

- ✓ Capturing health data
 - Storing digital health data
- ✓ Integrating digital health data
- ✓ Sharing digital health data in science
 - Exploiting digital health data in care



PROGRAMME
DE RECHERCHE
SANTÉ
NUMÉRIQUE



Data integration and sharing in the context of intracranial aneurysms

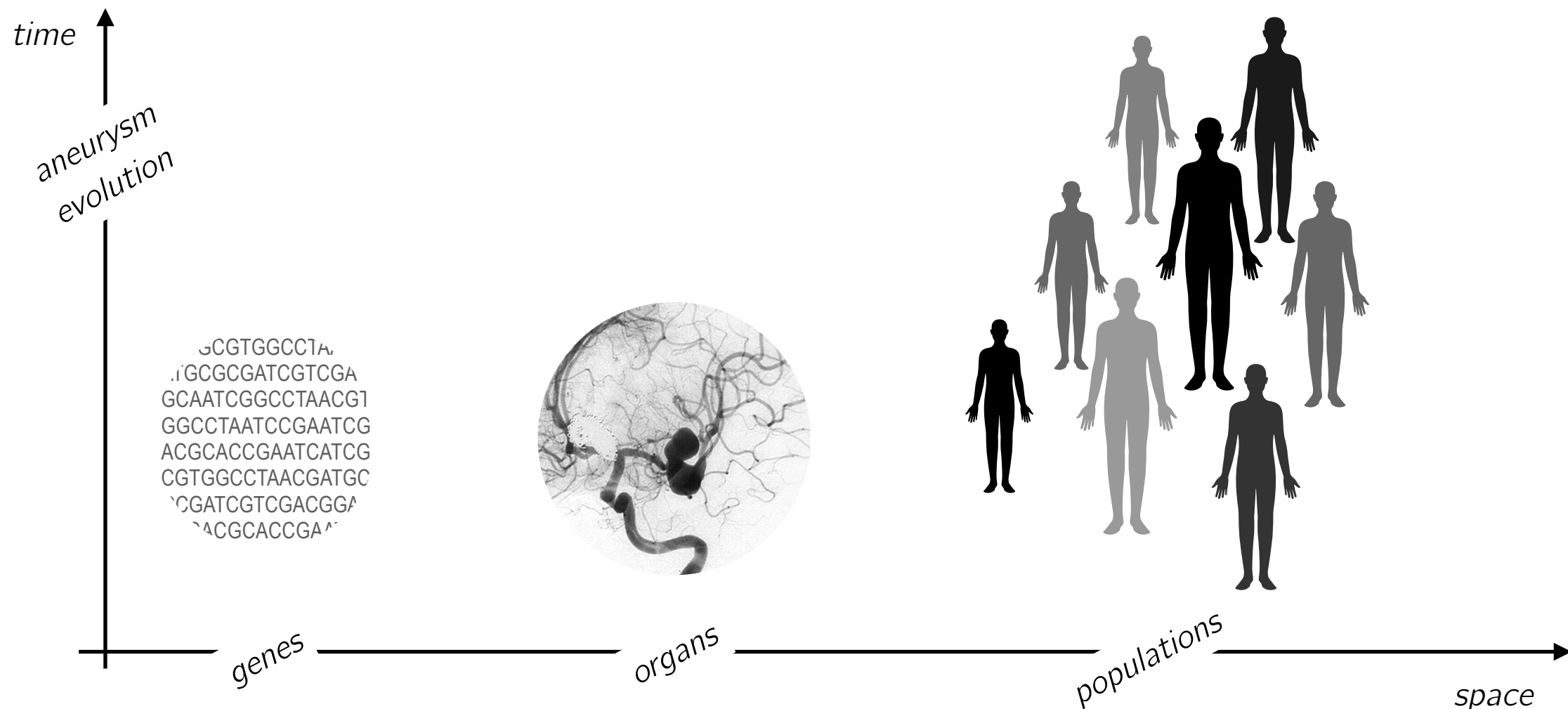
Alban Gaignard

ISGC IA group premeeting session Seoul
24th of September 2025



Multi-factorial disease → multi-scale data

- ▶ Inter-disciplinary efforts needed for a better understanding of the pathology
- ▶ Specific data produced at very specific scales



Neurovasc project

- ▶ Neurovasc: a national programme funded for 4 years by the french research agency to build a digital infrastructure to manage and exploit intracranial aneurysm data
 - 3 Research Institutes (Inria, Inserm, IMT Atlantique)
 - 2 Clinical Research Teams (Brest & Nantes academic hospitals)
 - 3 Universities (Bordeaux, Paris-Saclay, Nantes)

WP 1: A model of interoperable infrastructure between research and healthcare

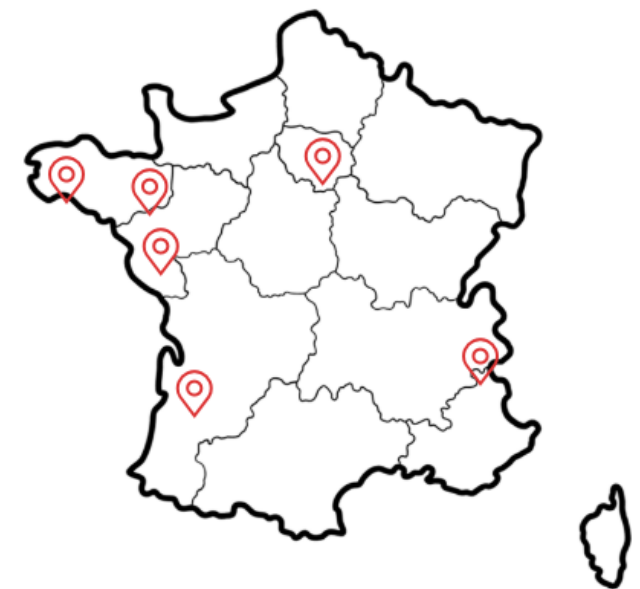
- Task 1.1. Managing clinical data
- Task 1.2. Managing imaging data
- Task 1.3. Managing genetic data

