



Oncovalue: Using Real-World Data for Real-World based Health Technology Assessment

Cancer Economics WG Session

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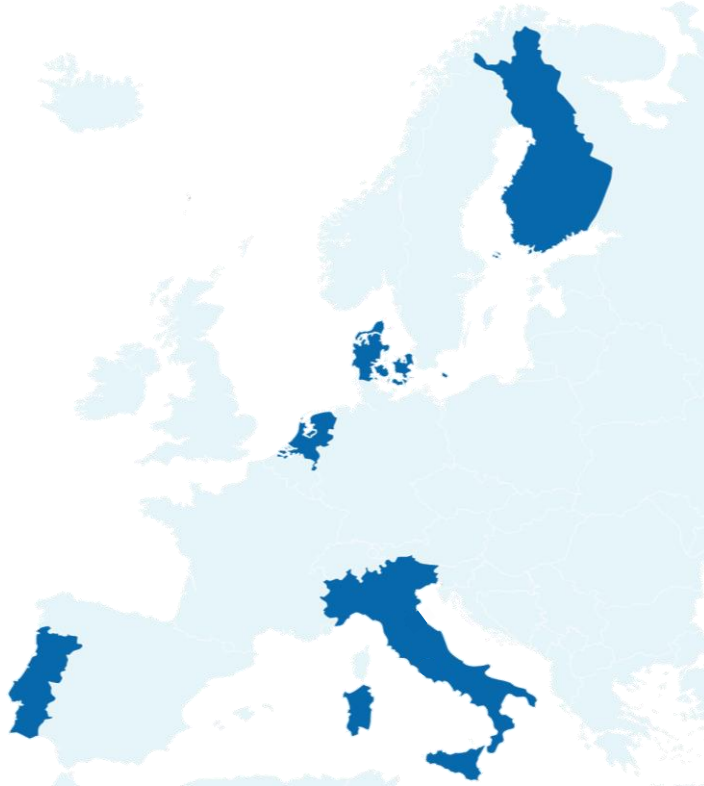
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ONCOVALUE

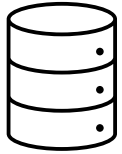
Objective: To further unlock the full potential of real-world hospital data, generated in European cancer centres, for efficient use in health technology assessments [HTAs] of novel cancer treatments.



Real-World Hospital Data



Real-World Hospital Data



Available?

Structured?

High-quality?

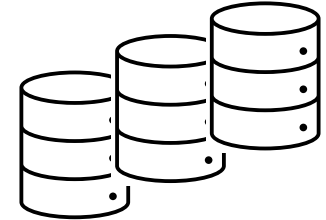
Hospitalisation due to adverse events
 Individual drug exposure Adverse events
 Dose reduction Concurrent therapy

Reason for treatment discontinuation

Patient-reported outcomes Real-world costs

Medical history Reasoning behind clinical decisions
 Previous anticancer treatment

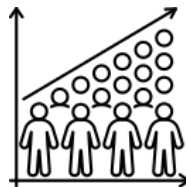
Treatment for adverse events Comorbidities



Standardised?

Interoperable?

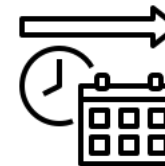
Linkage?



