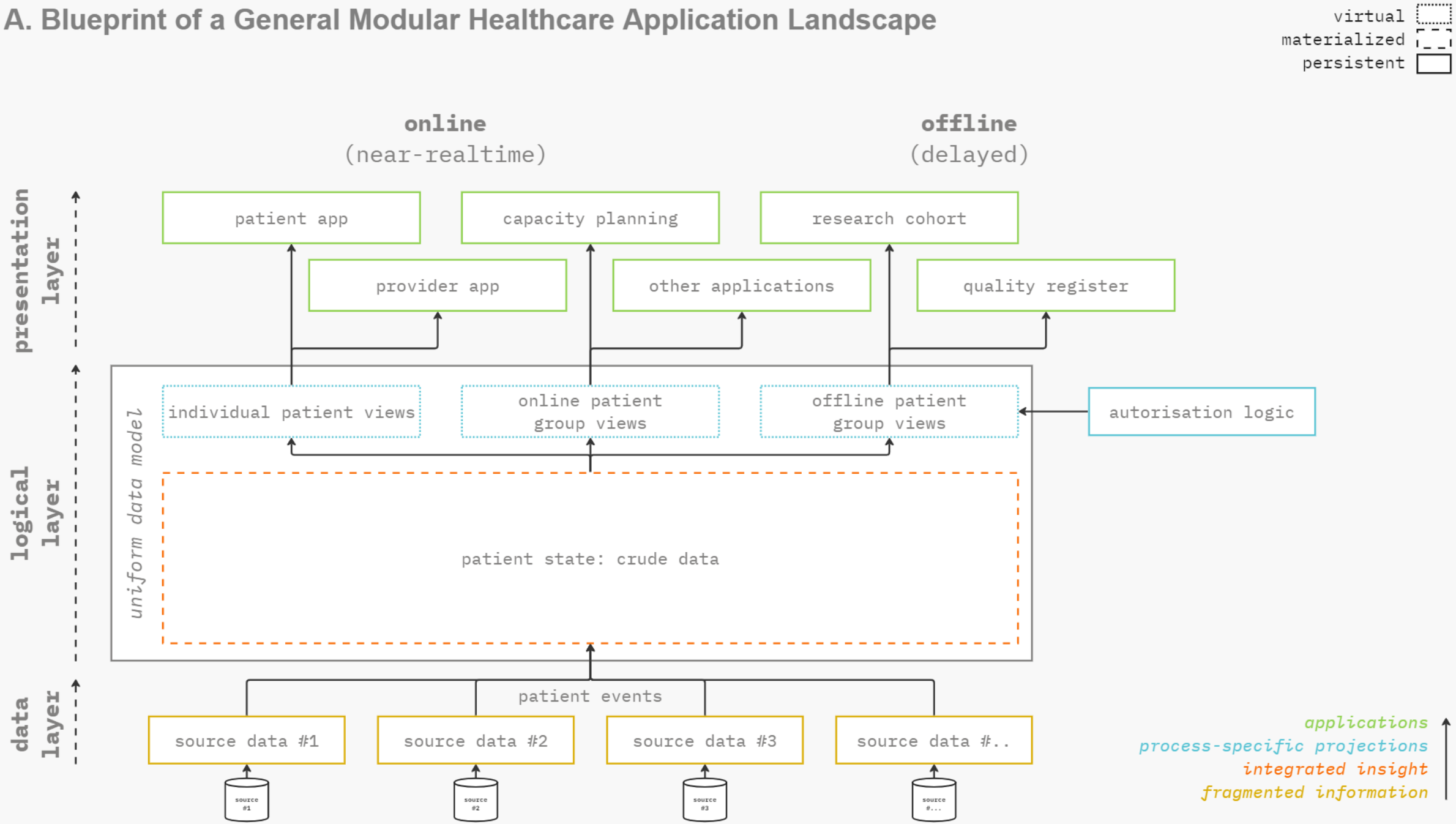
A. Blueprint of a General Modular Healthcare Application Landscape



