



Data- and knowledge-driven multimodal learning in Computational Pathology: A comprehensive survey

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1. Motivation & Scope

Why multimodal CPath matters?

Histology alone captures morphology, but clinical decisions combine tissue context with genomic, radiologic, and longitudinal patient evidence.

WSI

Radiology

EHR & reports

Omics profiles

What this survey organizes?

1. Heterogeneous clinical evidence

WSIs describe tissue morphology;
Radiology captures organ-level context;
Genomics reveal functional perturbations;
Reports encode clinical trajectories and expert reasoning.

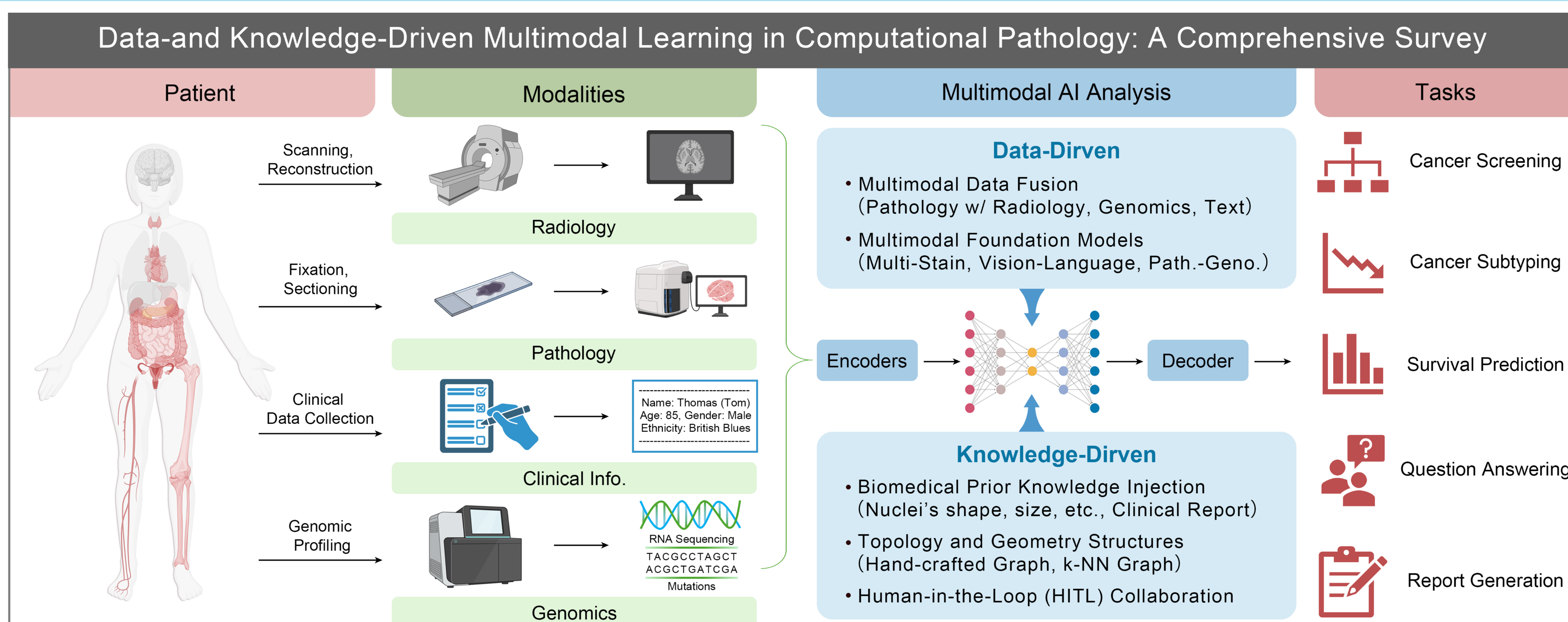
2. Two methodological engines

Data-driven models learn alignment, fusion, and scalable representations.
Knowledge-driven methods inject topology, prompts, and human feedback for interpretability and trust.

