



HORIZON  
EUROPE BRIDGING THE ATLANTIC



# Motivation (MULTIR)



1 237 009 new cases



1 444 949 new cases

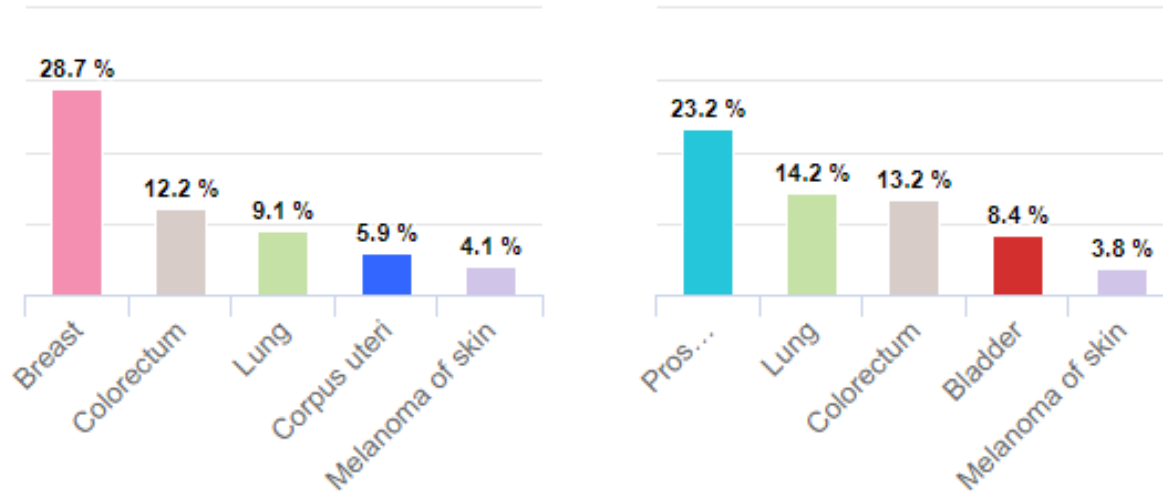


555 650 deaths

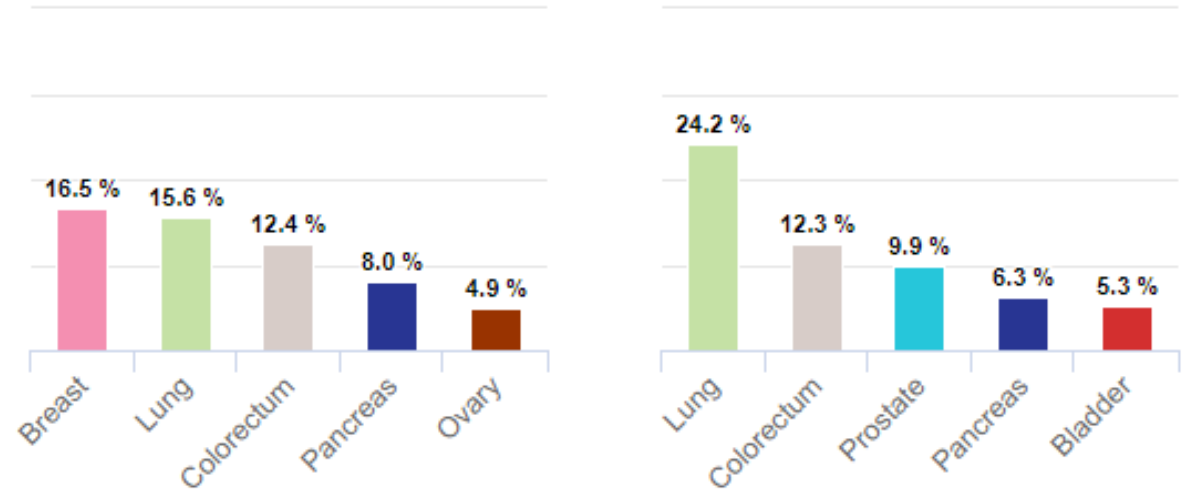


706 072 deaths

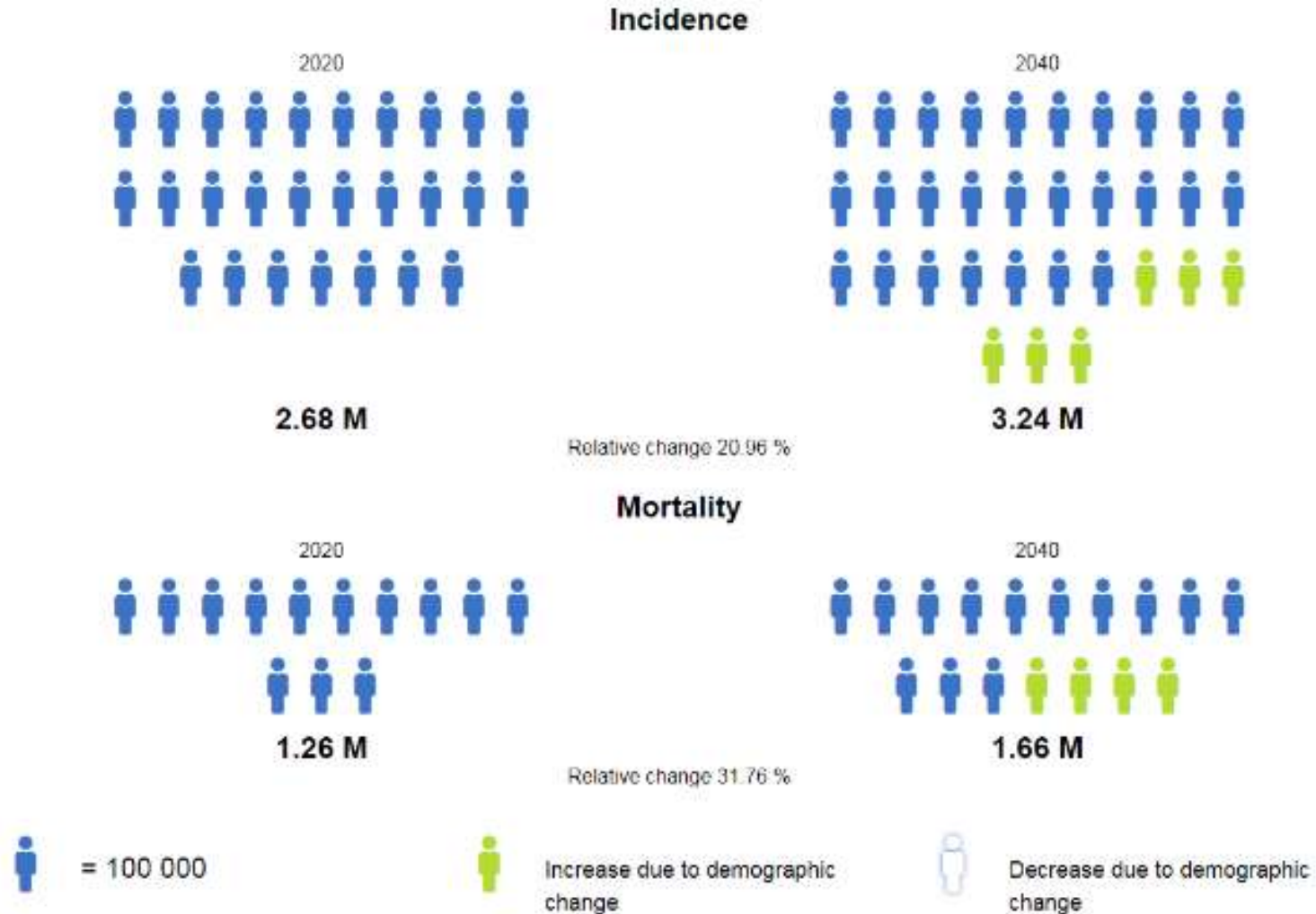
## Most common cancers



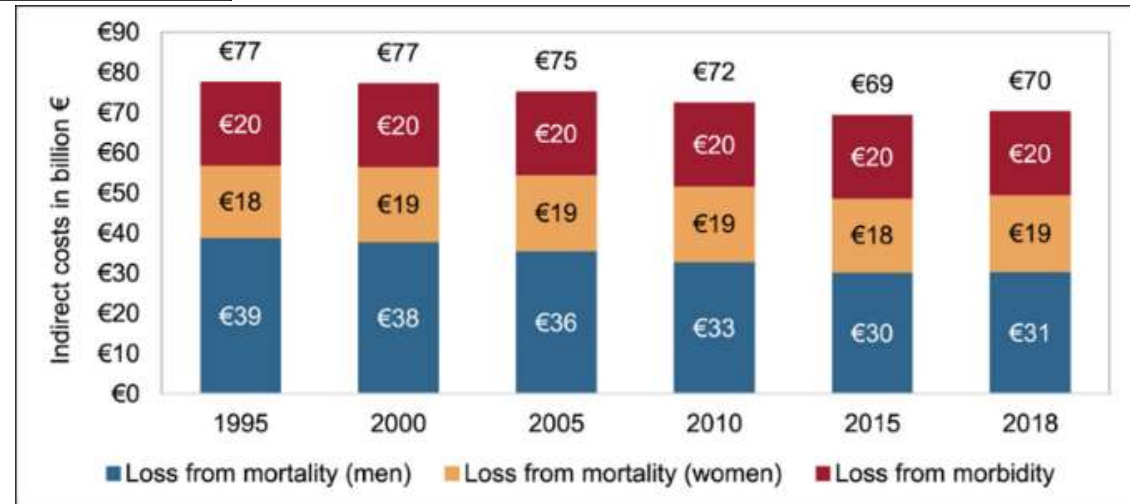
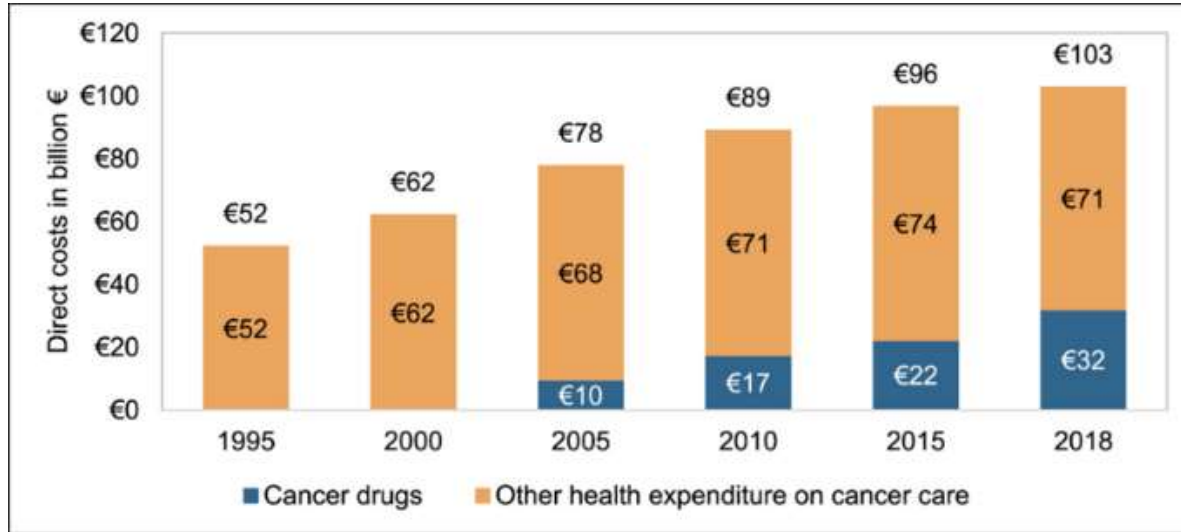
## Most common cancer causes of death