Generalise to the normal population



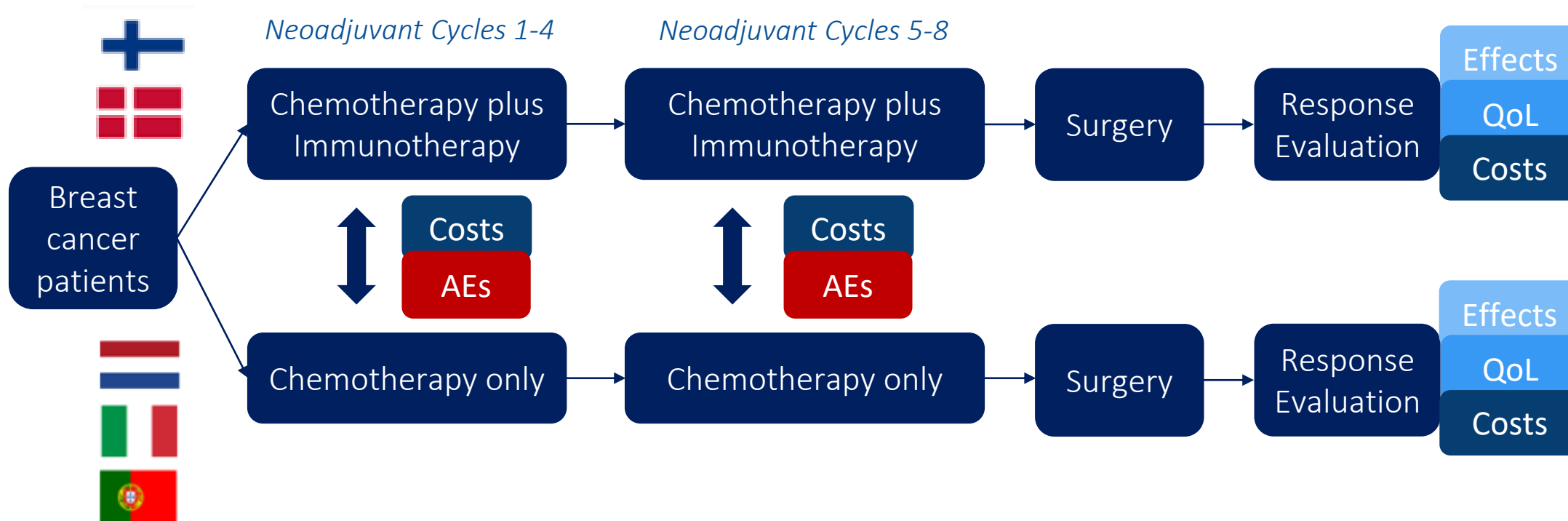
Results from clinical practice



Longer follow-up period



Health Technology Assessment

Illustrative example



ONCOVALUE output



- NLP-tool to structure free text 
- AI-tool to quantify tumour growth 



- Federated analysis infrastructure 



- Mapping data to the OMOP Common Data Model 



- Hospital RWD-based HTA framework



Main questions

1

What is the **current status** of real-world hospital data integration in Europe?

2

What **challenges and issues** arise when working with real-world hospital data?

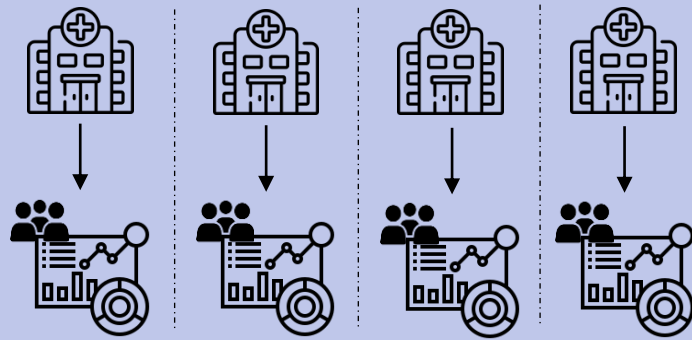
3

What **improvements** are needed to advance the use of hospital data for HTAs?

ONCOVALUE feasibility study

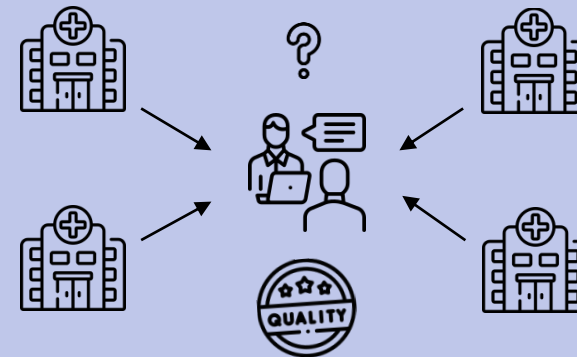
Objective: To investigate the **quality** and **suitability** of real-world hospital data to conduct an HTA of neoadjuvant therapies for early breast cancer patients treated between 2015 and 2023.