WP 2: Interoperable datasets and predictive models for ICA diagnosis and outcomes

- Task 2.1: FAIR genomic data demonstrator
- Task 2.2: Mining healthcare circuits following ICA diagnosis
- Task 2.3: A non-additive model for global genetic-risk prediction

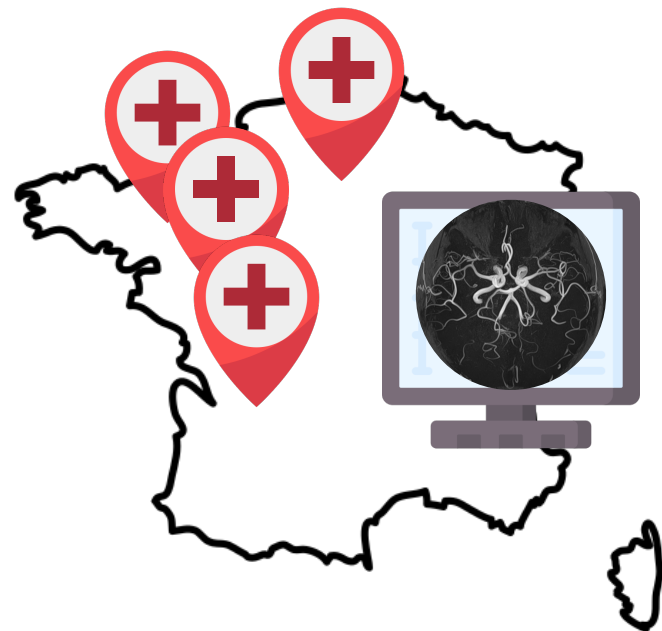
WP 3: Proof-of-Concept studies with digital companions

- Task 3.1: Accompanying patients with diagnosed unruptured ICA
- Task 3.2: Post-stroke prevention through mobile applications and digital monitoring



Multiple data integration sharing issues

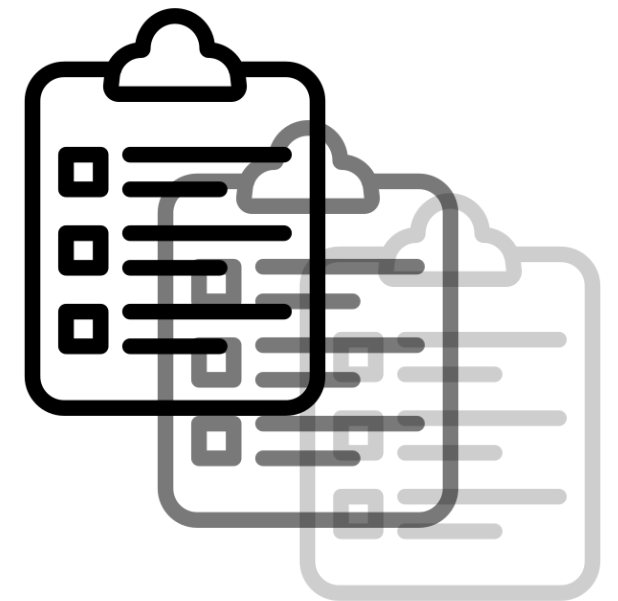
❶ How to **collect high-quality medical images** from multiple hospitals/MRIs ?



❷ How to **interlink and query multi-modal and multi-scale data** while preserving privacy constraints ?