3. Clinical translation lens

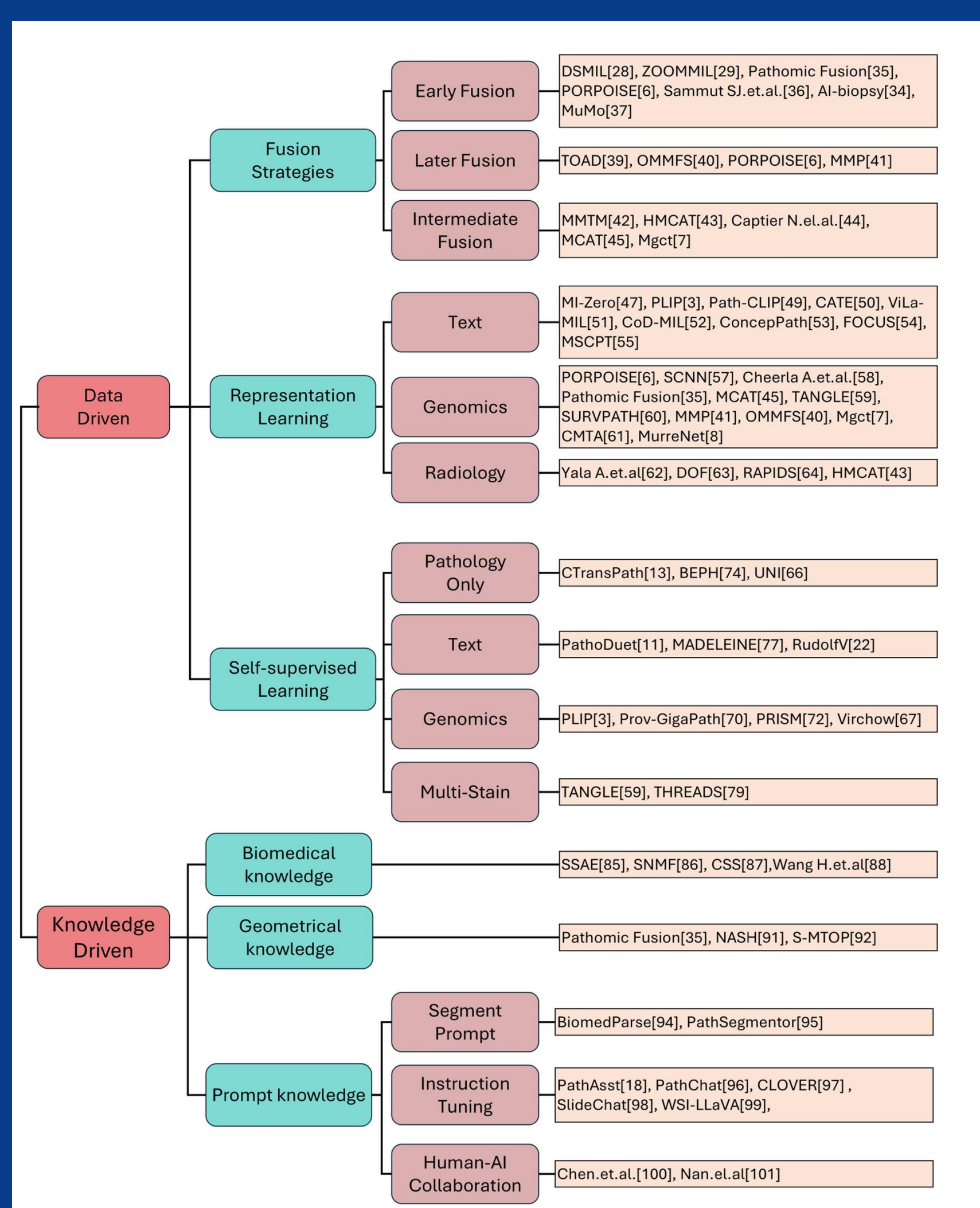
Links technical advances to deployment barriers: missing modalities, scanner and stain variation, and the need for pathologist-valid explanations.