Retrospective Cohort Study



*Monocenter study
separately in each clinical center*

Semi-Structured Interviews



*Multicenter study
interviews with each clinical center*

Retrospective cohort study data

1. Baseline Characteristics

Demographics

Clinical (General)

- Performance status
- Anthropometric measures
- Comorbidities
- Medication use

Cancer-specific

- Risk factors
- Hereditary predisposition
- Previous anticancer treatment
- Tumour (sub)type
- Pathology-specific criteria
- Staging at diagnosis
- Biomarker analyses
- Metastases

2. Comparators

Neoadjuvant systemic therapy

- Types of medication given
- Dosage amount/form
- Length/number of cycles
- Start/end dates

Surgery

- Type of breast cancer surgery
- Date of surgery

Radiotherapy

- Type of radiotherapy
- Start/end dates

General considerations

- Treatment discontinuation

3. Outcomes & Endpoints

Tumour-related and survival

- Partial/complete response
- Stable/progressed disease
- Local/regional/metastatic recurrence
- Death

Treatment-related and safety

- Adverse events

Patient-reported outcomes

- Quality of Life questionnaires

Costs

- Diagnostic tests
- Follow-up related checkups
- Procedures
- Medications
- Hospitalization

Semi-structured interviews

Participating centers



Methods



The ISPOR EHR Data Suitability Framework and SUITED Checklist¹.



Targeted literature review for data integration concepts and definitions.



Flowcharts of the hospital data architecture and pipeline across centres.

EHR-Derived Data Suitability for HTAs

EHR-Derived Data Characterization

- Characteristics
- Provenance
- Governance

EHR-Derived Data Fitness-for-purpose

Data Reliability

- Completeness
- Accuracy

Data Relevance

- Data content
- Care Settings & Time Period
- Sample Size & Follow-up Period

Preliminary results

Clinical information systems

Clinical information systems of ONCOVALUE centres differ considerably in terms of **architecture** and **maturity**.

- Most centres ($n = 5$) employ **data warehouses** and **repositories** containing structured and modelled data.
- Some centres ($n = 4$) (plan to) build **data lake(house)s** where all (un)structured data are integrated with improved quality and data linkage.
- Some centres ($n = 4$) build an **OMOP database** and ($n = 1$) **federated data infrastructure**.

Heterogeneity in system architecture and maturity affects the availability, quality and fitness-for-purpose of data.