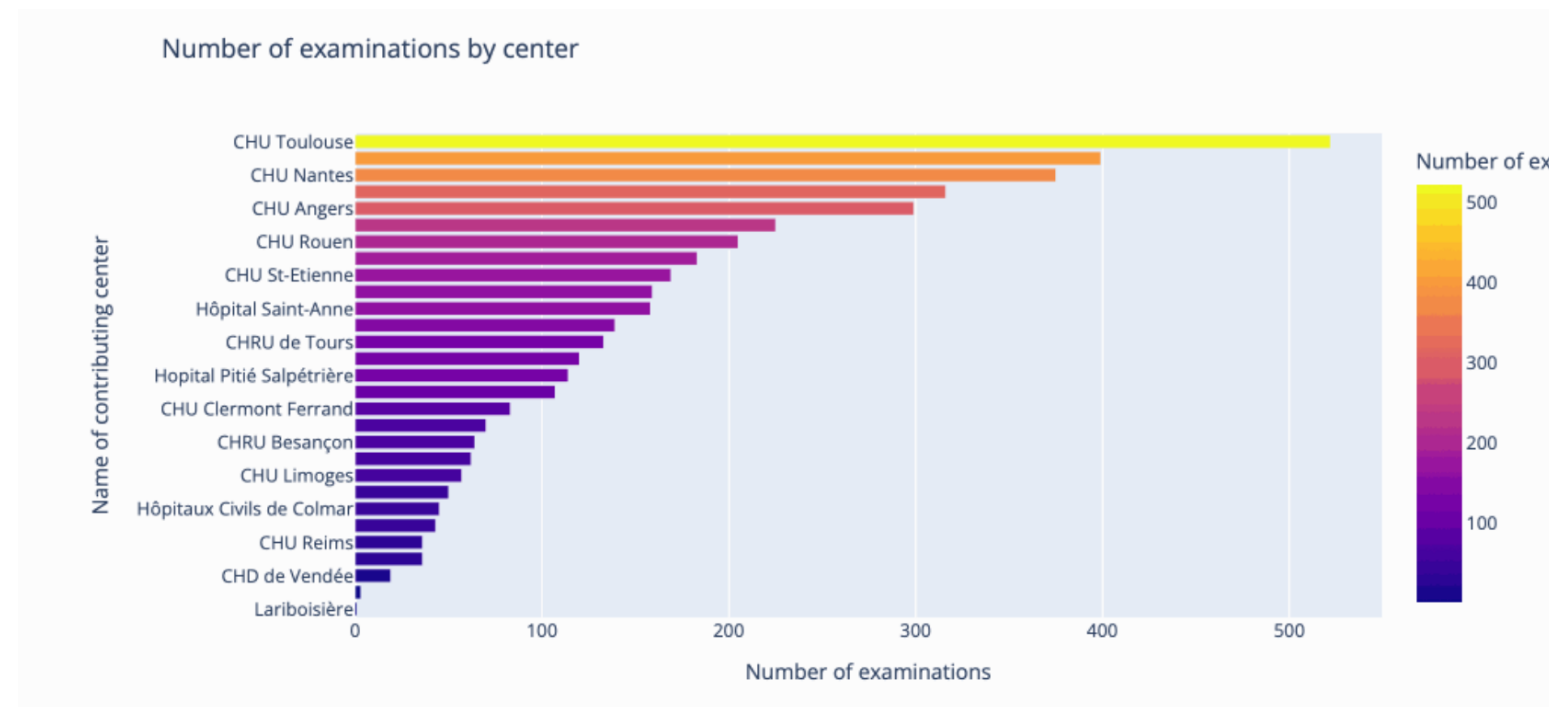
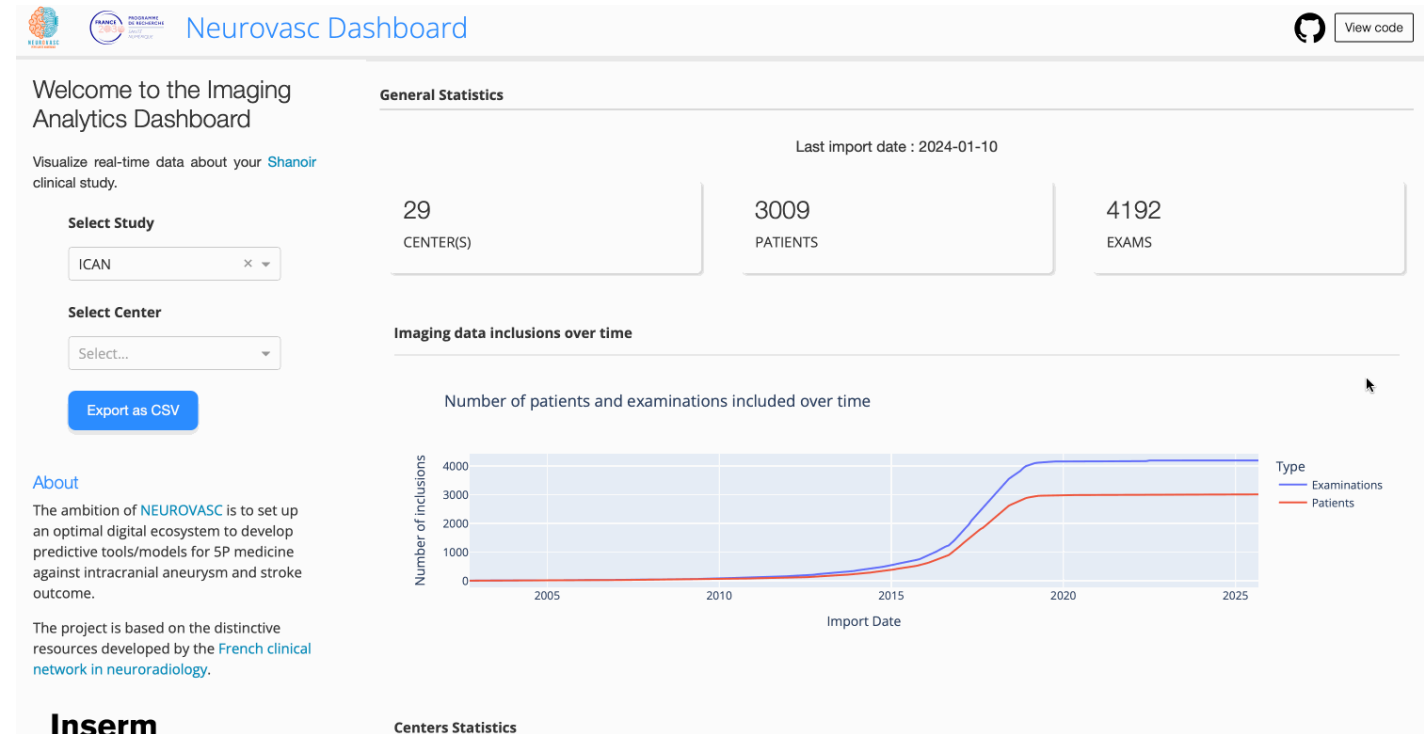
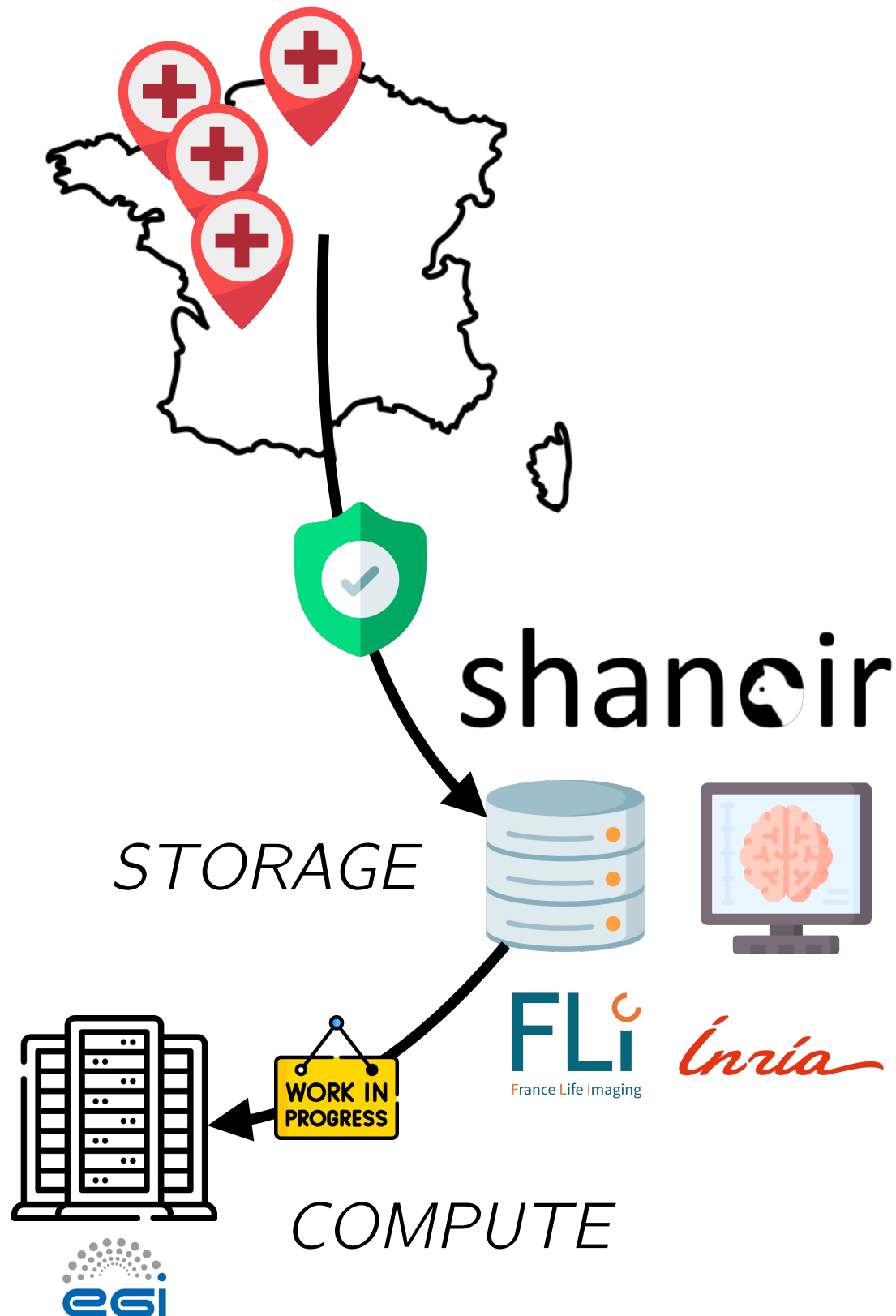


