Clinical Data Wrangling

An Introduction

Aaron S Coyner, PhD

HIP 523

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

Introduction

Aaron S. Coyner, PhD

- Senior Computational Biologist
  - Casey Eye Institute
  - Data Scientist
  - Machine Learning Engineer
- Computer Vision + Clinical Data
- Bioinformatics + Clinical Informatics

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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

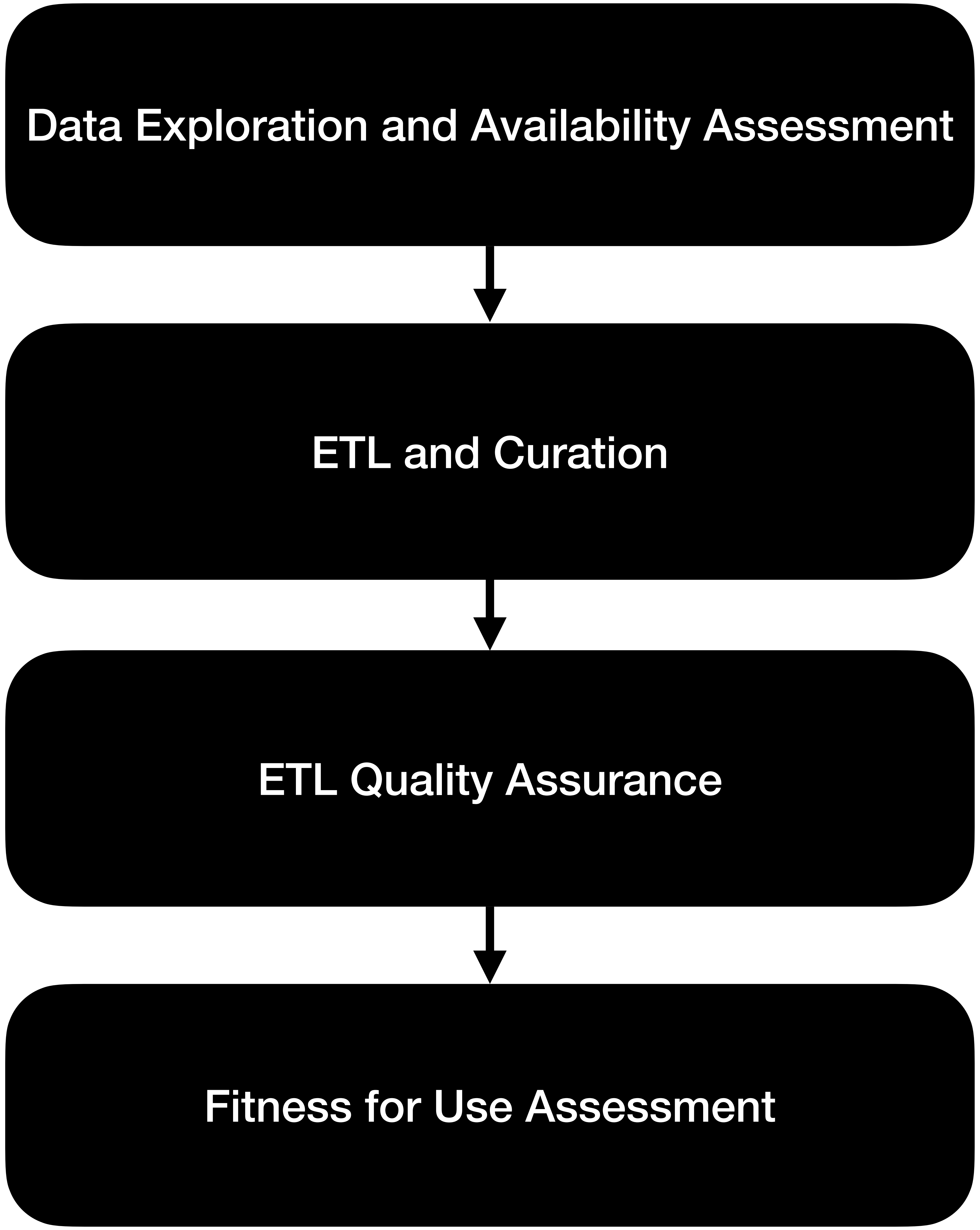
Construct a Hypothesis