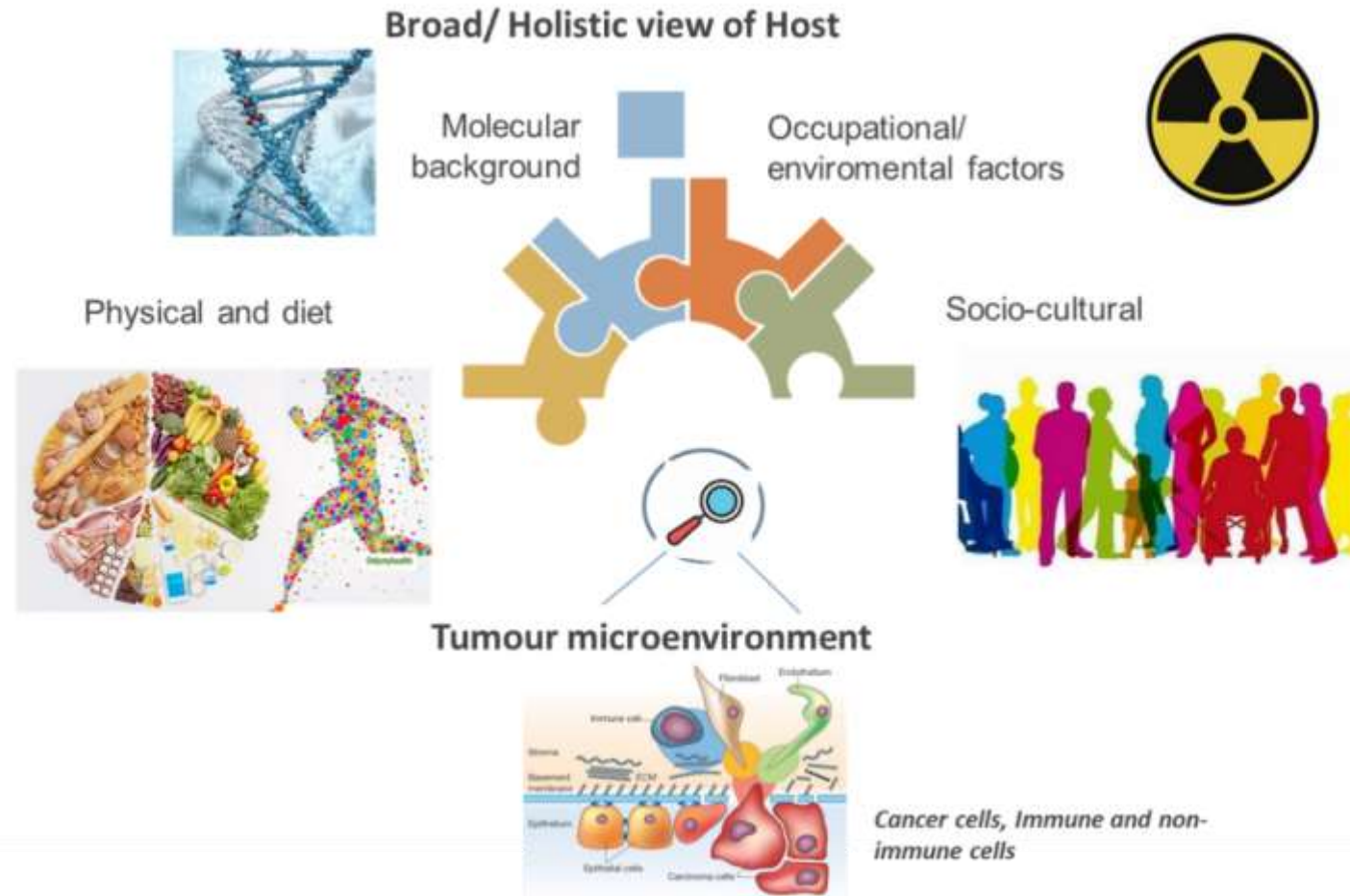
# Incidence vs Mortality within EU-27



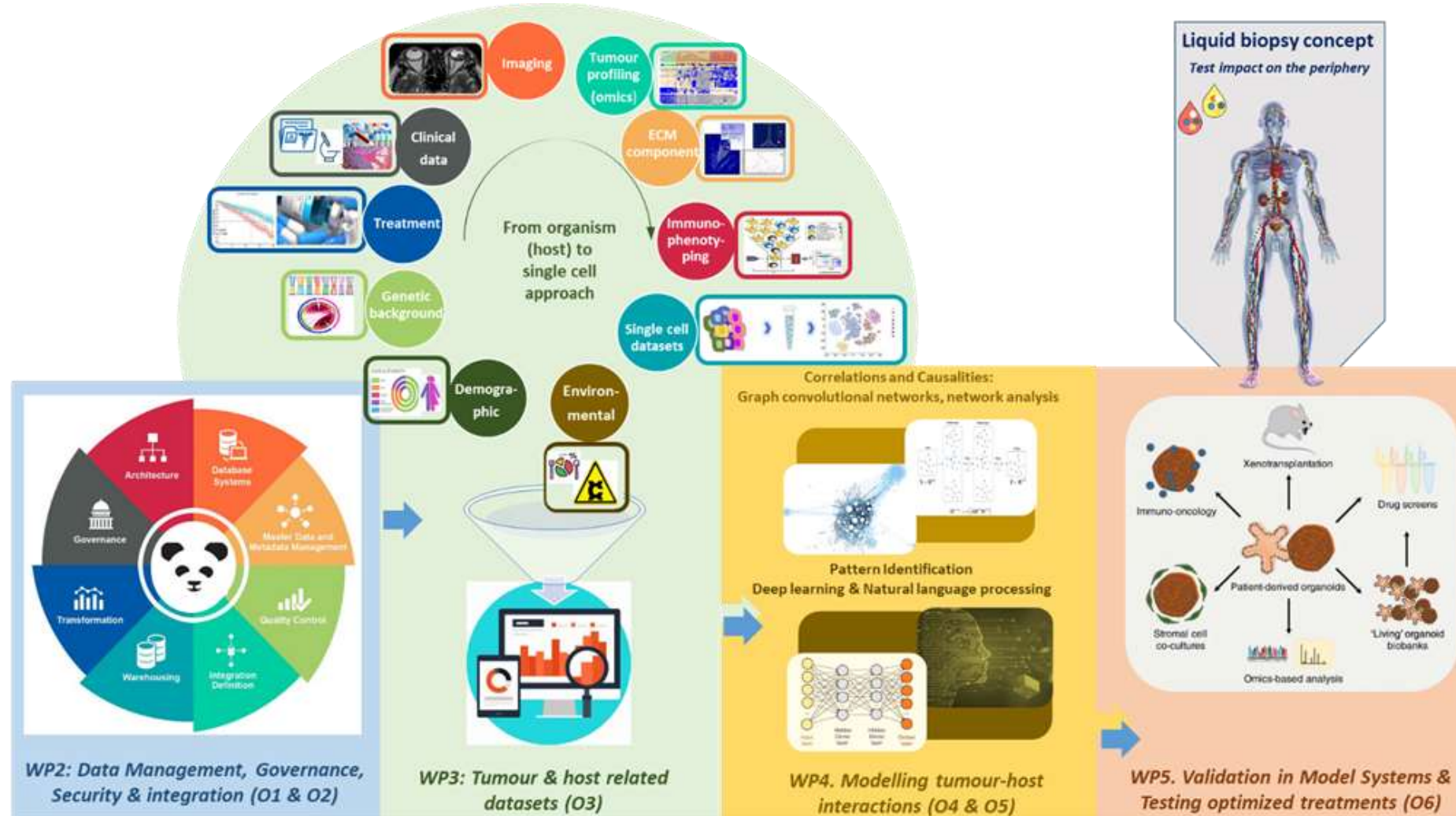
# Costs of cancer in EU in 1995–2018



# Rationale for holistic consideration of tumor-host interactions

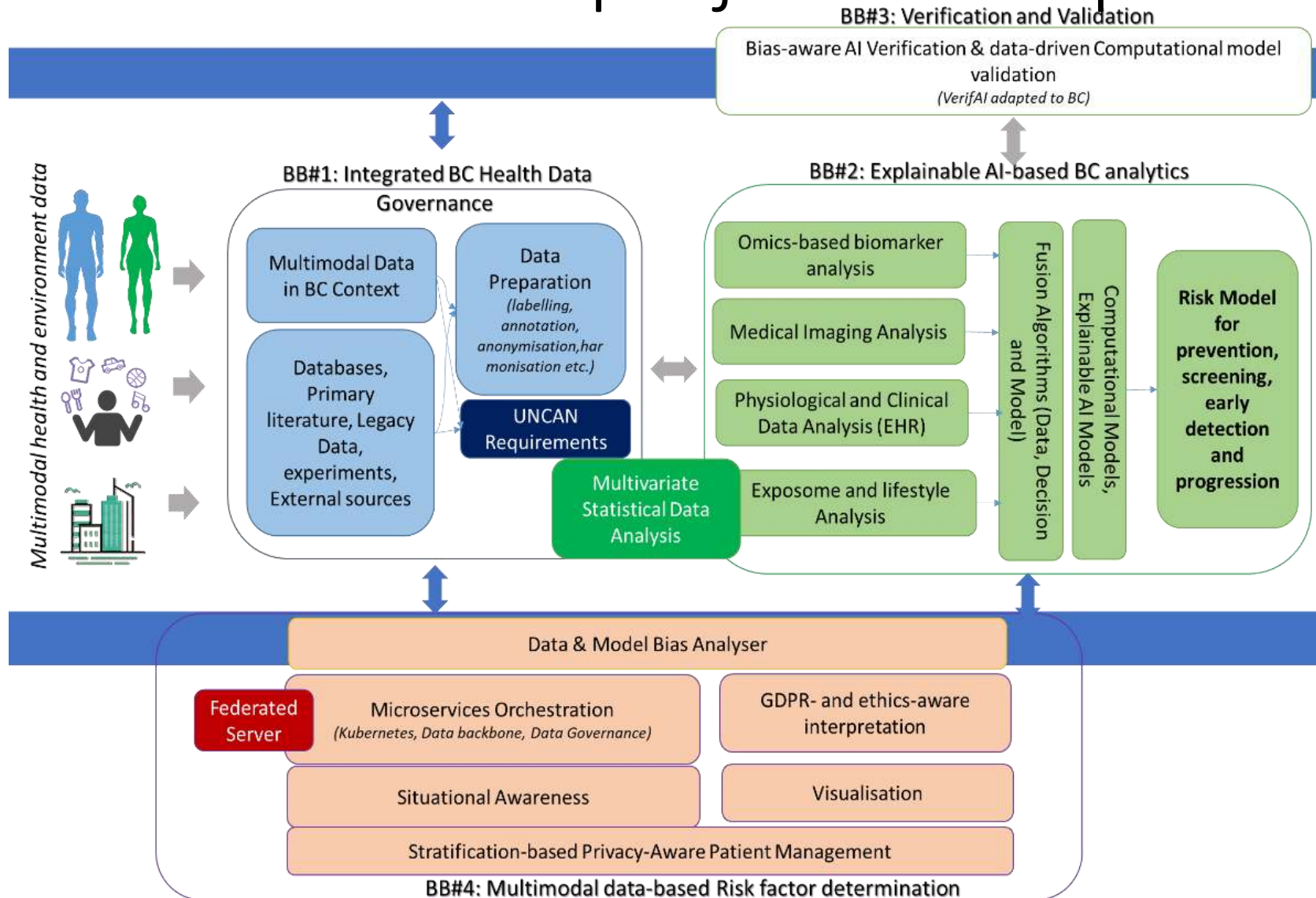


# MULTIR project concept





# MULTIR – project concept



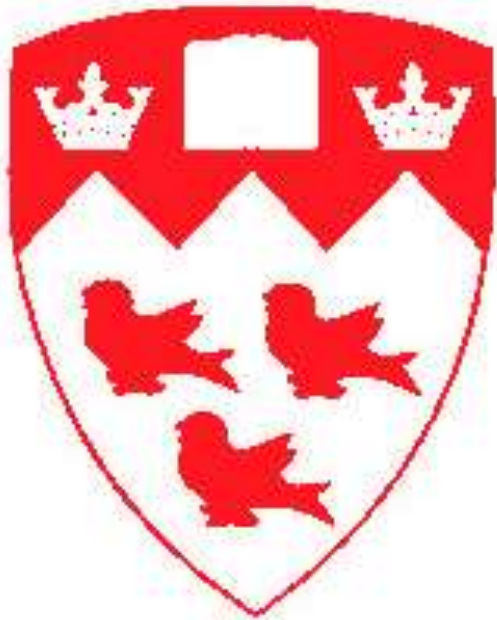
[illegible]



# Consortium



# McGill University



# McGill

UNIVERSITY

# McGill University (MGU)

Logan Walsh, PhD Professor, Group leader

- McGill University (MGU) is an expert in spatial proteomics and will generate and analyze highly multiplexed imaging data.
- They also have consented well over 1500 patients with various stages of lung cancer and other rare thoracic malignancies.
- The most unique and scientifically versatile aspect of our biobank effort has been the development of a living tumour bank which includes a large array of extensively characterized patients derived xenografts and organoid models.
- The biospecimen collections are accompanied by an extensive clinical annotation and comprehensive clinical grade next generation sequencing data.