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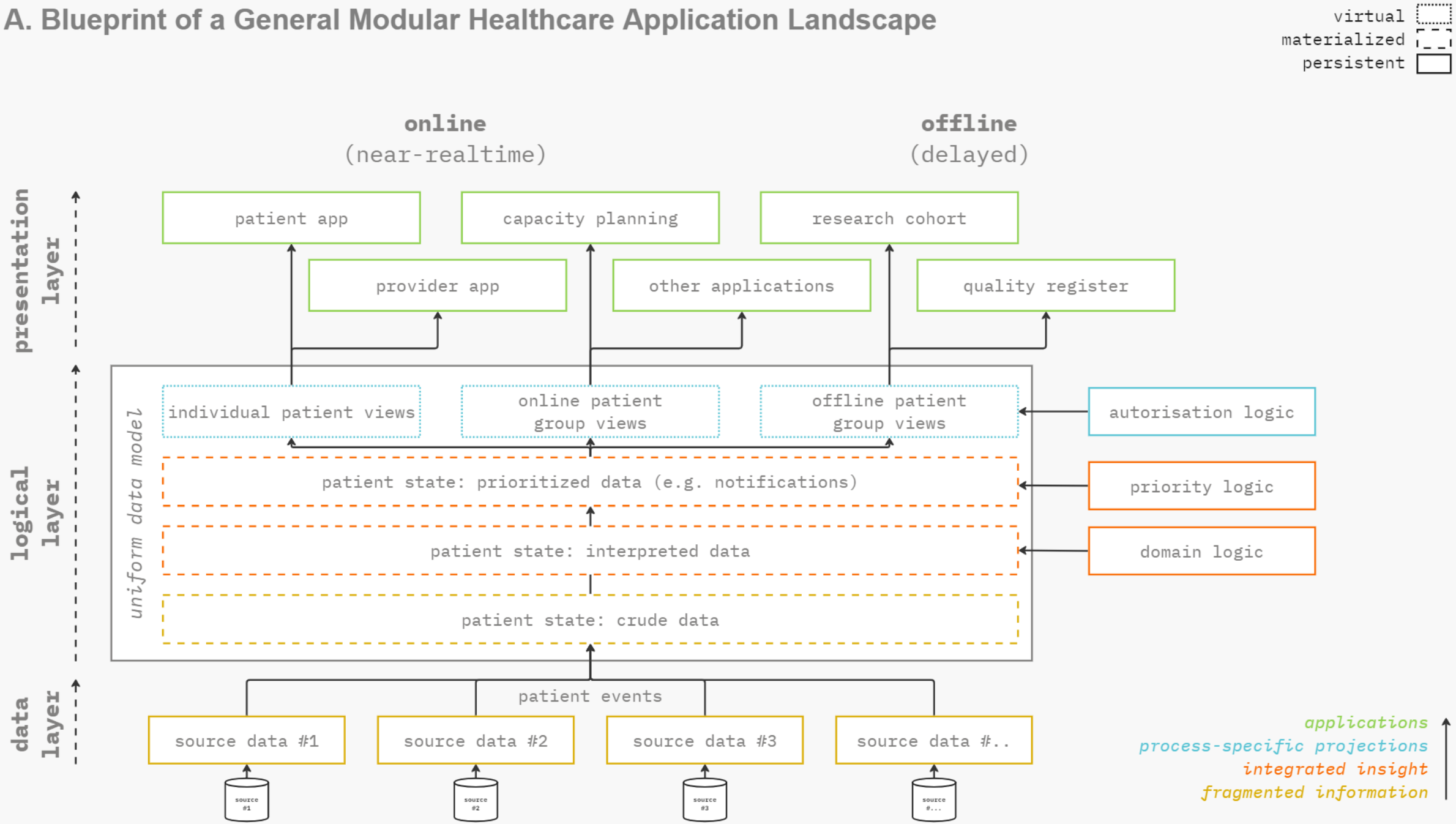

