# Synthetic Multimodal Data Modelling for Data Imputation

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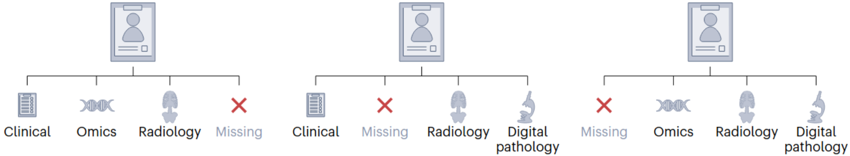
## Paper Background

**Problem:** Missing data is a persistent problem in biomedical research.

- Acquiring multiple data modalities for each patient is often expensive.



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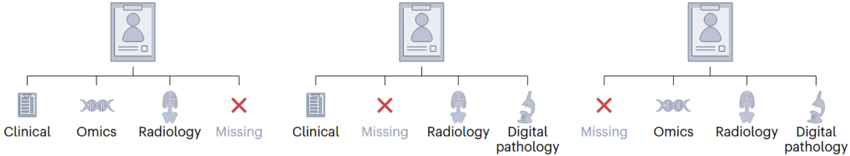


**Challenge:** Most of the existing data-imputation techniques can only handle a single data modalities.

- Their predictions rely heavily on “similarities” between data points.

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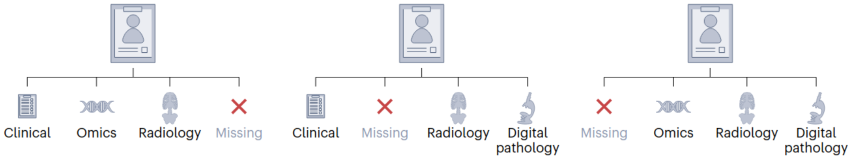
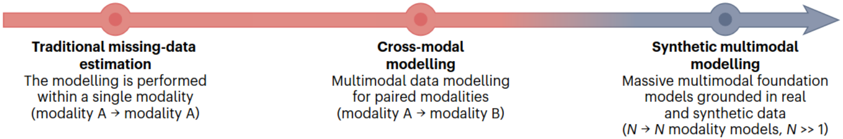


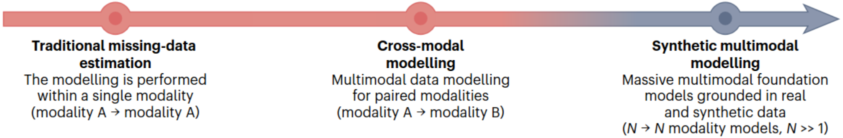

**Challenge:** Most of the existing data-imputation techniques can only handle a single data modalities.

- Their predictions rely heavily on “similarities” between data points.

- Diverse test and data modalities supply complementary insight into a distinct facet of the patient’s health or disease state.

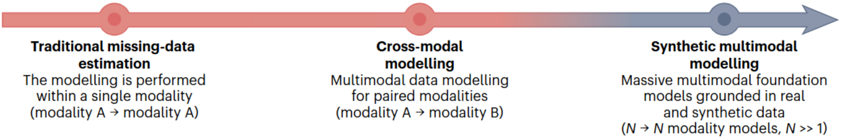


# Paper Exposition



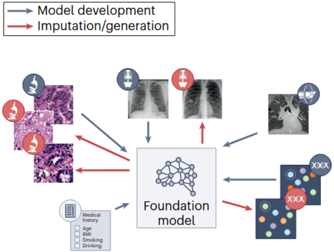

**Prospective Solution:** Synthetic multimodal data modeling.

- This framework utilizes foundation models to impute missing data and to generate realistic synthetic samples (Carrillo-Perez et al., 2024).




**Prospective Solution:** Synthetic multimodal data modeling.

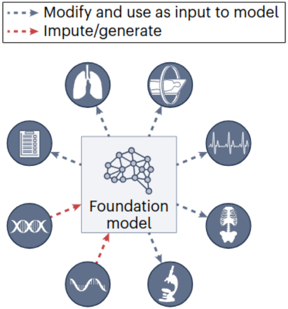
- This framework utilizes foundation models to impute missing data and to generate realistic synthetic samples (Carrillo-Perez et al., 2024).
- Foundation models integrate multimodal information into (low-dim) embeddings so as to capture complex interactions between modalities.