# WP2 Tasks



## T2.1

Development of a data security architecture based on AI PANDA



## T2.2

Developing the healthcare data space for data sharing and curation



## T2.3

Developing AI powered digital tools for sensitive data, generation of synthetic data



## T2.4

Integration of the digital tools and federated learning



D2.1

- MULTIR data security architecture

D2.2

- Data anonymization modules

D2.3

- Building synthetic data generation models

D2.4

- Data space and digital tools for data sharing

D2.5

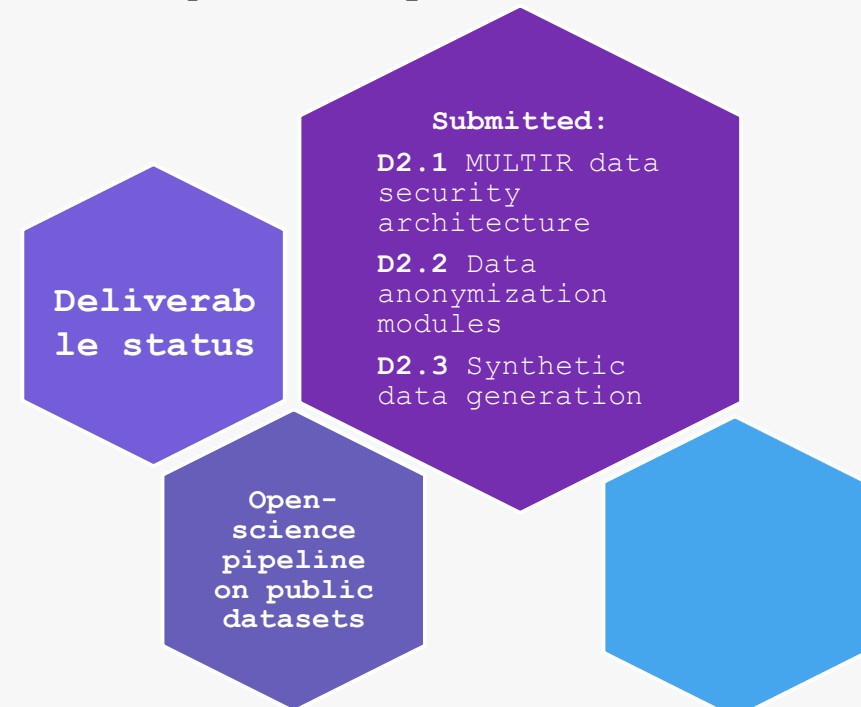
- Autonomous, Adaptable & Federated Learning Models

# WP2 Review (to date...)

- **Scope:** Build and operate the MULTIR healthcare data space underpinning all downstream analytics.
  - **T2.1 Security architecture (ATMC):** AI PANDA-based, defense-in-depth, IAM, encryption, secure pipeline, audit.
  - **T2.2 Data space for sharing & curation (ATMC):** IDSA-compliant connector, policy-driven data handling, metadata catalog.
  - **T2.3 Synthetic data generation (ATMC+MOS):**