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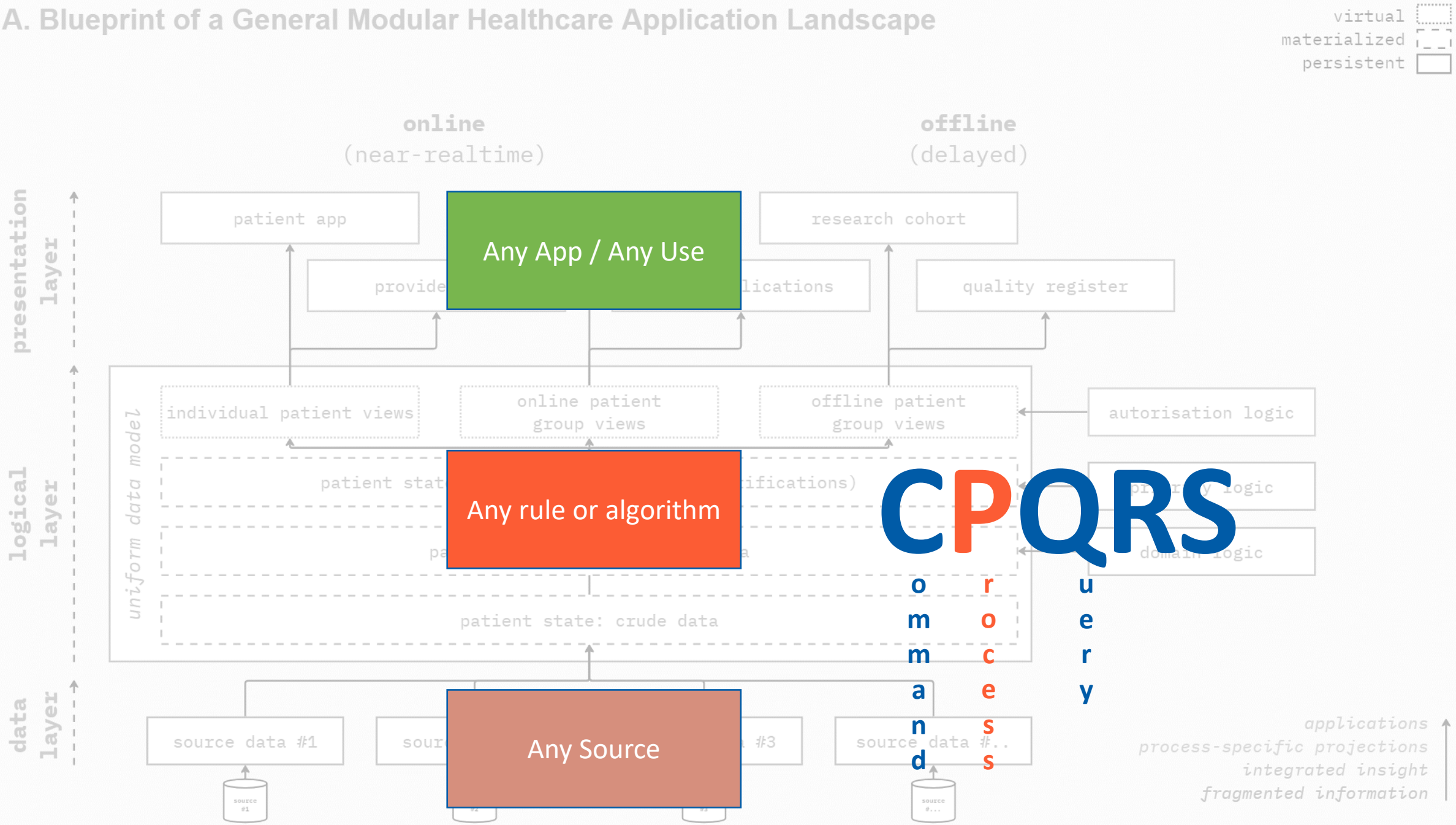

Het Dataplatform

Wat betekent dat voor deze use case?