2. Graphical Abstract: multimodal pathology AI at a glance

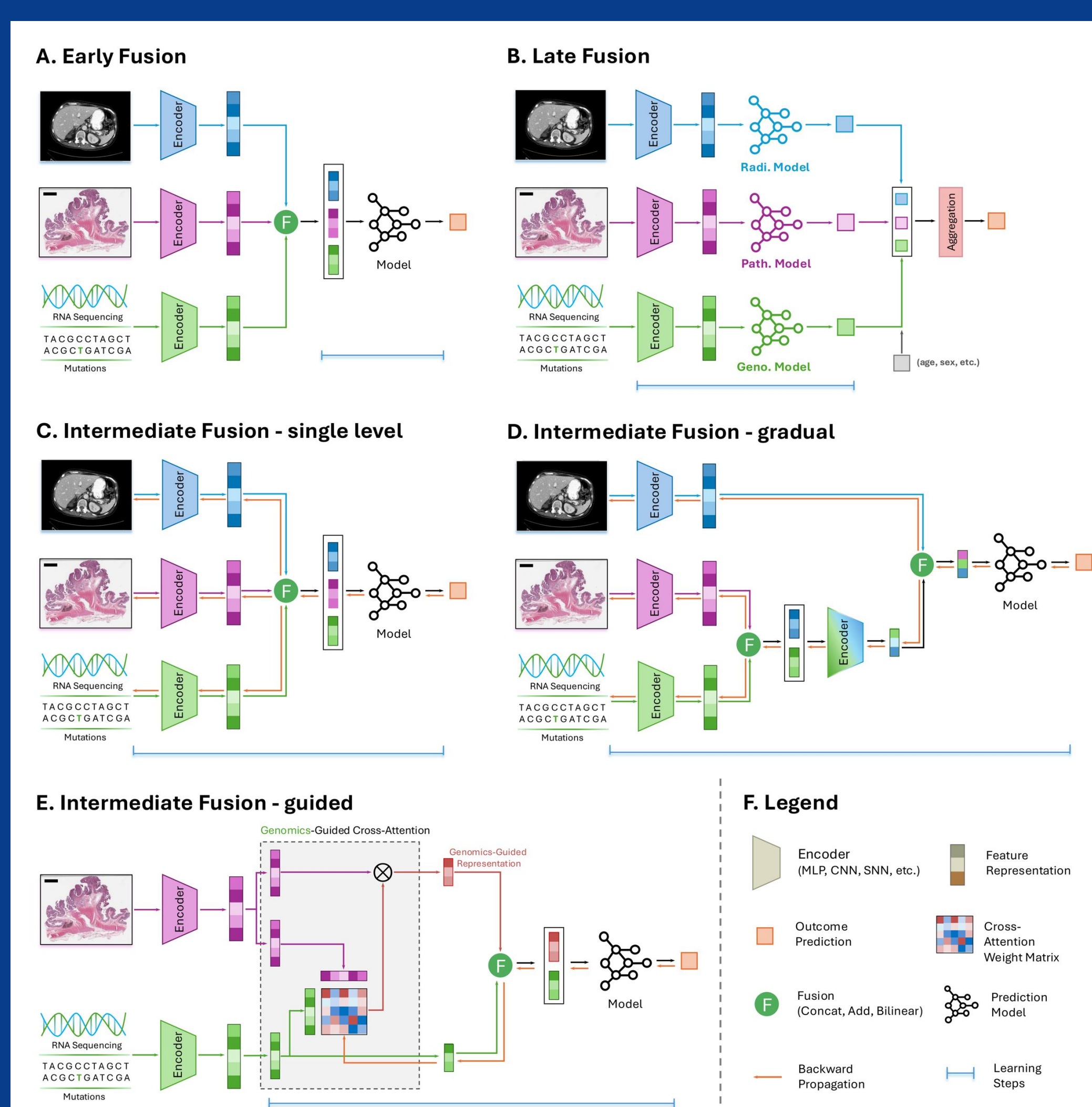


Multimodal CPath connects patient-level data with data- and knowledge-driven AI to support diverse downstream tasks in clinical practice.