**Operating principles:** GDPR-by-design, ISO 27001 alignment, API-first, FAIR data, EOSC/UNCAN.eu interoperability.

**Execution mode M1-M18:** Isolated ATMC environment, no real cohort data processed (JCA/DPA not yet signed).





# Summary of Activities



## D2.1 (Security architecture):

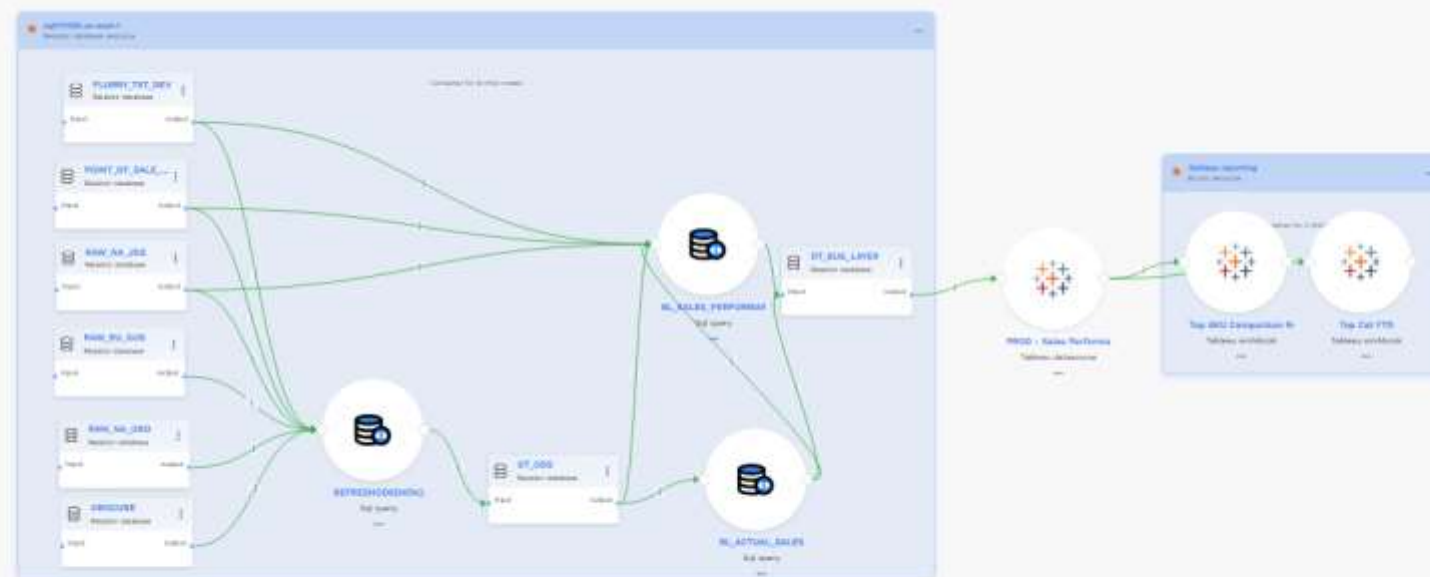
Deployed **AI PANDA** in isolated ATMC DC (Kubernetes).

**IAM:** Azure AD integration + AI PANDA user/role model, MFA **to-be** enforced.

**Encryption:** TLS in-transit, AES-256 at rest, secrets management; key rotation.

**Network security:** Segmented namespaces, allow-lists, hardened ingress.

**Monitoring & audit:** Centralized immutable logs, alerting rules.





# Summary of Activities



## D2.1 (Security architecture):

Deployed **AI PANDA** in isolated ATMC DC (Kubernetes).

**IAM:** Azure AD integration + AI PANDA user/role model, MFA **to-be** enforced.

**Encryption:** TLS in-transit, AES-256 at rest, secrets management; key rotation.

**Network security:** Segmented namespaces, allow-lists, hardened ingress.

**Monitoring & audit:** Centralized immutable logs, alerting rules.

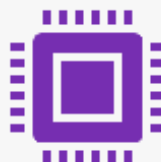


## D2.2 (Anonymization modules):

**Metadata-level pseudonymization/g**eneralization/suppression ruleset.

**Policy engine** integrated with AI PANDA profiling/classification.

**IDSA-compliant connector** design for future partner exchanges.



## D2.3 (Synthetic data):

Built **Gaussian copula** pipeline, validated on public peptidomics datasets.

**Benchmarks:** PCA/MDS overlap, SVM parity, preserved clinical correlations (e.g., eGFR).  
MIT-licensed repo, joint manuscript with MULTIR members (MOS, etc.).



## Governance & QA:

ISO-aligned SOPs, **internal audits**, DR tests, evidence packs compiled.

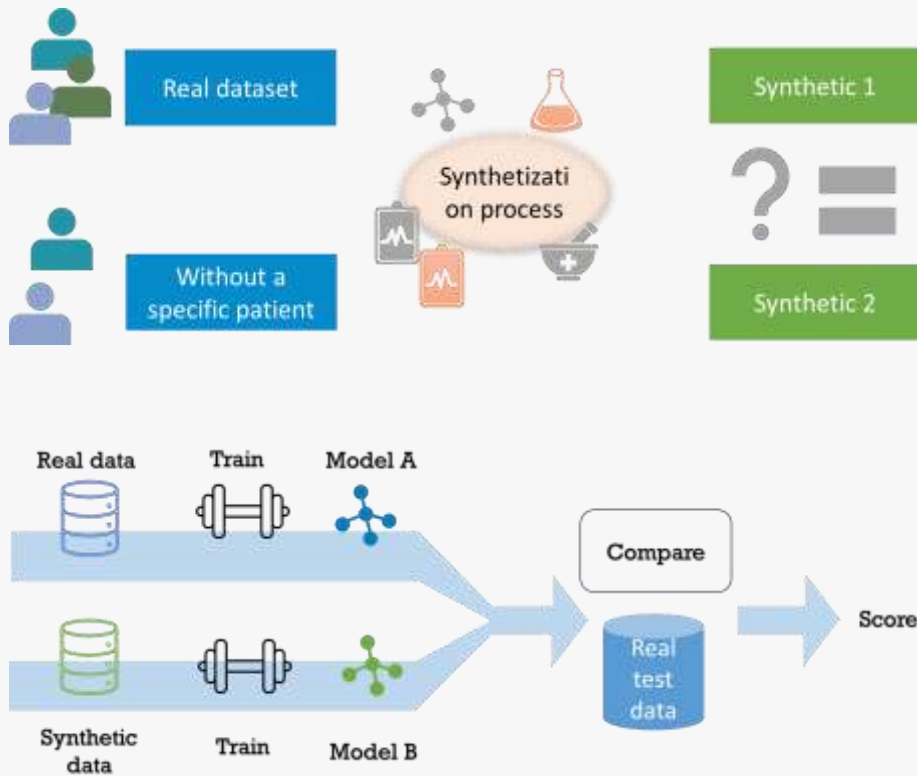


## Constraint:

**No internal cohort ingestion** until **JCA/DPA** are signed (technical onboarding runbook prepared).

# Results

## Achieved – Synthetic Data Validation (D2.3)



### Why synthetic now:

- Enables development/validation **without PHI** while JCA/DPA are pending, reduces re-ID risk.

### Method:

- **Gaussian copula** for high-dimensional tabular/omics; stable, interpretable dependence modeling.

### Co-development of copula-based synthetic pipeline

### Validation leadership on public datasets:

- peptide data (MS), additional diseases for generalization.

### Evidence produced:

- PCA/MDS cluster preservation
- **SVM performance parity** (train-synthetic/test-real and vice versa)
- **Clinical association** preservation (e.g., eGFR).

### Reproducibility:

- Contributed scripts, experiment configs, figure generation; coordinated analysis narrative.

### Dissemination:

- Co-authored manuscript
- open-science alignment
- readiness to extend to MULTIR cohorts post-JCA/DPA.

### Feedback loop:

- Provided requirements for rare-class handling; roadmap to hybrid deep generative components.

# D2.5 Autonomous, Adaptable & Federated Learning Models (M36)

## Data access pattern (with Data Shield/Data Broker)

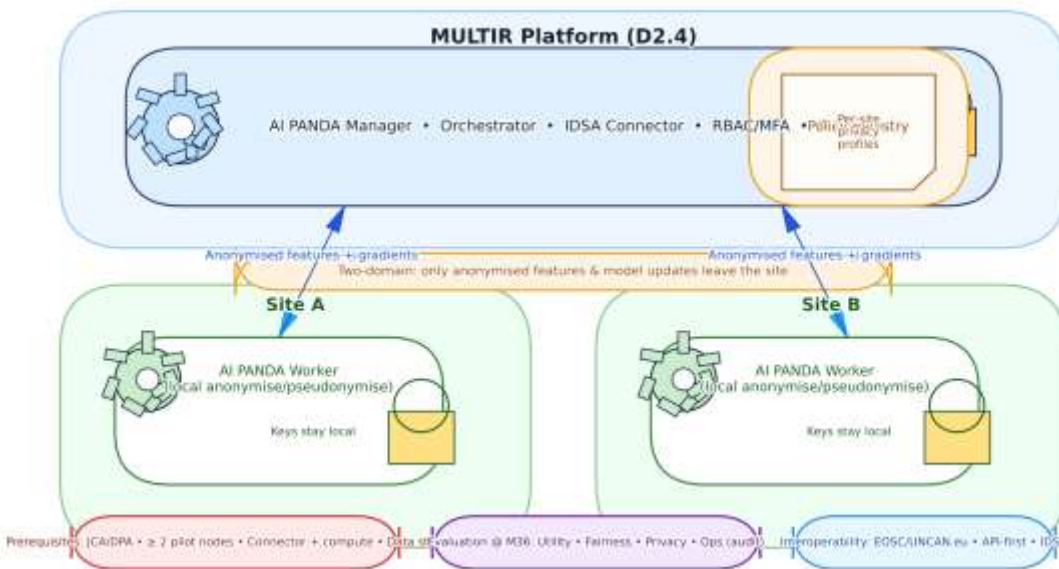
- **Manager/Worker** design: the **ATMC AI PANDA Manager** deploys a **Worker** at each site to pre-process and **anonymise/pseudonymise** locally; only anonymised features and model gradients/updates leave the site.
- Aligns with the **two-domain approach** (keys remain local) and supports sharing only anonymised outputs to the MULTIR platform.