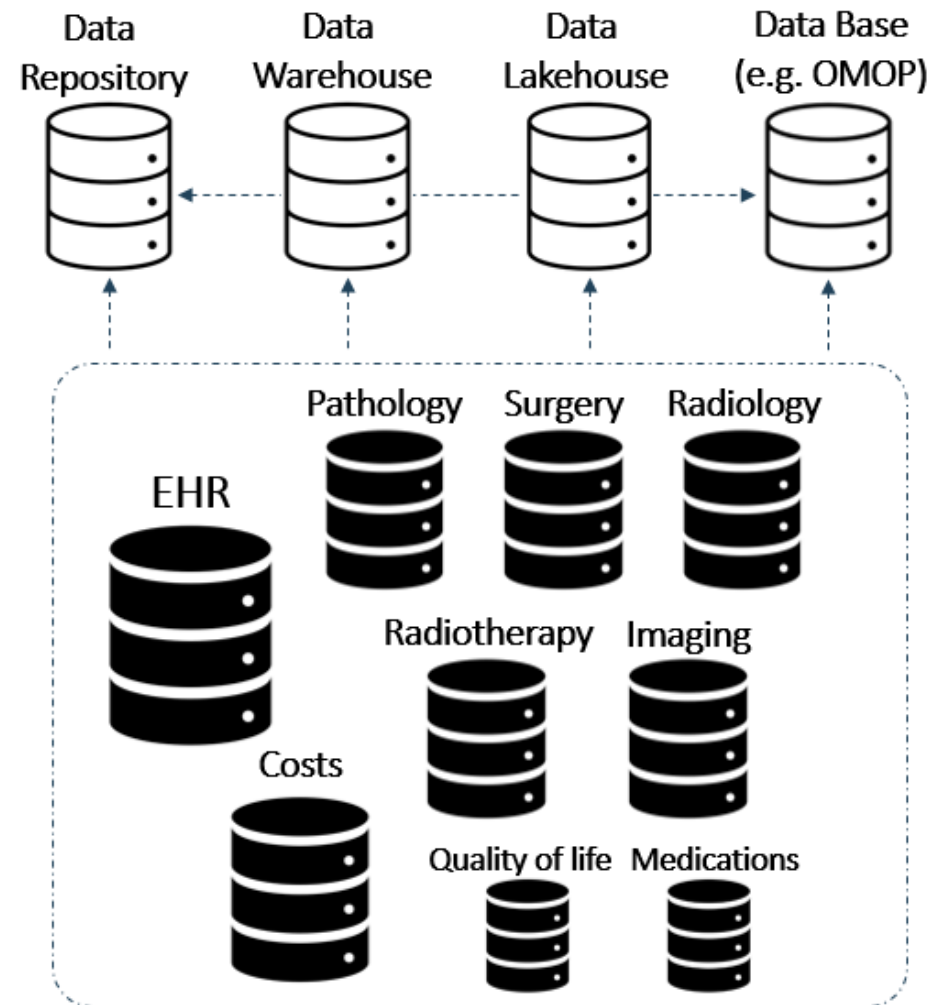


Figure. Example of clinical information system architecture

Preliminary results

Data availability

Table. Breast cancer **data availability** for a selection of data blocks.

	Hospital A	Hospital B	Hospital C	Hospital D
Demographics	●	●	●	●
Tumour characteristics	●	●	●	●
Neoadjuvant therapy	●	●	●	●
Survival	●	●	●	●
Adverse events	●	●	●	●
Costs	●	●	●	○
PROMS / QoL	●	●	●	○

Generally collected
 Partially collected
 Not collected

Data availability varies over time, patient groups, and data domains.

- Lack of data for earlier years and for patients coming from or moving to other care centres.
- Only proxies or partial collection for certain variables (e.g. severe adverse events).
- Quality of life and real-world costs not collected or accessible in multiple centres.

Multiple centres are reforming their data collection (e.g. adverse event forms, QoL questionnaires).

Preliminary results

Data structure

Often multiple sources (e.g. EHR fields, forms, reports, notes) are needed to derive one variable of interest.

- Various ways in which clinicians denote variable outcomes complicate data processing.
- Data managers and researchers do manual processing using complex logic and interpretation.

Next generation NLP tools seek to derive data from heterogeneous clinician notes and reports.

Table. Breast cancer [data structure](#) for a selection of variables.

	Hospital A	Hospital B*	Hospital C
Breast cancer diagnosis	●	●	●
Performance status	●	●	●
ER-/PR-/HER2-status	●	●	●
Tumor grade	●	●	●
Pathological response	●	●	●
Residual cancer burden	●	●	●
Death	●	●	●