❸ How to mine and **model patient trajectories** from eHR data ? can we predict clinical outcomes ?



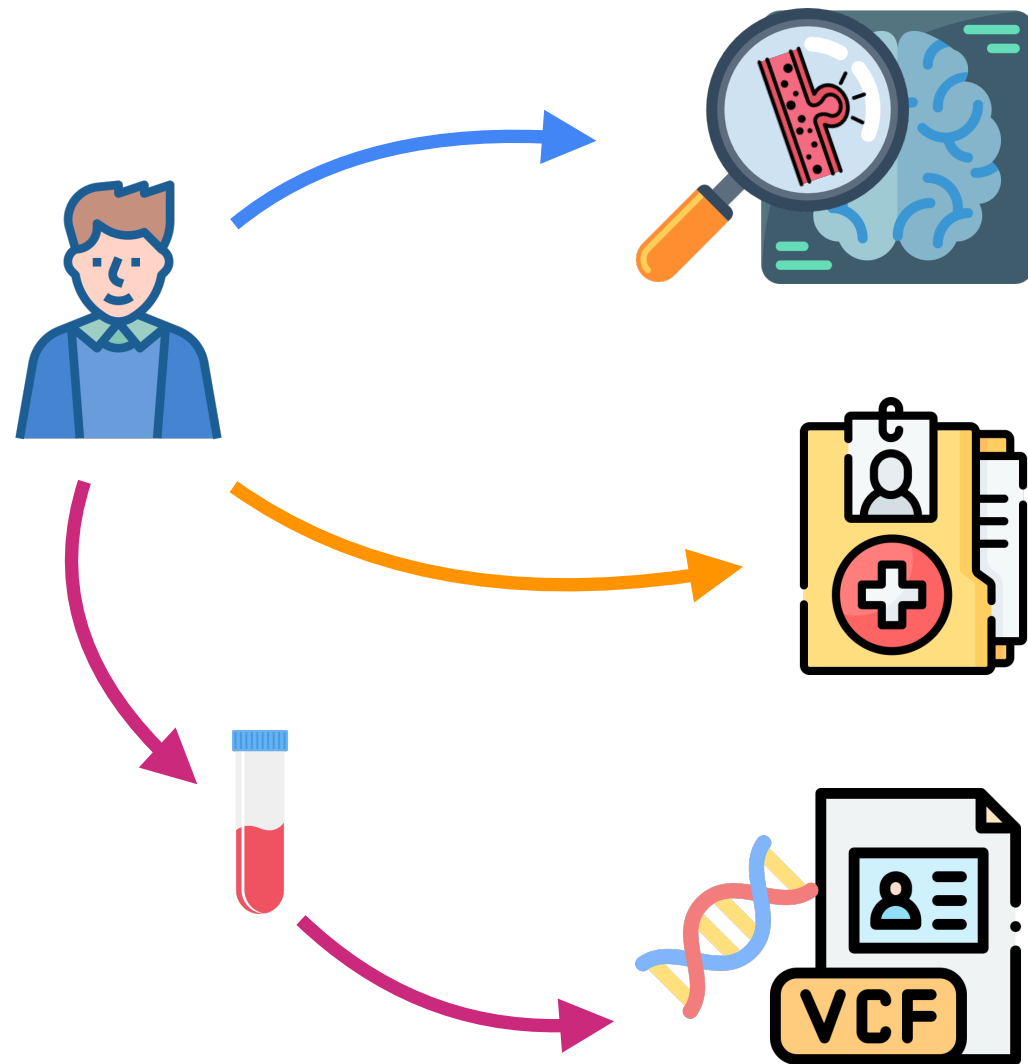
① How to collect high-quality medical images from multiple hospitals/MRIs ?