## Integration & dependencies

- **Built on D2.4:** uses the governed **IDSA connector**, site identities/attestations, and platform RBAC/MFA.
- **Interoperability:** API-first; prepared for **EOSC/UNCAN.eu** endpoints once cohorts are live; metadata/ontology alignment inherited from D2.4.
- **Prerequisites:** JCA/DPA signed; at least two pilot nodes with connector + basic compute (CPU/GPU) and a nominated data steward.

## Evaluation & acceptance (evidence at M36)

- **Utility:** cross-site AUC/F1/PR-AUC; calibration (ECE); survival concordance for time-to-event tasks.
- **Fairness & robustness:** stratified performance (site/tumour/type), sensitivity to missingness, and shift tests.
- **Privacy/security:** DP  $\epsilon$ -budgets documented; penetration of secure-agg; audit trail coverage for every round.
- **Ops:** successful multi-round federations with **automatic recovery**, reproducible model artefacts, and signed **model cards**.



# Data Shield



## Goal:

- process data where it resides,
- minimize data movement
- share only GDPR-compliant outputs

## Manager/Worker architecture:

- ATMC AI PANDA Manager orchestrates workload
- Worker performs local anonymization/pseudonymization

## Configuration-driven:

- per-site privacy/security policy
- workers pulled on-demand
- ephemeral and auditable

## Outcome:

- standardized, repeatable local processing with platform-only receiving anonymized results

# Cross-WP links (WP2 to WP3 & WP4)

## WP3:

- method development consumes D2.4 APIs
- synthetic data from D2.3 supports method pre-validation

## WP4:

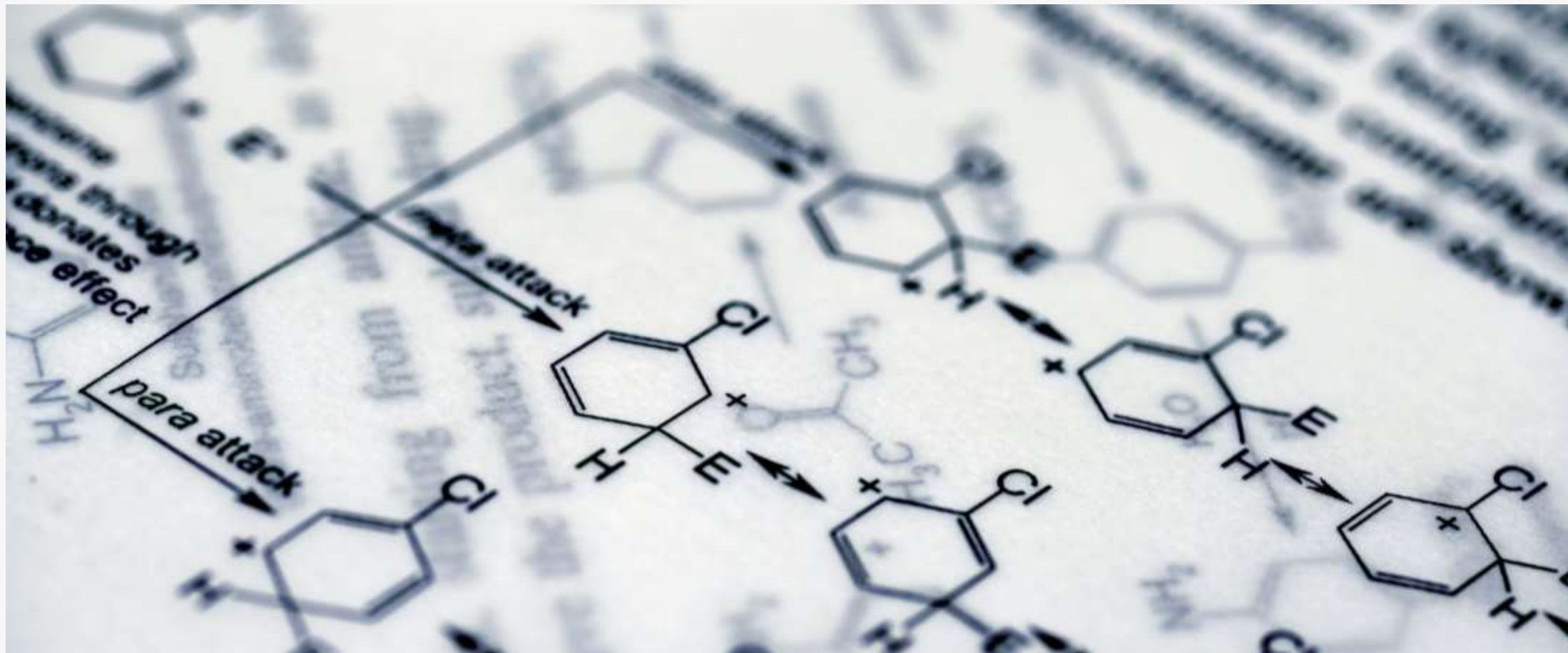
- statistical associations (D4.2) rely on curated datasets and audit trails from D2.4
- publication-grade provenance

## Feedback loops:

- WP3/WP4 findings refine D2.2 policies and D2.5 federated model requirements



WP3 - Clinical, pathology, molecular, immunology and imaging data: integration of existing and newly acquired datasets





## Description

T3.1 - Collection and curation of clinical datasets, treatment and follow-up datasets for lung cancer, bladder carcinoma and melanoma patients [M3 – M12] [Lead – NUH, Participants –HORG, UK-E, UZ, NUH, MGU, MOS, BRFAA, RadboudUMC, AU)

T3.2 - Collection and curation of broader host-related factors (including demographics, germline DNA variation) [M3 – M22] [Lead - RadboudUMC, Participant: AU, HORG]

T3.3 - Collection and curation of tumour molecular datasets (genomics, transcriptomics, epigenomics, proteomics datasets) [M3 – M22] [Lead - BRFAA, Participants AU, UK-E, UZ, HORG, MGU, RadboudUMC, MOS]

T3.4 – Collection and curation of immunophenotyping datasets including immunofluorescence and multiplexed mass cytometry[M3 – M22] [Lead - MGU, Participants AU, UK-E, HORG]

T3.5 – Collection and curation of ECM related data and peripheral immune-related metabolic datasets [M3 – M22] [Lead -MOS, Participants AU]

T3.6 – Integration of existing literature data on known molecular, immunologic and broader host-related factors for BC, lung cancer and melanoma [M3 – M22] [Lead – RadboudUMC, Participants AU, UK-E, HORG] [M3 – M22]

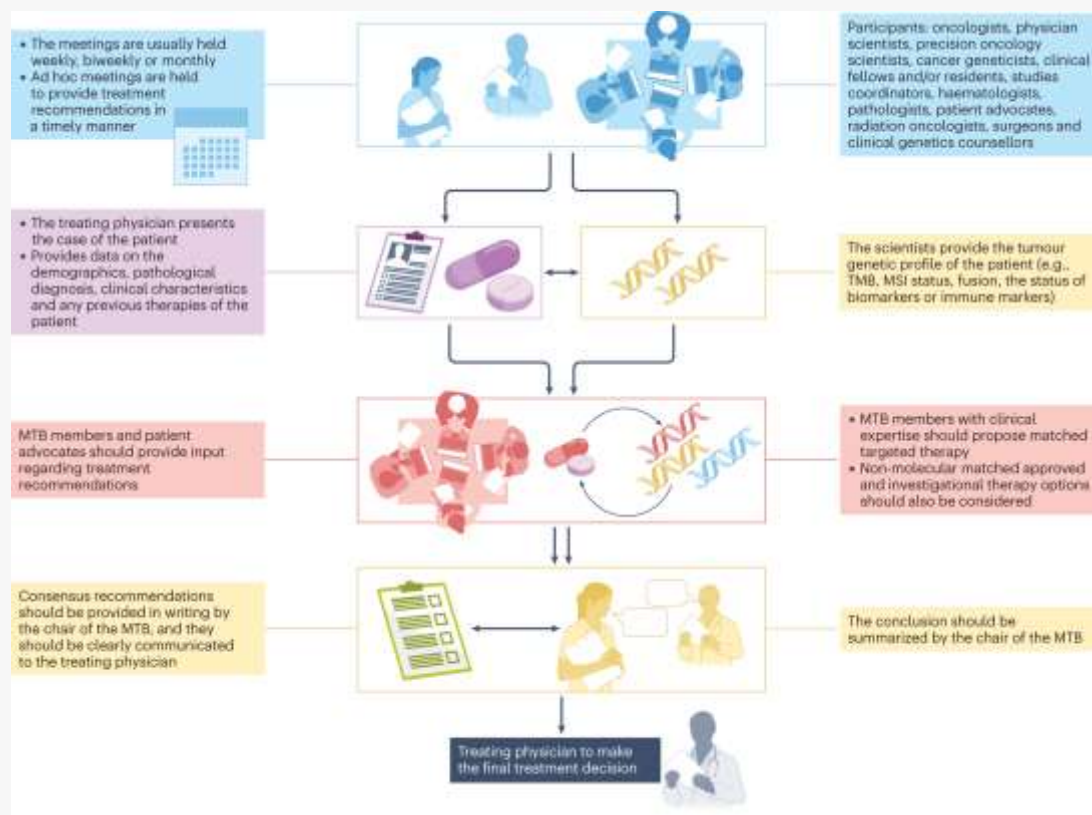
T3.7 - Single cell datasets and newly acquired data to supplement fragmented data [M3 – M24] [Lead - UZ, Participants –UK-E, MGU]

T3.8 – Imaging datasets and digital pathology assessment [M3 – M22] [Lead - UVIE, Participants –HORG, INS, NUH, AU, UK-E]



# MGU Contribution to T3.3

## Collection & Curation of Tumour Molecular Datasets



• Provides **tumour molecular datasets** including:

• **Genomics:** WES/WGS data for mutational landscape, CNVs, epigenetic modifications.