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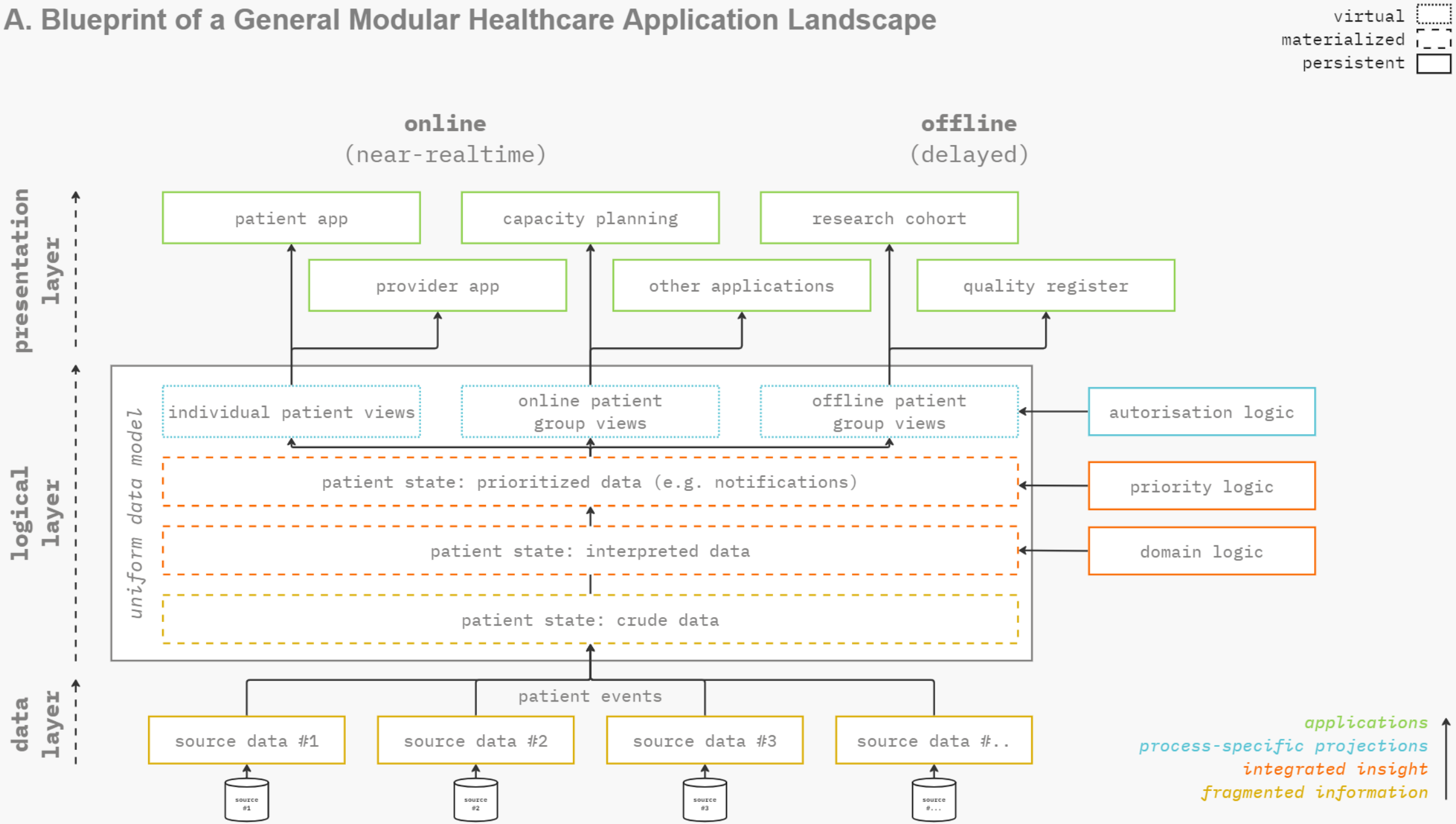