1 Collecting multi-source medical images



② How to interlink and make query-able multi-modal and multi-scale data while preserving privacy constraints ?

② FAIRifying clinical & genomic data



Neuro-vascular imaging / tissues ?

- **UBERON**
- **NCIT**

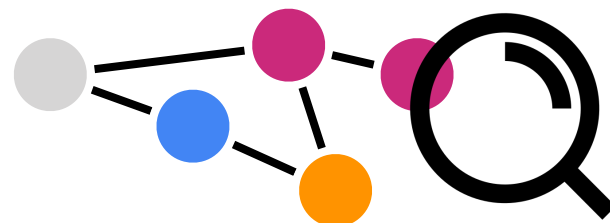
Clinical data / phenotypes ?

- **SPHN**
- **HPO**
- **DUO**

Genomic data ?

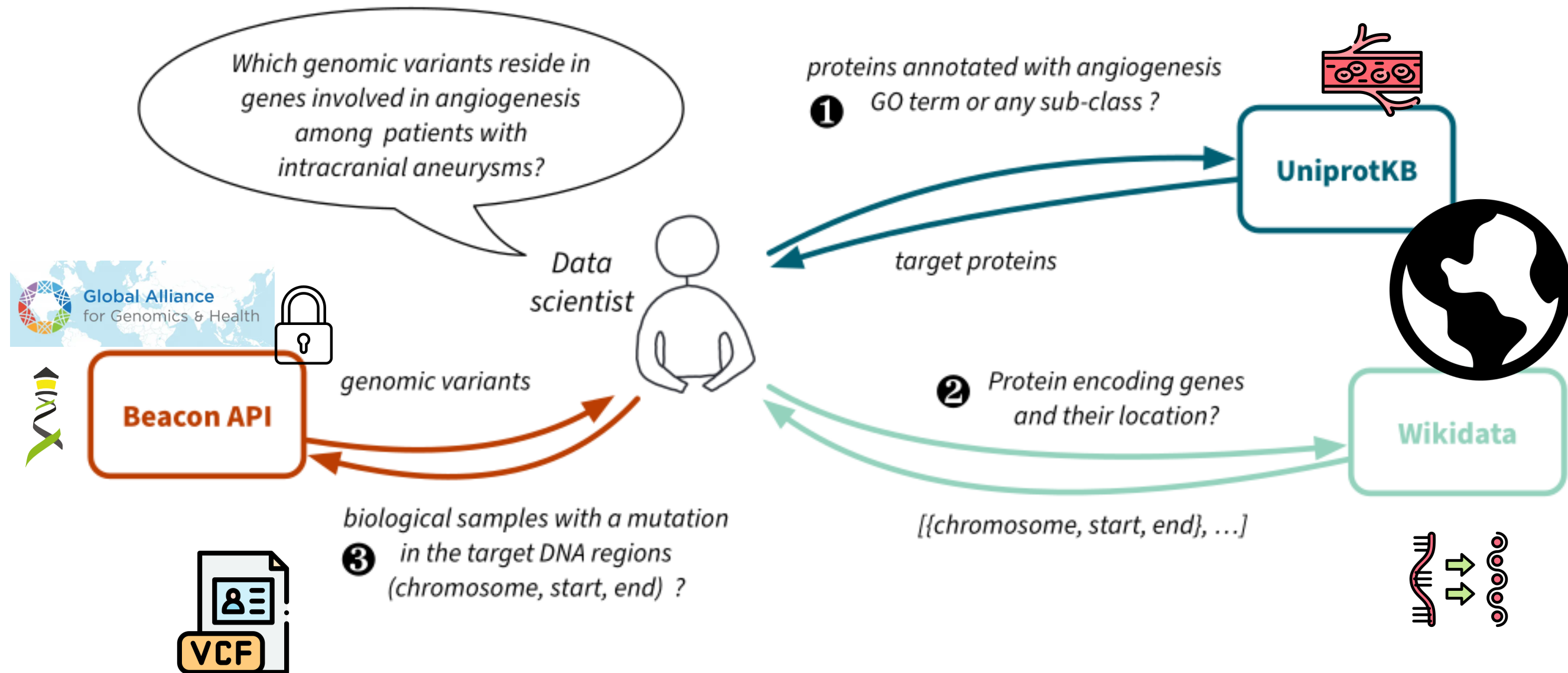
- **FALDO**
- **SO / GENO**
- **SIO**

A clinical and genomic
intracranial aneurysm
knowledge graph



Find/Exchange
phenotypes - variants
with reference terminologies !

② Making genomic data interoperable with public knowledge bases



→ A single fedetared SPARQL query over 3 data sources (1 non-RDF)

③ How to mine and model patient trajectories from eHR data ? can we predict clinical outcomes ?

③ Evaluating clinical data models for patient outcome prediction

- Predict outcome of intracranial aneurysm patients after certain medical procedures or treatments.