• **Epigenomics:** DNA methylation profiles (Illumina-based).

• **Transcriptomics:** Contributes datasets to be **remapped and requantified** using MULTIR-specific pipelines.

• Ensures MGU-generated molecular data adheres to **normalization and quality-control** procedures required for integration with consortium datasets.

# Contribution to T3.4

## Immunophenotyping Datasets

### Immunofluorescence (MGU-led) :

- Performs **multistaining and multiplexed immunofluorescence** to characterize immune infiltration:
  - Tumour periphery vs. tumour core.
  - Spatial heterogeneity of immune cell subsets.
- Uses **RNAscope** to identify functional subpopulations of **T cells, B cells, plasma cells, macrophages**.

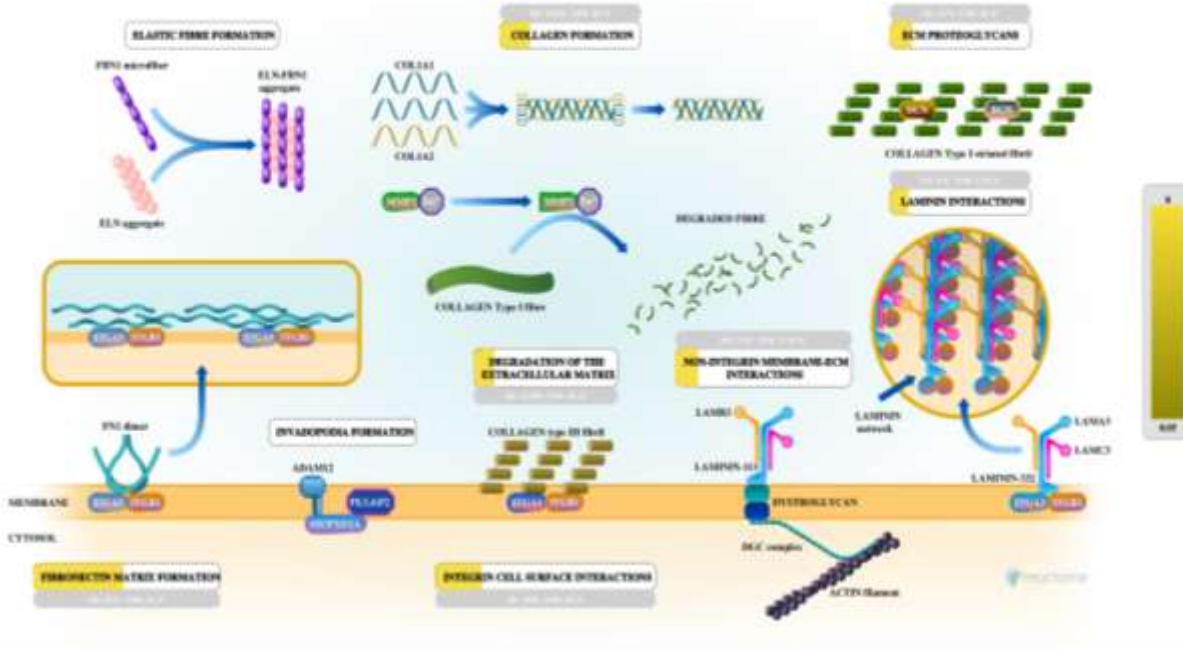
### Imaging Mass Cytometry (IMC) :

- Develops and applies **innovative analysis pipelines** providing:
  - Fully automated **ML-based cell segmentation**.
  - **Lineage assignment** and phenotype identification.
  - **Cell-cell interaction mapping**.
  - Detection of **cellular neighbourhoods/communities** with spatial resolution.
- Integrates IMC data from partners (AU, UK-E) into a unified spatial immunophenotyping framework.



# Contribution to T3.7 Single-Cell & Newly Acquired Datasets

## Extracellular matrix organization (R-HSA-1474244)



- Contributes to **single-cell immune repertoire studies** in collaboration with UZ and UK-E.

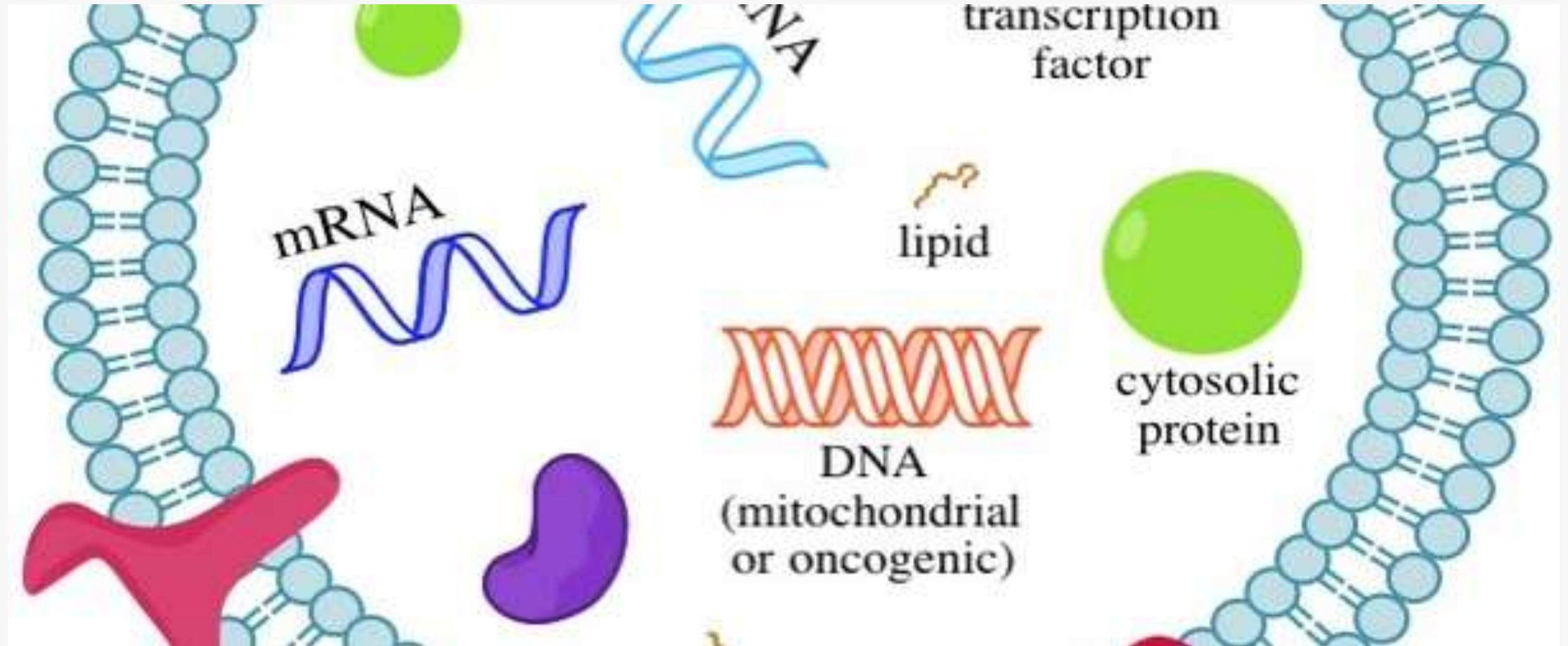
- Supports:

- Preparation and integration of **TCR/BCR sequencing data**.
- Quality assessment and downstream analysis of immune-profiling outputs.
- Applies internal expertise to help harmonize **gene expression** and **immune repertoire** single-cell datasets for use in MULTIR.