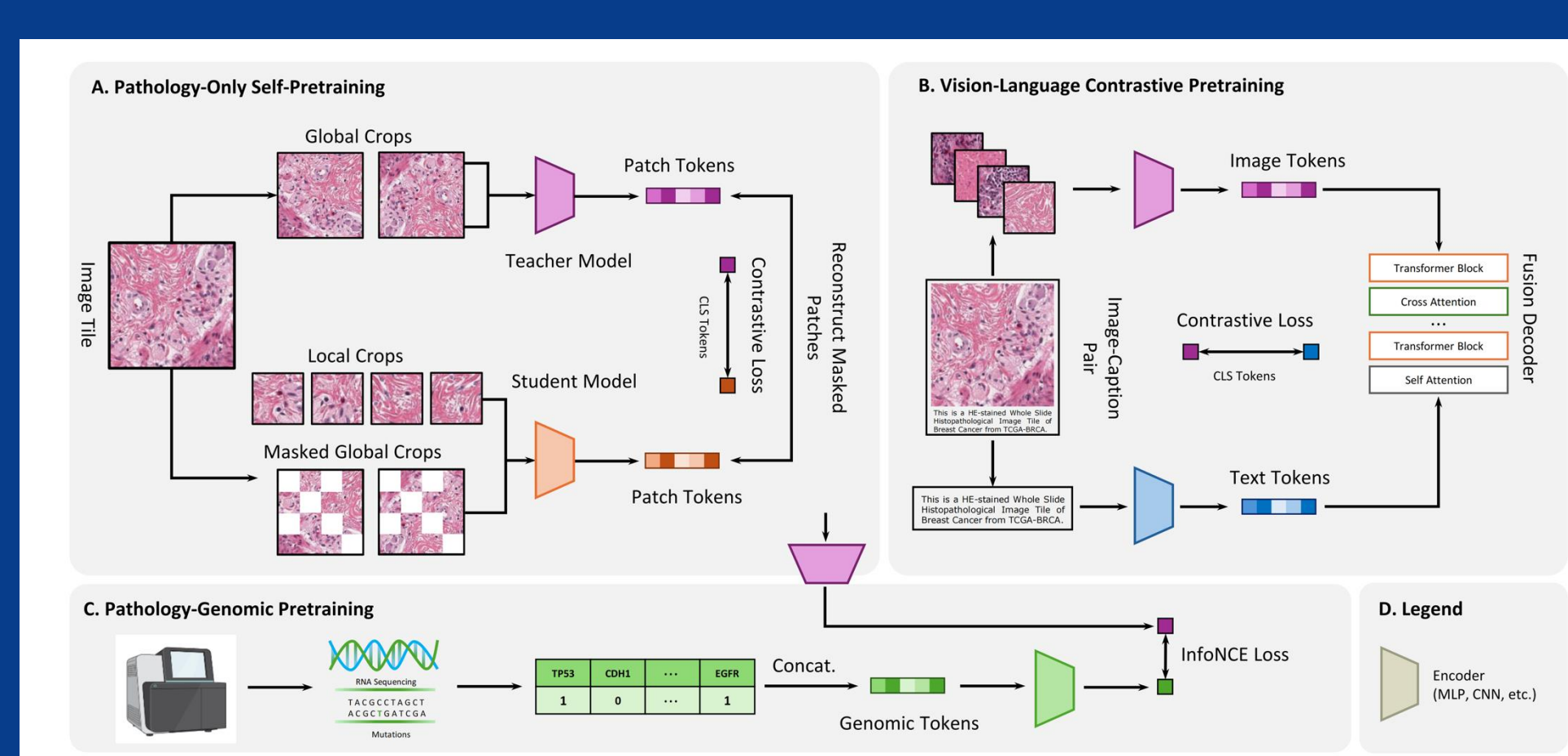
3. Hierarchical design taxonomy



4. Multimodal fusion taxonomy



5. Multimodal alignment taxonomy



6. Foundation models taxonomy

- Modality & Knowledge:**
 - H&E / Multi-Stain / Vision-Language
- Pretraining framework:**
 - Contrastive / Distillation / Masked Modeling
- Architecture & Data scale:**
 - ViT-S / B / H / G & LongNet for Prov-GigaPath

7. Future directions for trustworthy multimodal CPath

Unified representations

Align WSIs, omics, radiology, reports, mIF, 3D pathology, and longitudinal slides

Dynamic fusion

Adapt to missing modalities, noisy data inputs, latency, and unequal data reliability

Knowledge-driven AI

Encode diagnostic criteria, biomedical priors, and pathologist-verifiable reasoning

Trustworthy evaluation

Avoid public-data leakage and build clinically meaningful, validated benchmarks

Robust generalization

Handle scanner, stain, center, specimen-quality, and rare-case shifts