Synthetic Clinical Data

- ▶ We generated **synthetic dataset** that follows the distribution and the correlations of variables from **real-world clinical data** provided by the Nantes University Hospital.
 - Synthetic tabular data of intracranial aneurysm (10,000 individuals)
 - 22 non-temporal features (4 numerical, 6 categorical, 12 binary)
 - 8 temporal features (e.g., drug administration)

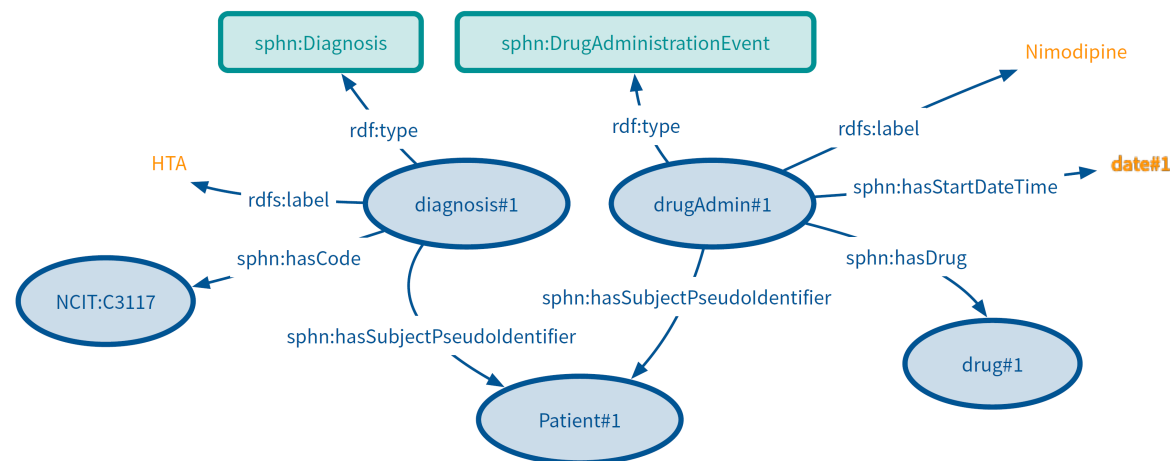
ID	Hospital stay length	Age	Gender	Entry unit	ICA	Diabetes	O2 clinic	Nimodipine	Paracetamol	Outcome
1	41.09	38	0	0	0	0	0	2023-04-08	0	0
2	21.70	58	0	1	2	0	0	2022-12-09	2022-12-09	1
3	4.63	76	0	2	2	0	0	0	2021-05-23	0
4	12.83	87	1	1	4	0	1	0	0	2
5	75.68	75	0	3	5	0	1	2020-11-23	0	1
6	41.95	59	0	2	5	0	0	2019-07-19	2019-07-26	0
7	27.54	42	0	4	5	0	0	0	0	0

Evaluating clinical data models for patient outcome prediction

- ▶ The structure of SPHN is more **patient-centric** compared to CARE-SM, which is more **diagnosis-centric**

SPHN

(Swiss Personalized Health Network)

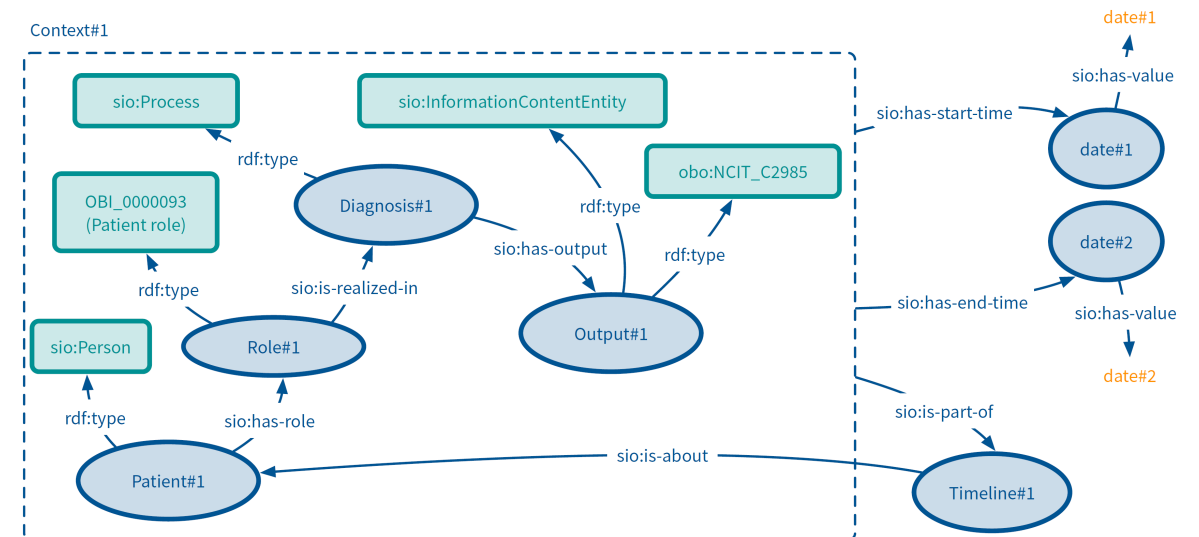


Adopted by the five Swiss academic hospitals for better data sharing and integration

Touré, V. et al. (2023)

CARE-SM

(Care and Registry Semantic Model)