- Ensures that MGU's single-cell datasets meet consortium-level standards for:

- Data preprocessing
- Metadata structure
- Compatibility with MULTIR analytic endpoints

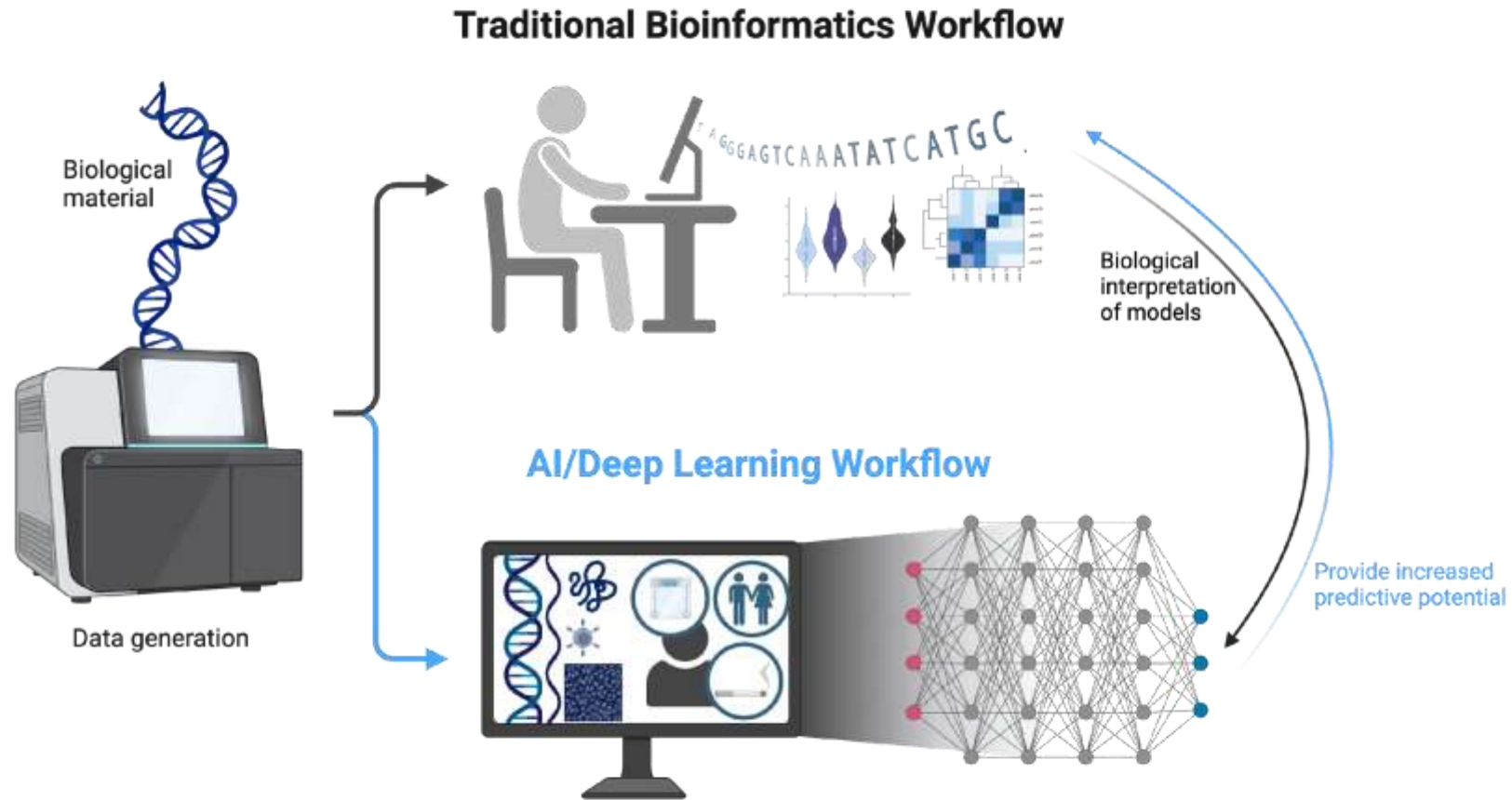
# WP4 – Modelling tumour host interactions and response





## WP4: From single data layers to complex models

Close interplay between T4.2 and tasks regarding AI-based modelling (T4.3-T4.7)



## Methodology:

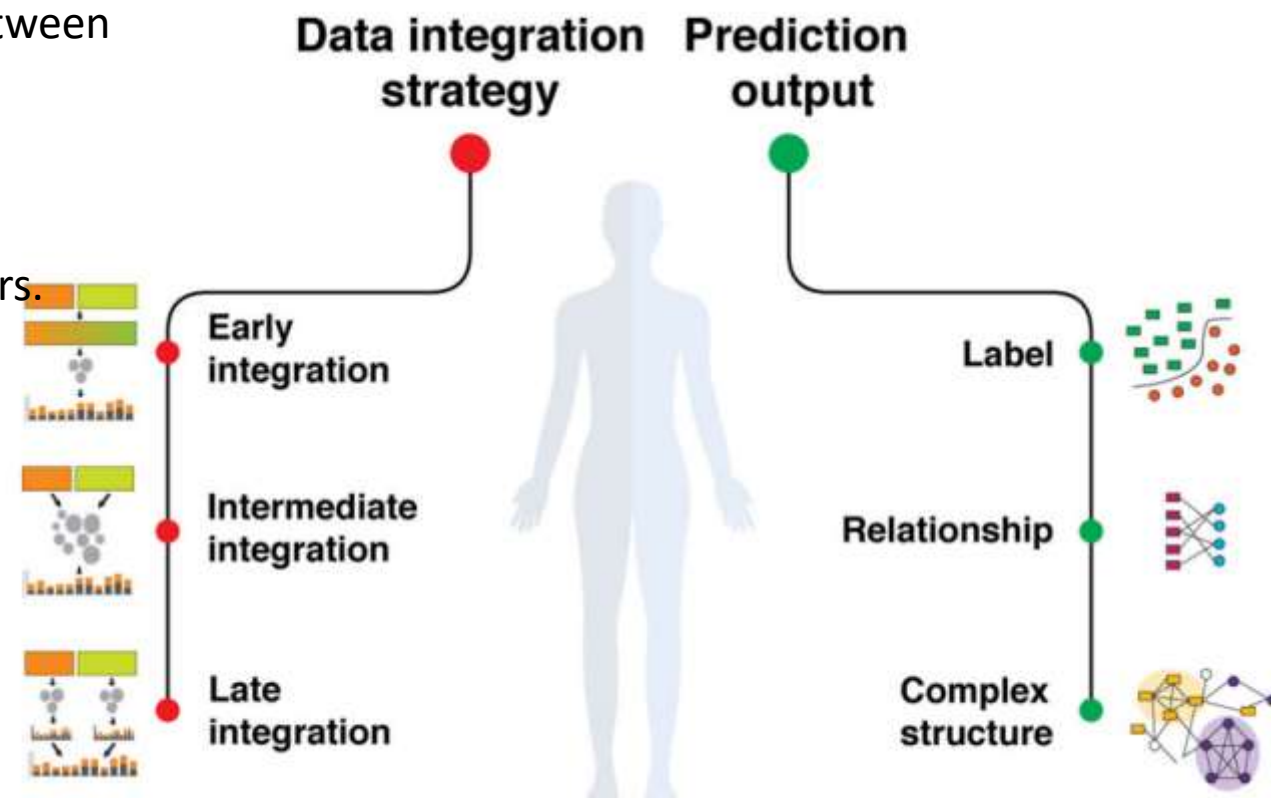
- Collection and analysis of data from individual tumors.
- Comparative analysis across multiple tumor types.

### Integration with Other Tasks:

- Utilizes data from WP2 and WP3 for analysis.
- Contributes findings to WP5 for model validation

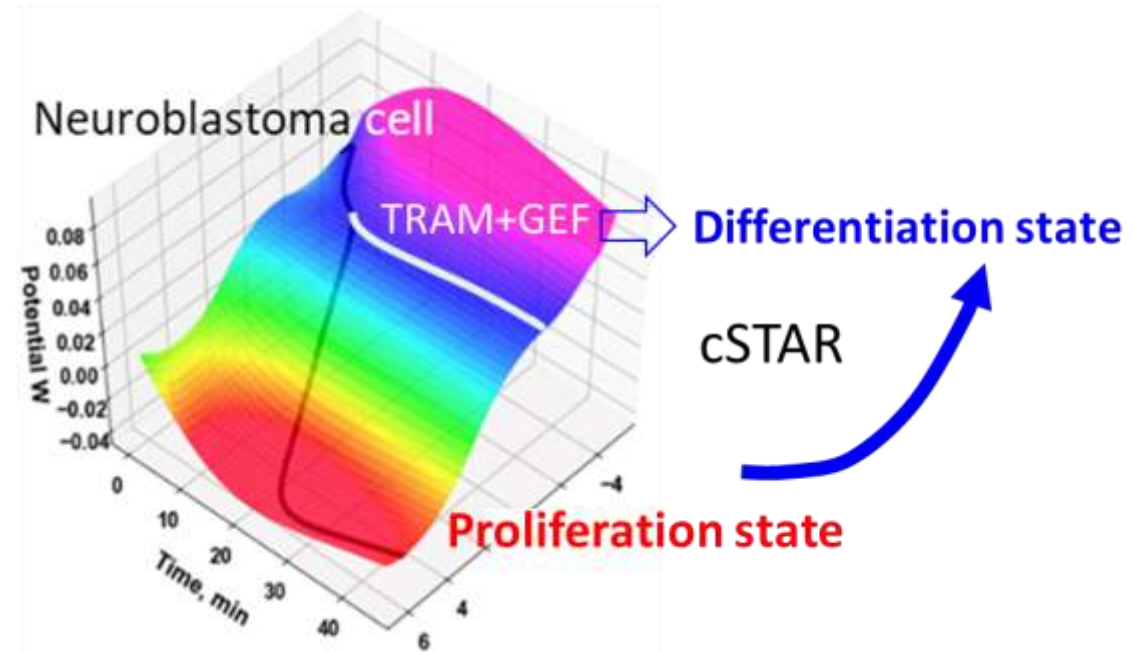
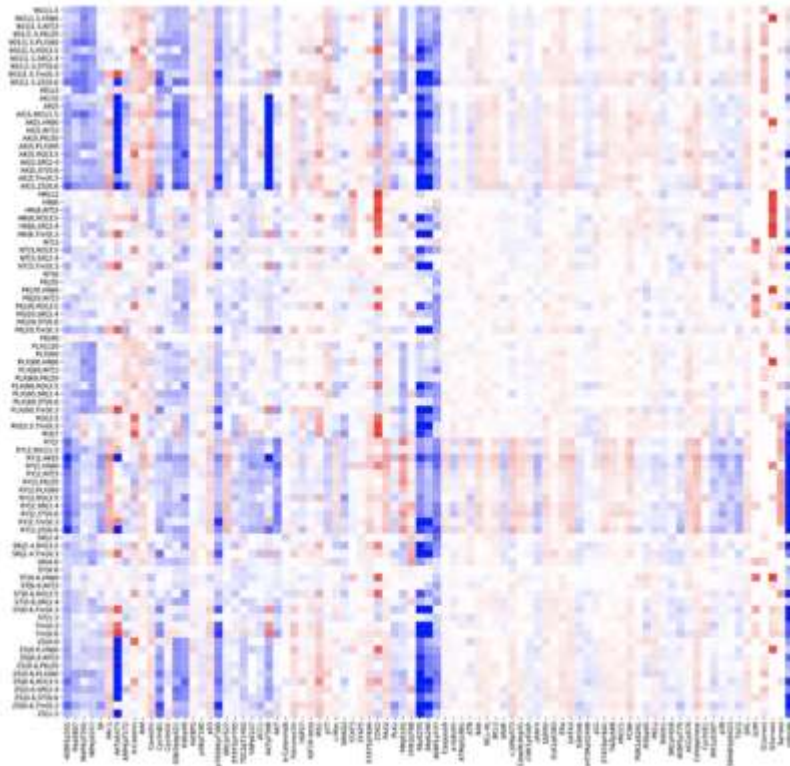
**Expected Outcome:**