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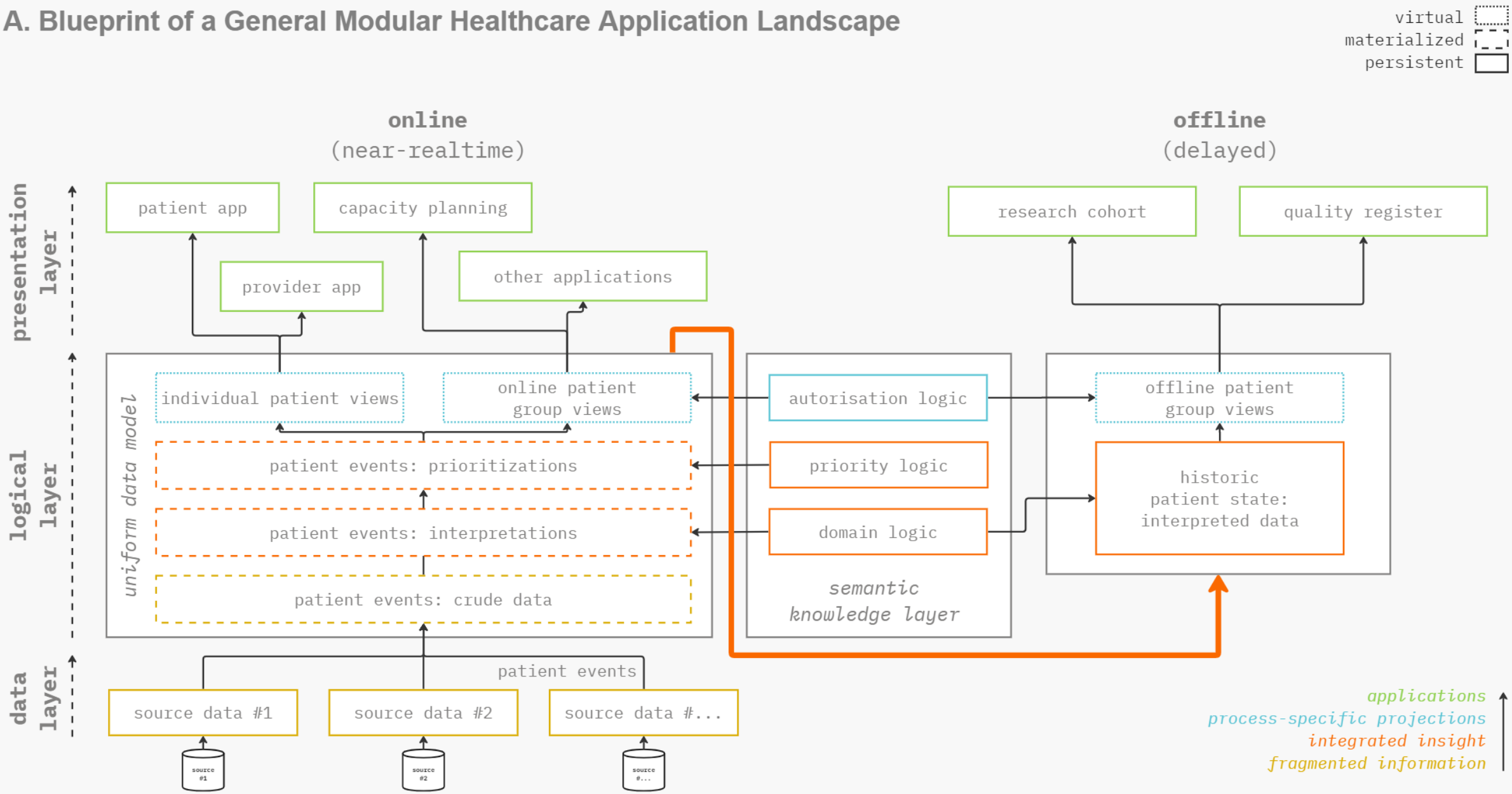