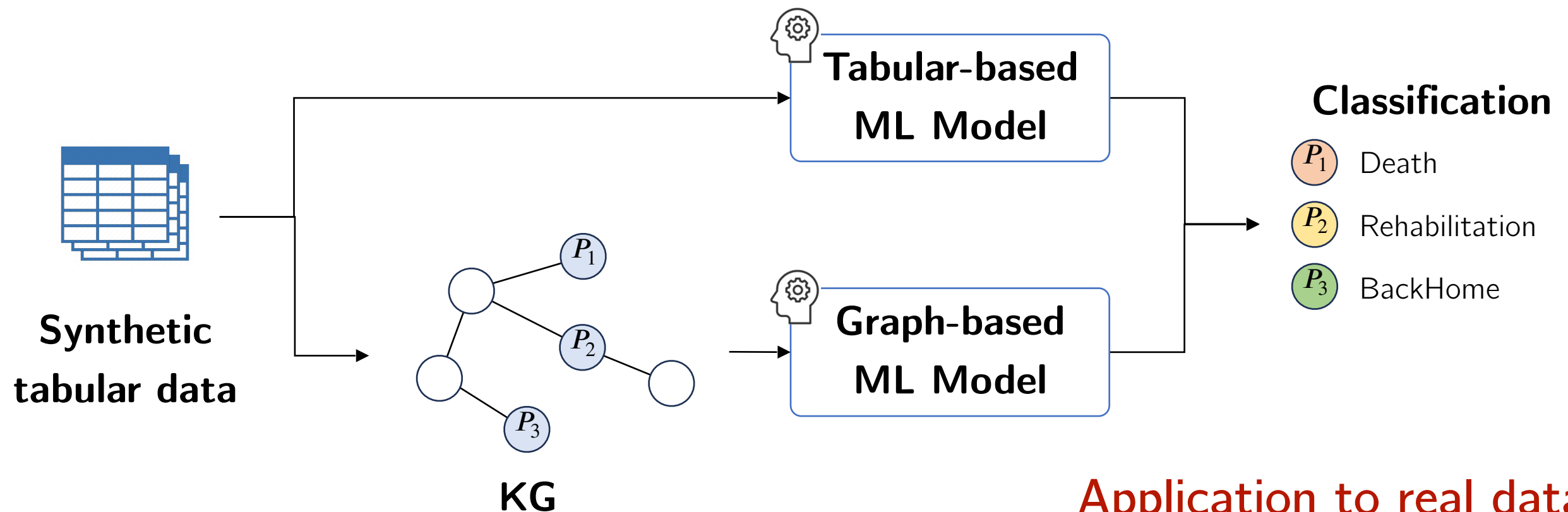
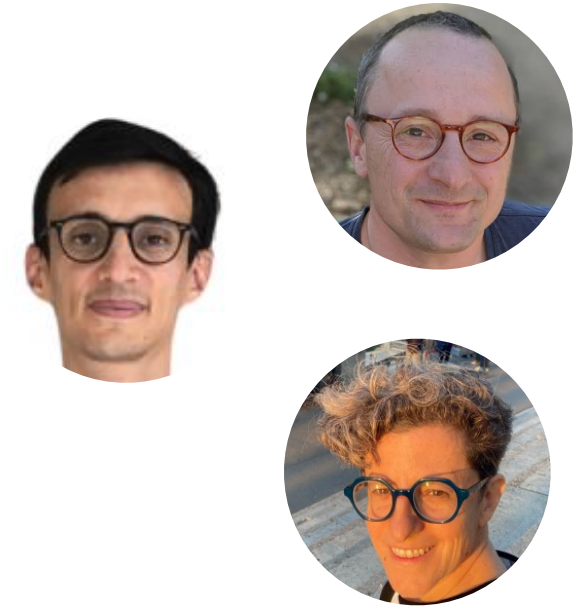
Initially designed to represent clinical data in the context of rare diseases

Kaliyaperumal, R. et al. (2022)

Predict outcome of intracranial aneurysm patients after certain medical procedures or treatments.

Key questions:

- Tabular data or Knowledge graph (KG)?
- What is the best KG structure for prediction tasks?
- How to represent temporal information in the KG?



Application to real data ?

Acknowledgments



Alexandrina
Bodrug



Laurent
Vallet



Richard
Redon



Adrien
Coulet



Matilde
Karakachof



Romain
Bourcier



Pacôme
Constant dit Beaufils

Small Animal Shanoir (SAS) A Cloud-Based Solution for Managing Preclinical MR Brain Imaging Studies

Michael Kain^{1*}, Marjolaine Bodin², Simon Loury², Yao Chi¹, Julien Louis¹,
Mathieu Simon¹, Julien Lamy³, Christian Barillot¹ and Michel Dojat^{2*}

¹INRIA U1228, INSERM, Université de Rennes, Rennes, France, ²INSERM U1216, Grenoble Institut des Neurosciences,
Université Grenoble Alpes, CHU Grenoble Alpes, Grenoble, France, ³ICube, University of Strasbourg-CNRS, Strasbourg,
France

Clinical multicenter imaging studies are frequent and rely on a wide range of existing
tools for sharing data and processing pipelines. This is not the case for preclinical

<https://doi.org/10.3389/fninf.2020.00020>

Semantic Beacons: a framework to support federated querying over genomic variants and public Knowledge Graphs

Alexandrina Bodrug-Schepers^{1,†}, Hugo Chabane^{2,†}, Gabriela Montoya²,
Patricia Serrano-Alvarado², Richard Redon¹ and Alban Gaignard^{1,3}

¹Nantes Université, CNRS, INSERM, l'institut du thorax, F-44000 Nantes, France

²Nantes Université, LS2N, Nantes, France

³IFB-core, Institut Français de Bioinformatique (IFB), CNRS, INSERM, INRAE, CEA, 91057 Evry, France

<https://hal.science/hal-04908530v2>

ARTICLE

Predicting Clinical Outcomes from Patient Care Pathways Represented with Temporal Knowledge Graphs

Authors: Jong Ho Jhee, Alberto Megina, Pacôme Constant Dit Beaufils, Matilde Karakachof
Redon, Alban Gaignard, Adrien Coulet [Authors Info & Claims](#)

The Semantic Web: 22nd European Semantic Web Conference, ESWC 2025, Portoroz, Slovenia, June 1–5, 2025,
Proceedings, Part I

Pages 282 – 300 • https://doi.org/10.1007/978-3-031-94575-5_16

Published: 01 June 2025 [Publication History](#)

https://doi.org/10.1007/978-3-031-94575-5_16

Backup slides

Results 1: Patient Outcome Prediction

Tabular vs. TKG (temporal knowledge graphs)

- Compared to tabular data, **TKG showed better performance** with RGCN3+lit.

