Clinical Data Wrangling

An Introduction

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HIP 523

Introduction

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  - Casey Eye Institute
  - Data Scientist
  - Machine Learning Engineer
- Computer Vision + Clinical Data
- Bioinformatics and Clinical Informatics

Acknowledgements

- Slides
  - Adapted from the Clinical Data Wrangling Workshop
  - Nicole Weiskopf, PhD
  - Ted Laderas, PhD
- Data
  - Adapted from the synthetic patient cohort used in BMI 569: Data Analytics

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- **Identify** when missing values in data may affect using clinical data for reuse
- **Identify** possible predictors of an outcome using exploratory data analysis

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- **Metric:** whether a patient has be readmitted to the hospital within 30 days

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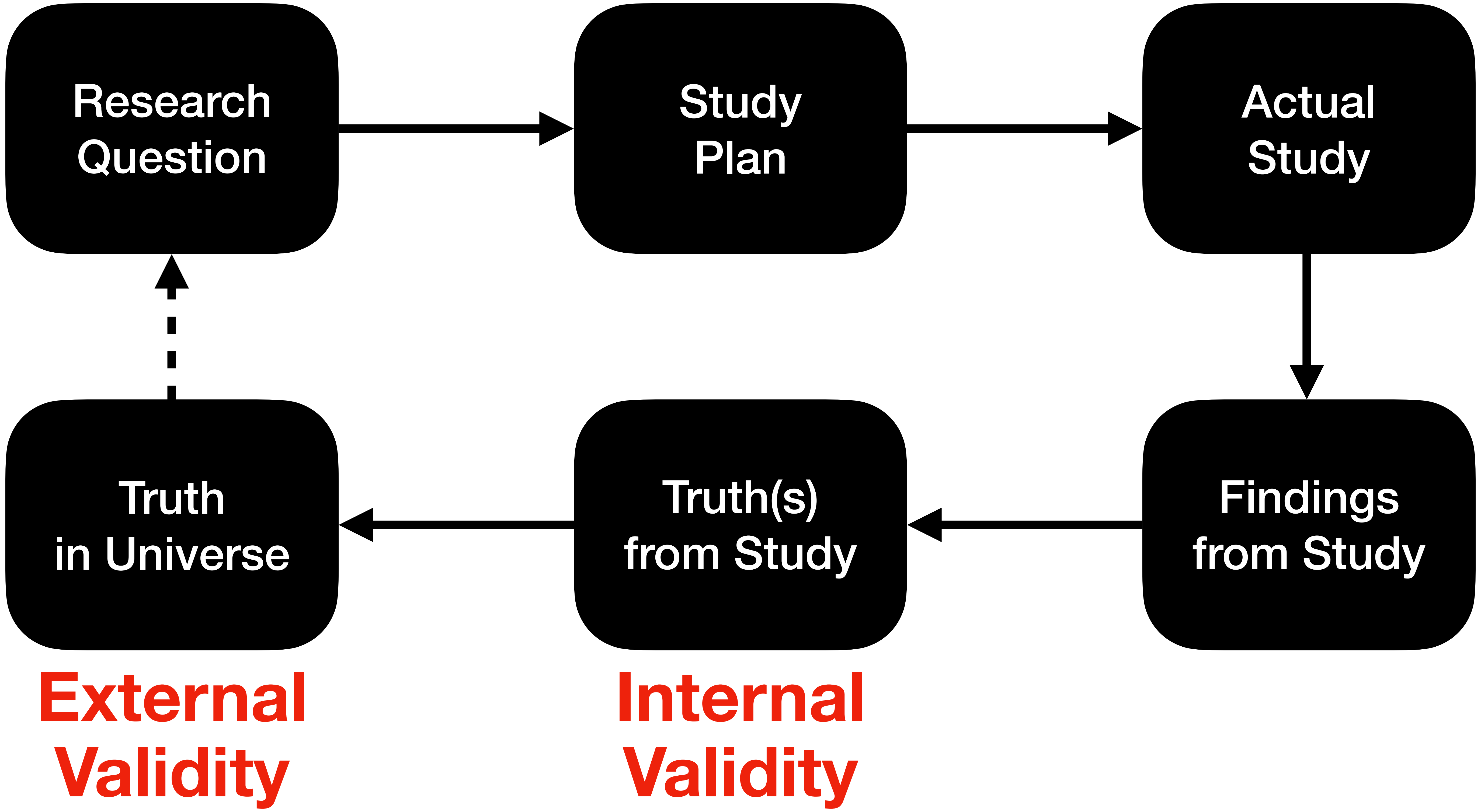
    - Length of Stay in Hospital
    - Age

Construct a Hypothesis

- How would one of these potential predictors impact whether a patient is likely to be readmitted to the hospital within 30 days?
  - History of diabetes
  - History of myocardial infarctions
  - Age
  - Length of stay

Research

Good Research Should Provide Broadly-applicable Truths



Adapted from Designing Clinical Research: An Epidemiologic Approach, Hulley SB, Cummings SR, Browner WS, Grady DG, Newman TB. Third edition, 2006.