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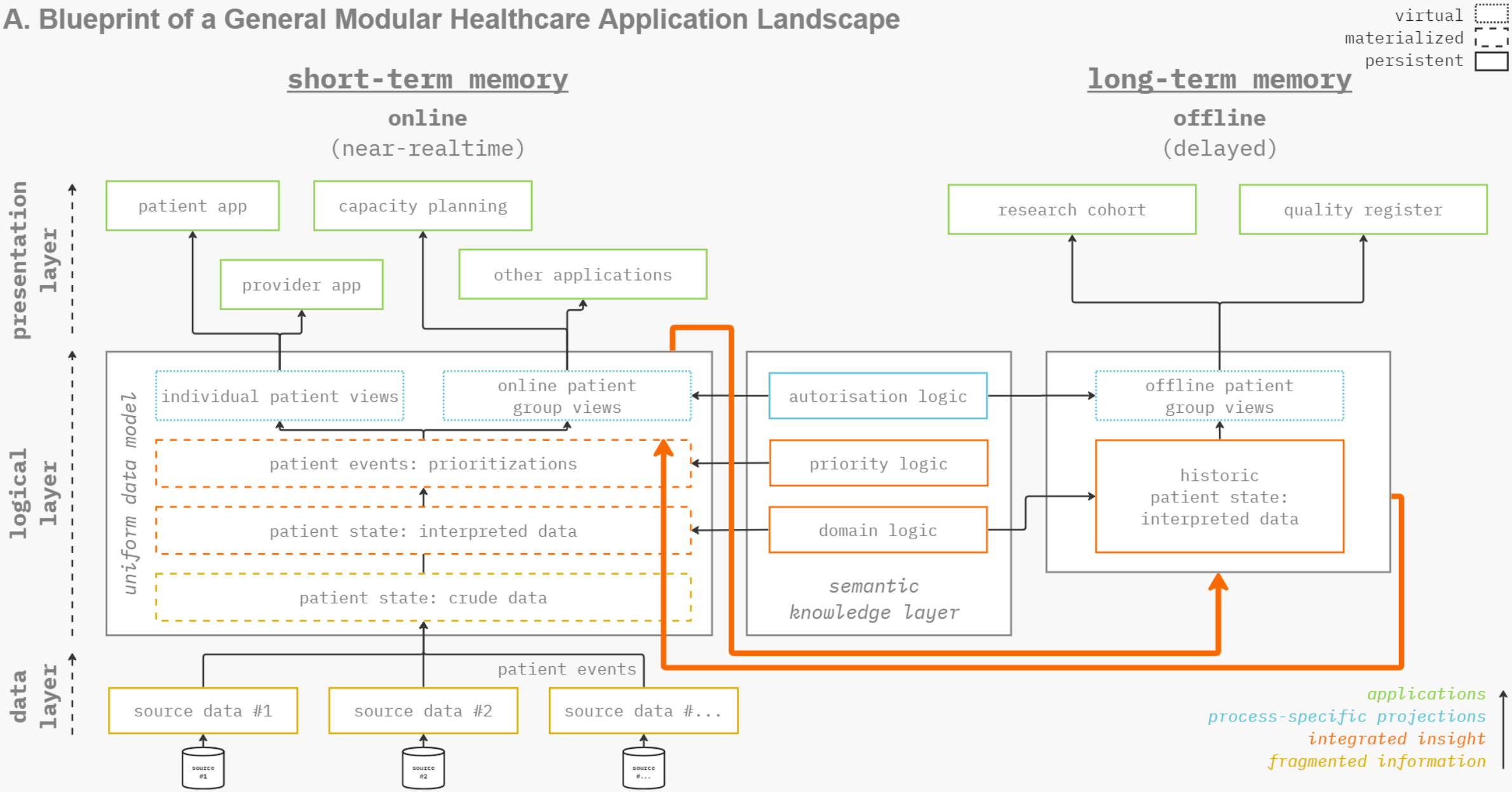
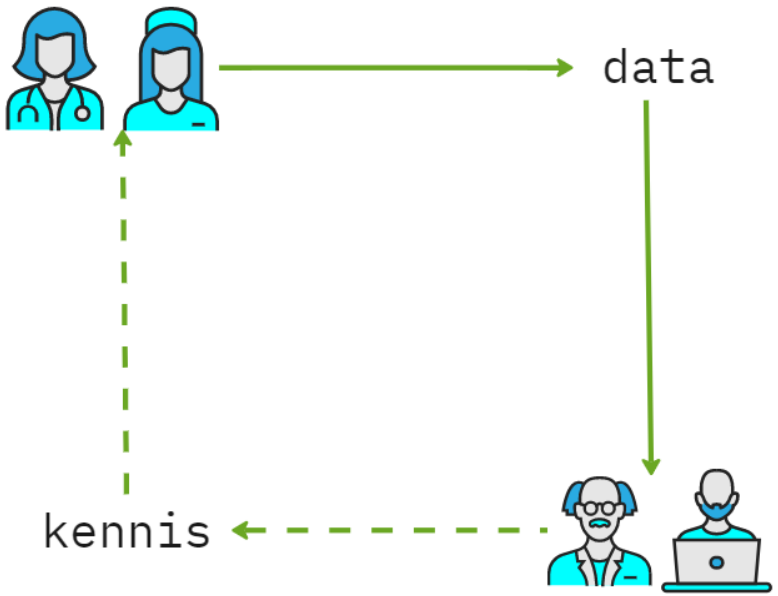


De zorg draait om data én kennis

a Knowledge-Driven Data Factory



a Data-Driven Knowledge Factory

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