Type	Model	F1-score					Accuracy	AUC
		BackHome	Rehab	Death	Macro	Weighted		
Tabular	LR	0.63±0.02	0.55±0.02	0.25±0.05	0.47±0.03	0.55±0.02	0.56±0.02	0.70±0.02
	RF	0.63±0.01	0.55±0.02	0.28±0.04	0.49±0.02	0.55±0.01	0.56±0.01	0.71±0.01
	NN	0.58±0.03	0.48±0.03	0.26±0.04	0.44±0.02	0.50±0.02	0.50±0.02	0.63±0.02
Graph (SPHN-tr)	TransE	0.49±0.04	0.40±0.10	0.02±0.04	0.30±0.03	0.40±0.03	0.43±0.02	0.50±0.01
	RDF2Vec	0.50±0.05	0.39±0.14	0.01±0.02	0.30±0.03	0.39±0.04	0.44±0.02	0.49±0.01
	RGCN3+lit	0.84±0.01	0.76±0.02	0.64±0.08	0.75±0.03	0.75±0.02	0.78±0.01	0.91±0.01

Results 2: Patient Outcome Prediction

Patient-centric (SPHN) vs. Diagnosis-centric (CARE-SM)

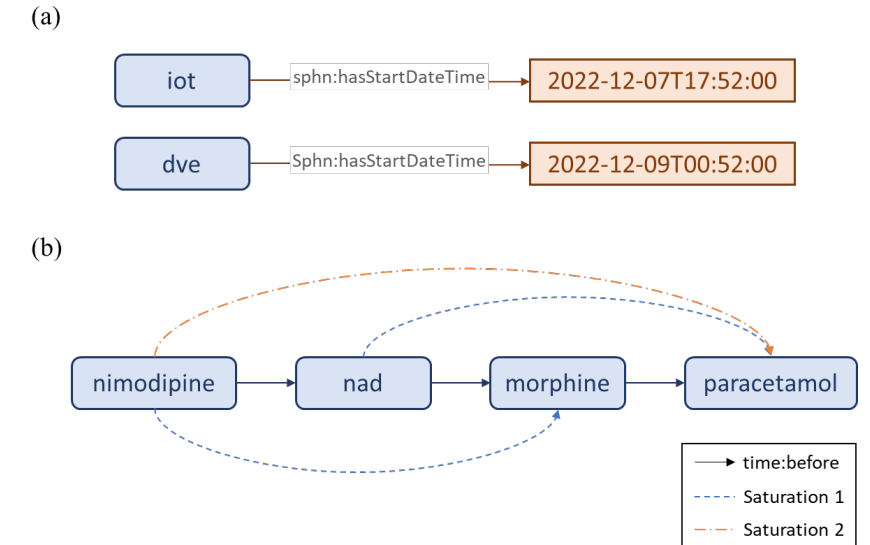
- This experiment shows the **importance of the structure of a KG.**

KG	Model	F1-score					Acc.	AUC
		Back2Home	Rehab.	Death	Macro	Weighted		
SPHN	TransE	0.510.07	0.330.16	0.020.04	0.290.04	0.370.05	0.430.02	0.500.01
	RDF2Vec	0.490.04	0.420.09	0.010.03	0.300.02	0.400.02	0.440.01	0.500.02
	RGCN+lit	0.830.01	0.760.02	0.660.04	0.750.02	0.780.01	0.780.01	0.910.01
CARE-SM	TransE	0.470.04	0.440.04	0.020.03	0.310.01	0.400.01	0.430.01	0.490.01
	RDF2Vec	0.510.07	0.380.11	0.000.00	0.290.02	0.390.03	0.440.02	0.500.01
	RGCN+lit	0.530.08	0.300.17	0.000.00	0.280.04	0.370.05	0.440.01	0.500.02

Results 3: Patient Outcome Prediction

Non-Temporal vs. Temporal

- Graphs with **temporal information showed improvements** in AUC compared to non-temporal graphs.



KG	F1-score					Accuracy	AUC
	BackHome	Rehab	Death	Macro	Weighted		
SPHN-nl	0.64±0.03	0.46±0.11	0.05±0.07	0.38±0.06	0.49±0.06	0.53±0.04	0.64±0.06
SPHN-nt	0.75±0.02	0.65±0.02	0.55±0.06	0.65±0.02	0.68±0.01	0.68±0.01	0.85±0.01
SPHN-ts	0.83±0.02	0.76±0.02	0.66±0.08	0.75±0.03	0.78±0.02	0.78±0.02	0.91±0.01
SPHN-tr	0.84±0.01	0.76±0.02	0.64±0.08	0.75±0.03	0.75±0.02	0.78±0.01	0.91±0.01
SPHN-ts _r	0.83±0.02	0.76±0.02	0.66±0.04	0.75±0.02	0.78±0.01	0.78±0.01	0.91±0.01
SPHN-sat1	0.83±0.01	0.76±0.02	0.64±0.06	0.75±0.02	0.78±0.01	0.78±0.01	0.91±0.01
SPHN-sat2	0.83±0.01	0.76±0.02	0.68±0.05	0.76±0.02	0.78±0.02	0.78±0.02	0.91±0.01