* NLP tool in use



Structured



Semi-structured



Unstructured

Preliminary results

Data processing steps

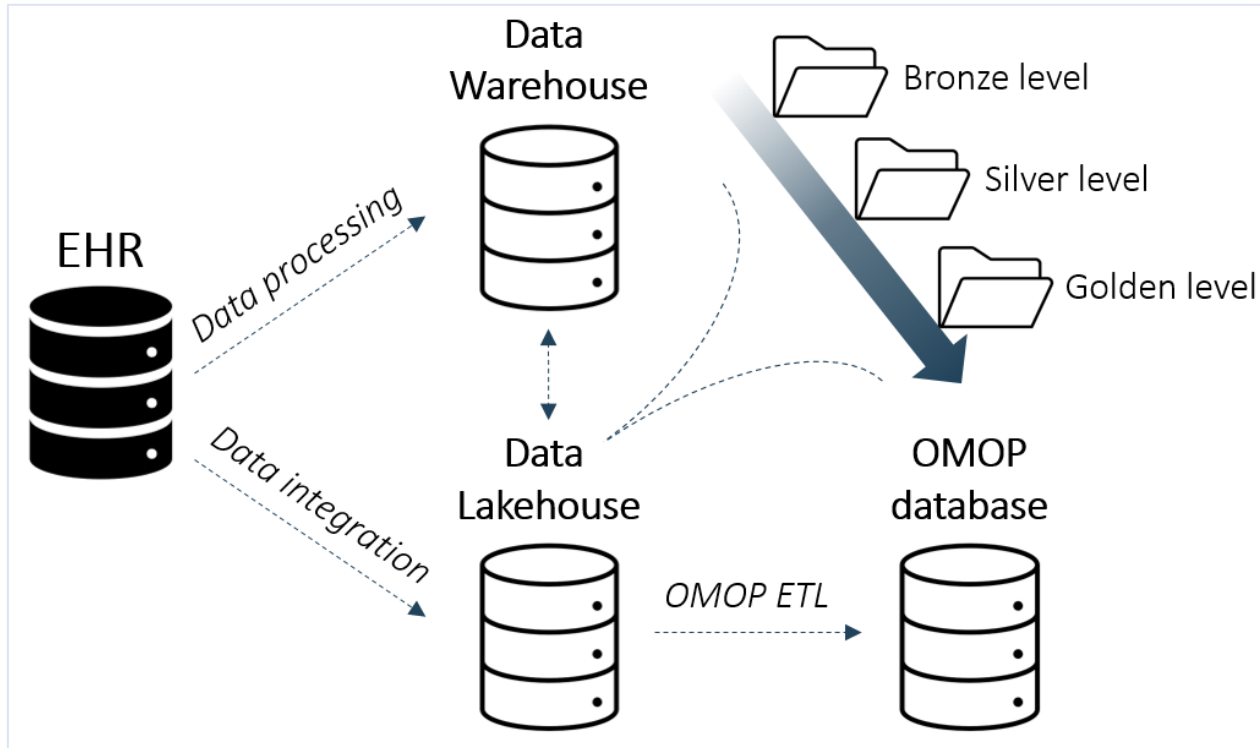


Figure. Example of **data manipulations** in ONCOVALUE centres.

From data collection by clinicians to data analysis by researchers, many processing steps manipulate the data.

- All centres still do manual processing, specifically for variables in need of interpretation (e.g. TNM status).
- The majority of data is modelled and integrated using automatic packages and SQL-based ETL processes.
- AI-tools (e.g. CTcue) are in use to process and retrieve data.

The implemented processing steps affect the availability, quality and fitness-for-purpose of the data.

Preliminary results

Data quality checks

From data entry to data analysis, all centres implement varying quality assurance procedures.

- Common quality checks at data entry:
 - Invalid data warnings
 - Incomplete entry warnings
 - Training
 - Blinded review
 - Regular quality reporting
- Extensive quality checks along data integration and OMOP CDM processes.
- Data lake(house)s consist of varying levels with different degrees of quality.