Clinical Data

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- **Primary purpose is *not* research**

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- Increased representativeness (i.e., generalizability and external validity)

Clinical Data

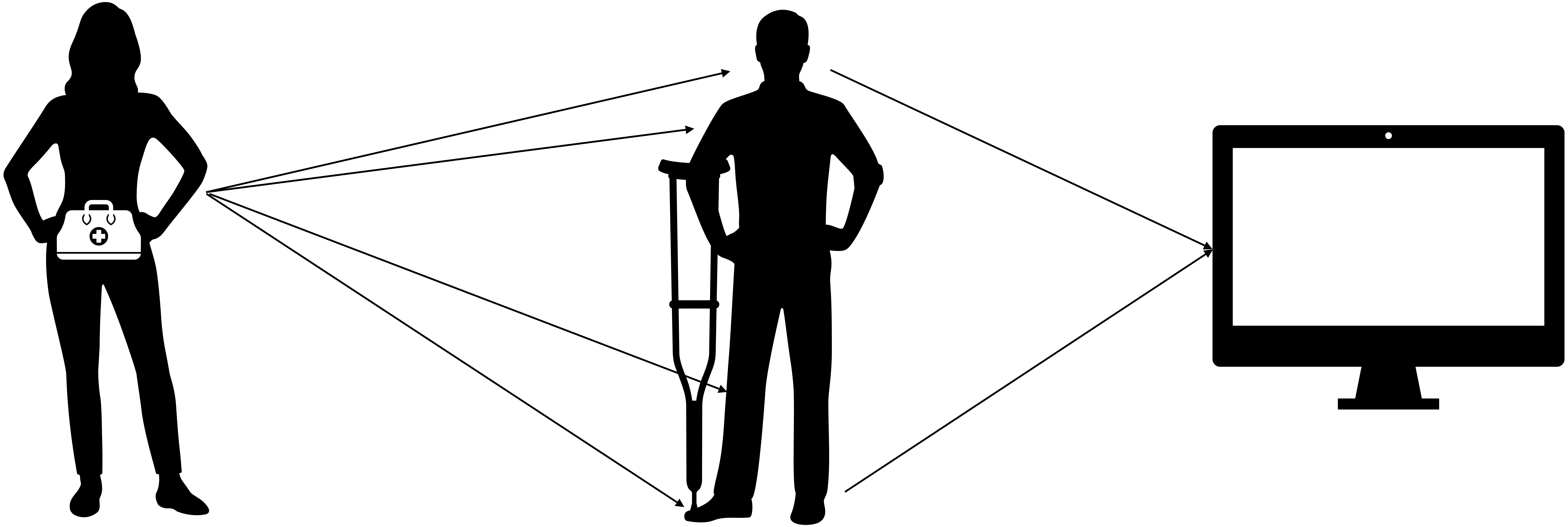
Electronic Health Record Data Quality

- Quality of data is **defined with respect to its intended use case**
    - Clinical data are collected for patient care and billing purposes
- The processes involved in taking a clinical truth about a patient all the way to a dataset being used for research is fraught with pitfalls

Hogan & Wagner (1997) Accuracy of data in computer-based patient records.
Chan et al. (2010) EHRs and the reliability and validity of quality measures: a review of the literature.

Clinical Data

Not all clinical concepts are observed. Not all observations are recorded.