- Comprehensive understanding of tumor behavior at different levels.
- Insightful data for model development and treatment strategies.



# cSTAR - cell State Transition Assessment and Regulation - Enables Us to Reverse Pathological States

cSTAR allows us to push cancer cells back to normal (differentiation)



Controlling the cell journey through Waddington's landscape

## Article

### Control of cell state transitions

*Nature*, 609, 975–985 (2022)

<https://doi.org/10.1038/s41586-022-05194-y>

Received: 11 January 2021

Oleksii S. Rukhlenko<sup>1</sup>, Melinda Halasz<sup>1,2,5</sup>, Nora Rauch<sup>1,5</sup>, Vadim Zhernovkov<sup>1</sup>, Thomas Prince<sup>1</sup>, Kieran Wynne<sup>1</sup>, Stephanie Maher<sup>1</sup>, Eugene Kashdan<sup>1</sup>, Kenneth MacLeod<sup>3</sup>, Neil O. Carragher<sup>3</sup>, Walter Kolch<sup>1,2</sup> & Boris N. Kholodenko<sup>1,2,4</sup>✉

**Objective:** To validate AI models against established parameters for accuracy and reliability.

### Methodology:

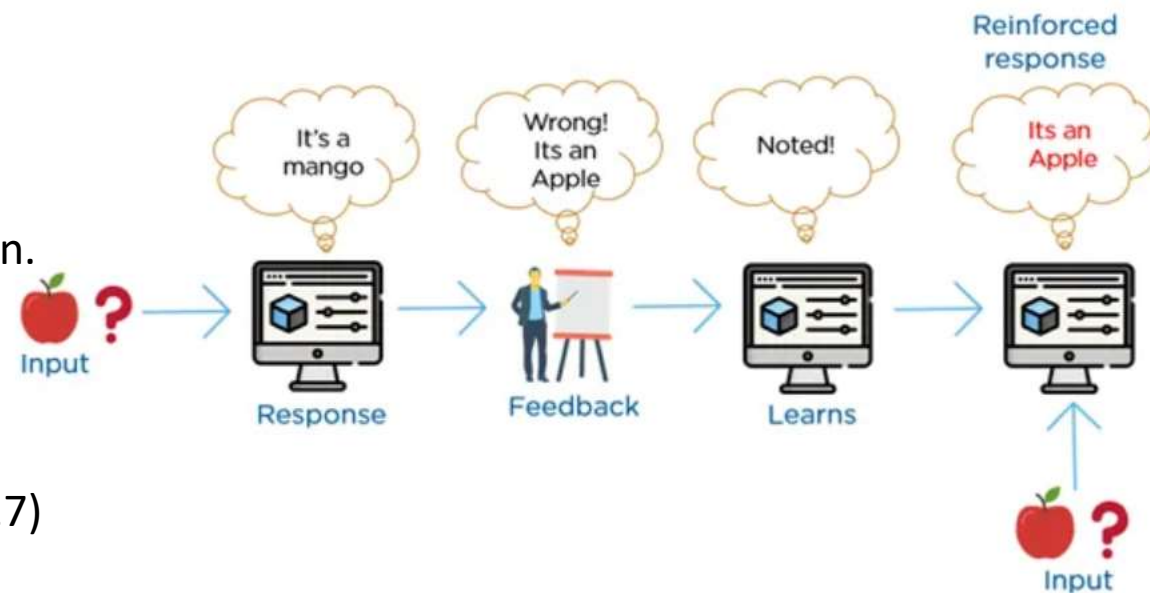
- Testing AI models using predefined parameters.
- Ensuring models meet set standards for clinical application.

### Integration with Other Tasks:

- Collaboration with WP3 for data integration.
- Utilizing outputs from WP4 for modeling (T4.2, T4.4 & T4.7)

### Expected Outcome:

- Reliable and clinically applicable AI models.
- Enhanced model credibility and trustworthiness.





### Approach:

- Utilize transfer learning techniques for model development.

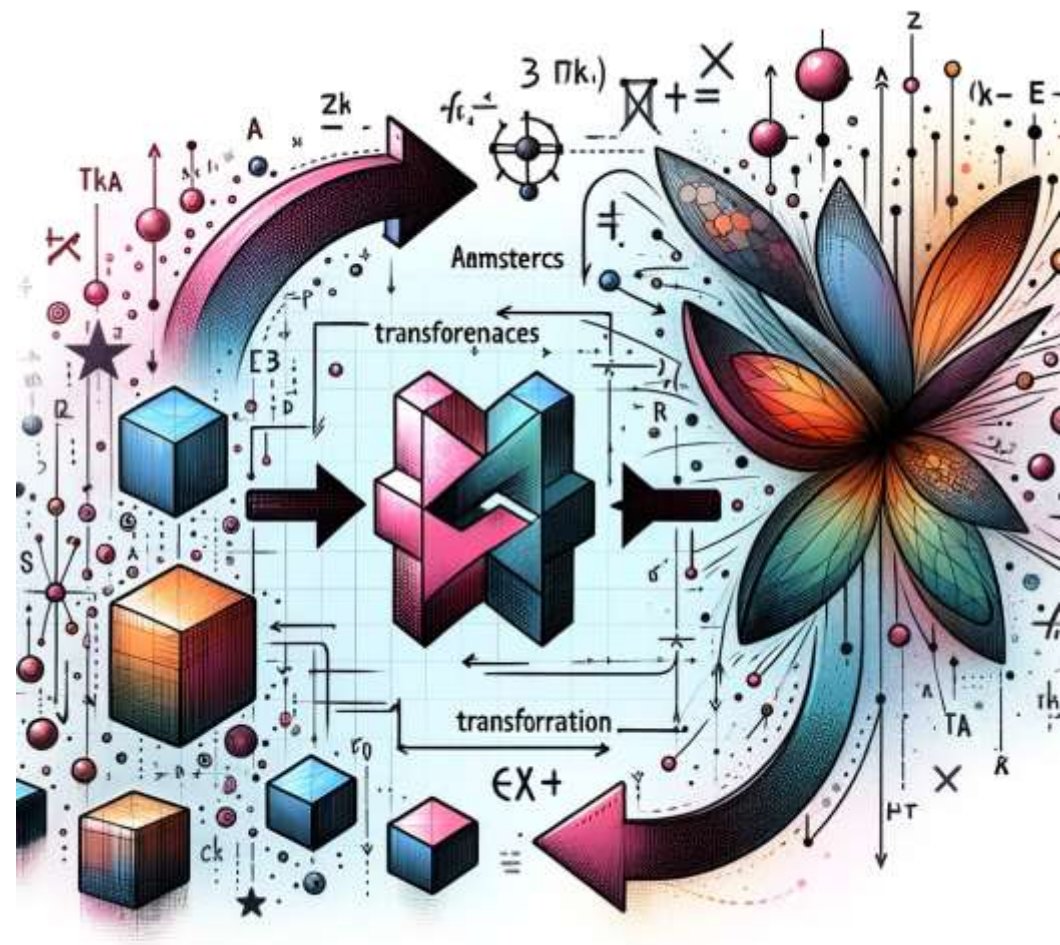
## Immunotherapy Outcomes=BMRA+GCN+Transfer Learning

T4.4. -> fine tune -> outcome prediction

- Incorporate diverse datasets to enhance model robustness.

### Expected Impact:

- Improved prediction accuracy of patient responses to immunotherapy.
- Tailored treatment plans based on model predictions.



### Task 6.6: Development of Web based application for predictive and guidance tool (M39-M44) [Lead – ATMC]

- Develop Web based applications to predict outcome and response to therapy based on multiple host (and tumour) features fed to AI models through a Web user interface
- App will be available for every project partner to deploy it on own IT landscape
- Web application to be created based on input from patients (partner PU) and regulators (EMA)
- App to be validated *in silico* using data available to the consortium and collected by consortium members over course of project duration
- Post-project prospective study planned for validation conform to EU regulation 2017/746