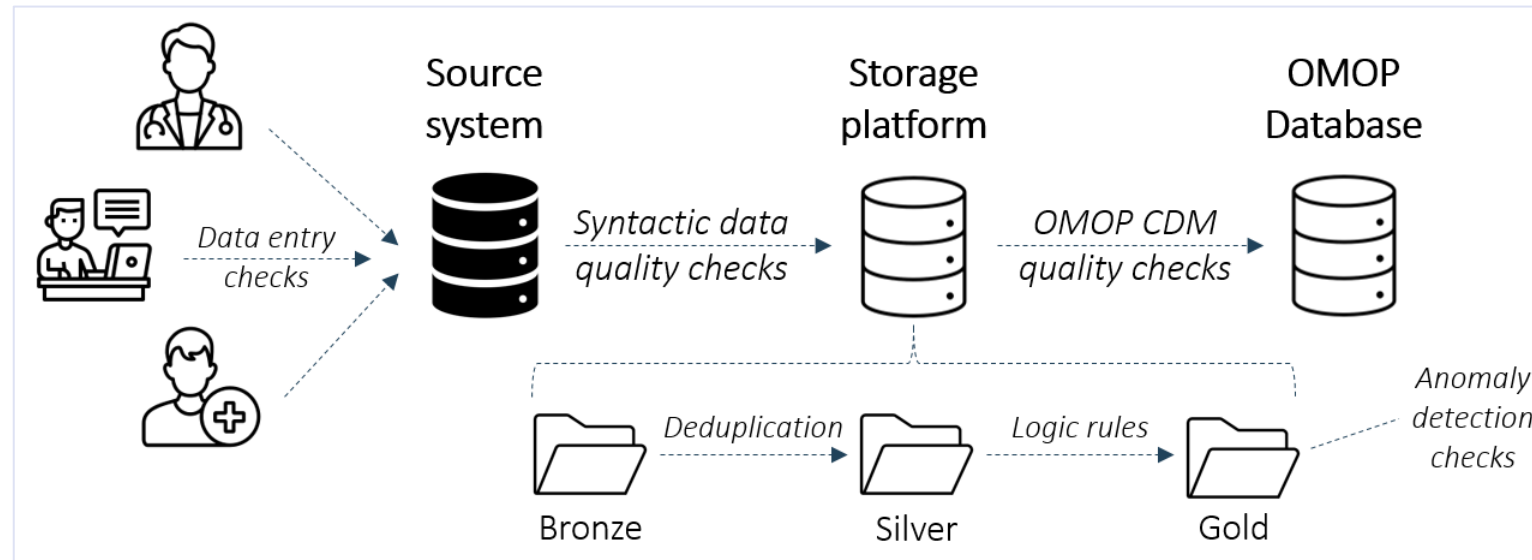


Figure. Example of **data quality checks** in ONCOVALUE centres.

Preliminary results

Data quality

Data completeness differs per data domain and data source structure.

- Data quality will further be assessed by
 - Data conformance
 - Data plausibility
 - Data uniqueness
 - Data persistence
 - Data accuracy
- Methods are needed to account for bias and uncertainties in the data.

Data quality reporting is paramount to generating trustworthy real-world evidence for HTA purposes.

Table. Breast cancer [data completeness](#) for a selection of variables.

	Hospital A	Hospital B	Hospital C
Breast cancer diagnosis	100%	100%	100%
ER-/PR-status*	100%	100%	75-99%
HER2-status*	50-74%	100%	100%
Tumor grade*	50-74%	100%	25-49%
Tumor histology*	100%	100%	100%
Neoadjuvant medications	100%	100%	100%
Medication dosage	100%	100%	100%
Death	100%	100%	100%

* Preoperative and postoperative

100% 75-99% 50-74% 25-49%

Preliminary results

OMOP CDM mapping

Mapping data to OMOP and the Oncology Module extension has started in 4 centres.

Complex albeit important for reliable and efficient multi-centre real-world data studies.

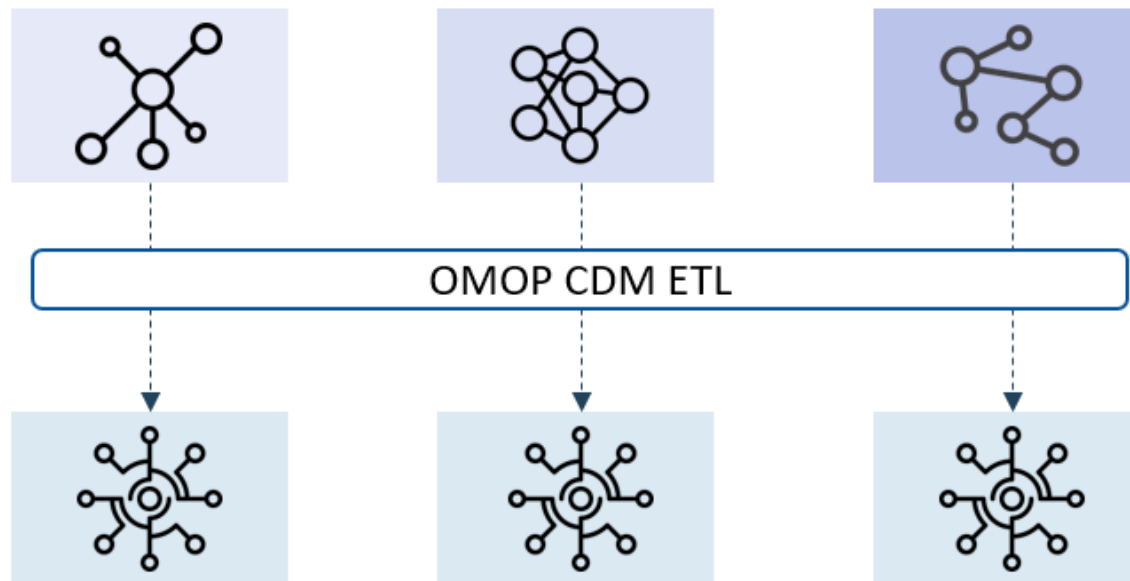


Figure. Data modelling to the OMOP CDM.