Clinical Data

Electronic Health Record Data Quality

- **Correctness:** 44–100%
- **Completeness:** 1.1–100%
- Examples
  - Completeness of smoking status: 10–38%
  - Completeness of blood pressure: 0.1–51%

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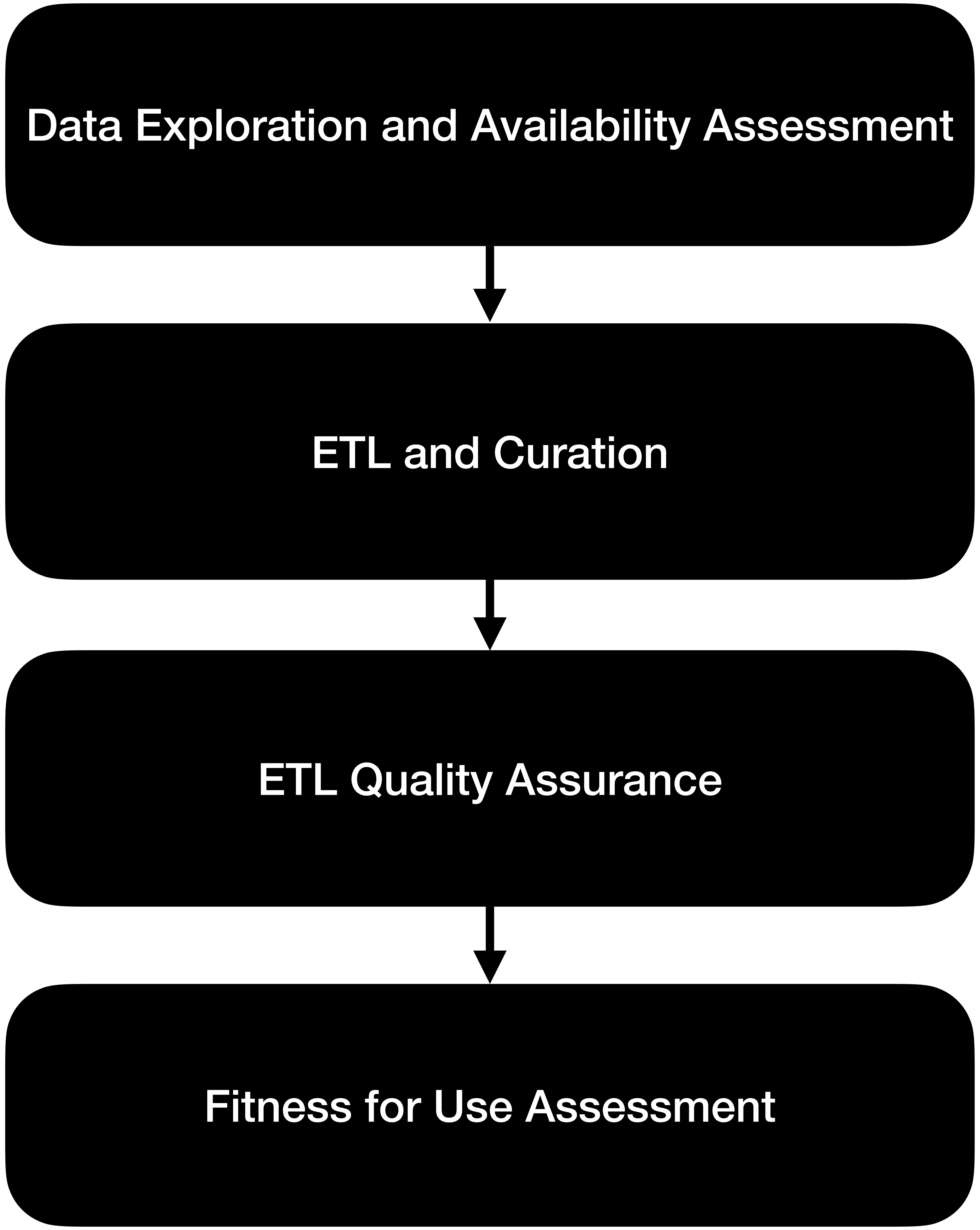
Clinical Data
Processing

A **systematic,** but **flexible,** approach to “wrangling” your clinical data, combined with basic competencies in exploratory data analysis, will get you where you want to go.

ETL: Extract, Transform, Load



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- **MNAR** — Missing Not at Random
  - Pattern of missingness is **related** to the values of the data that are **missing**

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Missingness

Simplified Example: Height Measurements

	Population Mean	Sample Mean (No Missingness)	Sample Mean (MCAR)	Sample Mean (MAR)	Sample Mean (MNAR)
Men	74.0	70.2	70.3	70.5	71.3
Women	64.0	64.2	64.1	64.2	65.5
Overall	67.0	67.2	67.1	66.3	68.4

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Sample of 200 men and 200 women

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50% of men
did not want to share their height

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Half of the shortest 25% of men and women
did not want to share their height

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  - Do not think of data quality as an issue of right versus wrong values
- **Systematic** data quality problems can drastically alter results
  - Data that are “bad” at random are not always an issue in research
- When you uncover potential data quality problems, be thoughtful in your attempts to compensate