# Advantages of Synthetic Multimodal Data Modeling

1. Dive deeper into the joint data distribution of modalities, and thus enhance imputation quality.

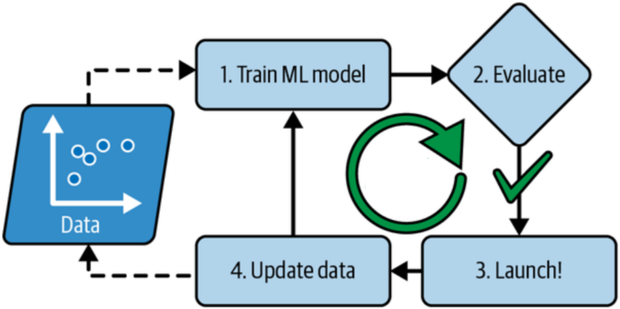
2. Explore multi-faceted knowledge through in silico hypothesis testing (*i.e.*, via computer simulations).
   - Perform interventions and ablation studies into certain data modalities or study the effect on generated synthetic modalities (Roohani et al., 2024).




   - Synthetic data from the model can be recycled, facilitating self-supervised learning (Krishnan et al., 2022).

# Advantages of Synthetic Multimodal Data Modeling

3. Offer unique flexibility when handling evolving patient data.
   - Dynamically update the model representation of all modalities available, *i.e.*, online learning mechanism.




   - This is achievable due to the gradient descent updates of modern ML model training scheme.

# Adoption Challenges of Synthetic Multimodal Data Modeling

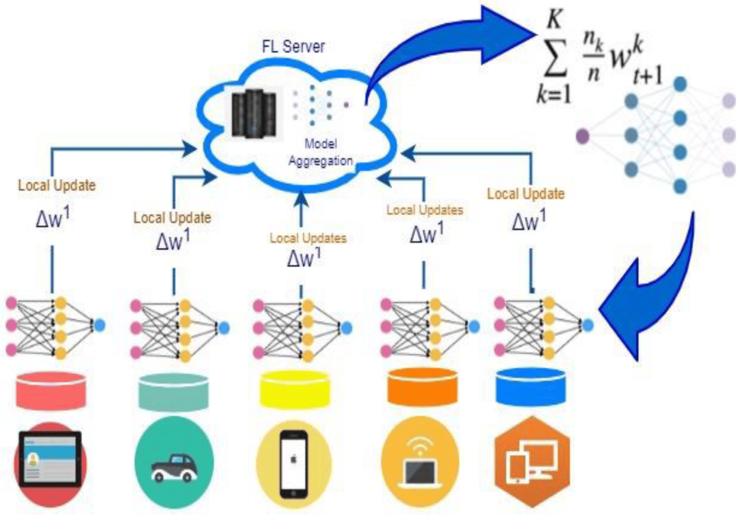
1. How can we evaluate the quality of generated data?
   - Existing metrics, such as Fréchet inception distance, may contain flaws (Stein et al., 2024).

$$d_F(\mu, \nu) = \left[ \inf_{\gamma \in \Gamma(\mu,\nu)} \int_{\mathcal{X} \times \mathcal{Y}} ||x - y||^2 \, d\gamma(x, y) \right],$$

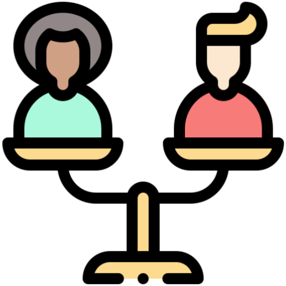
     where $\Gamma(\mu, \nu)$ is the set of measures on $\mathcal{X} \times \mathcal{Y}$ with marginals $\mu$ and $\nu$ on the first and second factor, respectively.

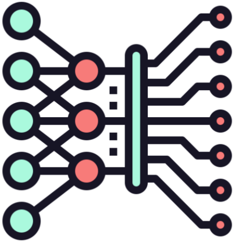
2. How can we address maliciously generated data, *i.e.*, deepfake?
   - Introduce visually imperceptible yet computationally detectable watermarks.

3. How can foundation models comply with data privacy regulations?
   - Perhaps we can use federated learning (Kairouz et al., 2021).



4. How can we maintain the algorithmic fairness of foundation models?
   - Current data sources are often skewed towards developed countries and male patients.





5. How can foundation models handle missing-not-at-random data?
   - Models may be overfitting to specific missingness patterns in the training data.

# Thank you!

More details can be found in

Carrillo-Perez, F., Pizurica, M., Marchal, K. and Gevaert, O. "Synthetic Multimodal Data Modelling for Data Imputation." *Nature Biomedical Engineering* (2024): 1-5. https://www.nature.com/articles/s41551-024-01324-1.

# Reference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