Preliminary results

Federated data analytics

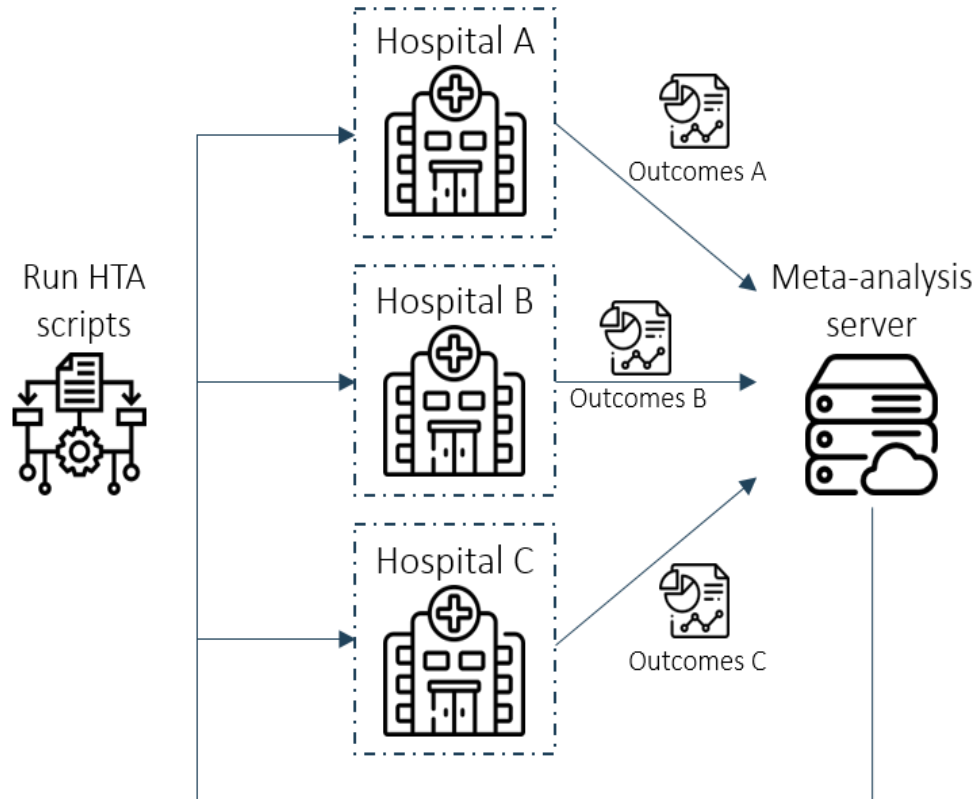


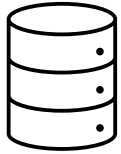
Figure. Federated data analytics infrastructure.

Federated infrastructure is tested and implemented in a first centre.

- Enables multi-centre analyses without sharing or centralizing patient-level to preserve patient privacy.
- Centres only share aggregate results to a meta-analyses server.

Relevant for multi-centre hospital RWD-based future-proof HTA

Discussion

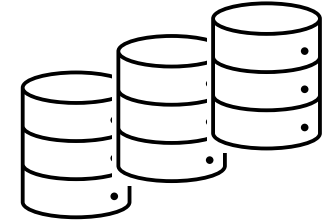


Available?

Structured?

High-quality?

Transparent data documentation is needed to understand the quality and suitability of real-world hospital data for HTAs.



Standardised?

Interoperable?

Linkage?



Hospital system architecture and maturity



Data processing and extraction using next generation AI



Standardising data to a Common Data Model (e.g. OMOP)



Thank you for listening!

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