- 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

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

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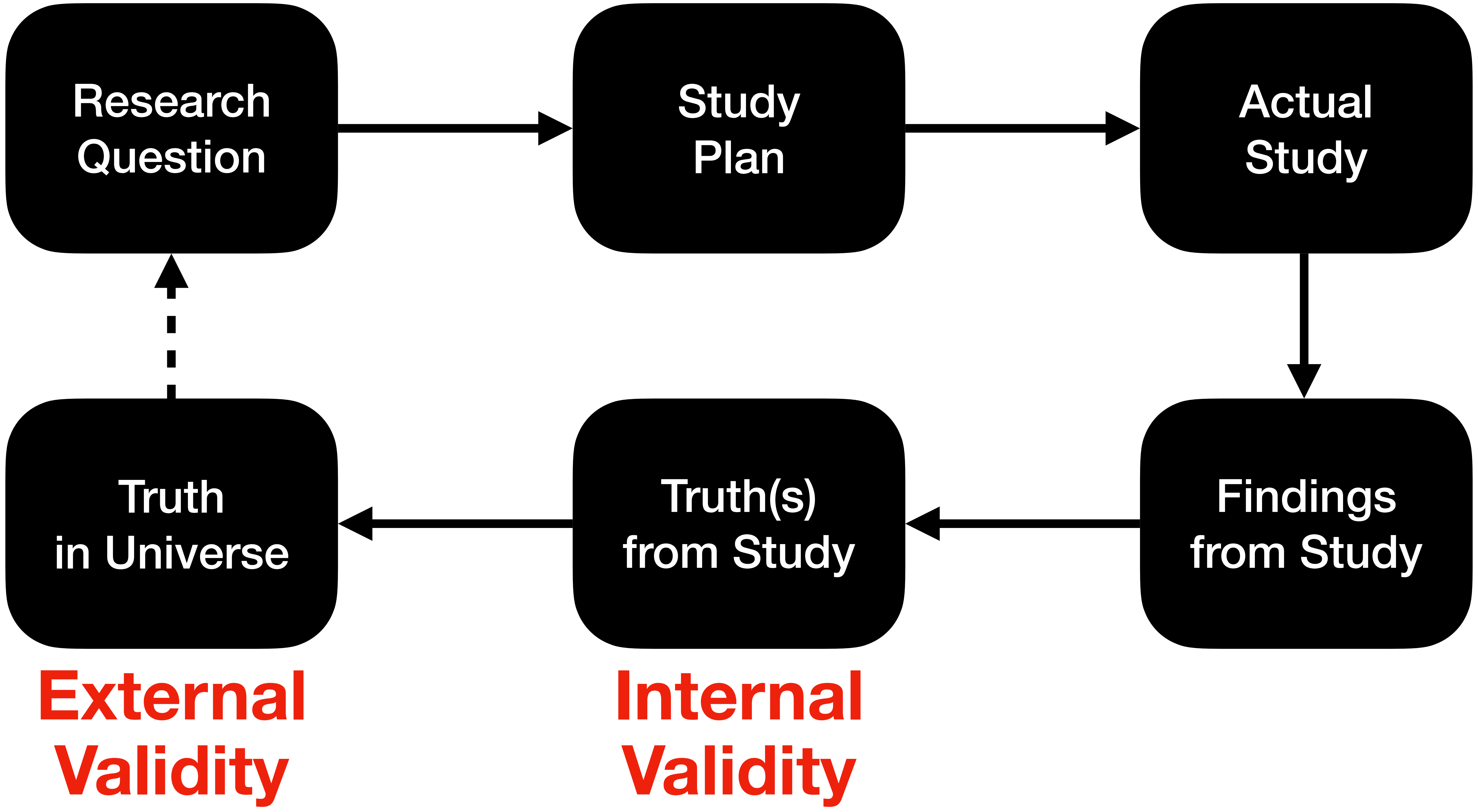
- Increased representativeness (i.e., generalizability and external validity)

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

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%

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

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

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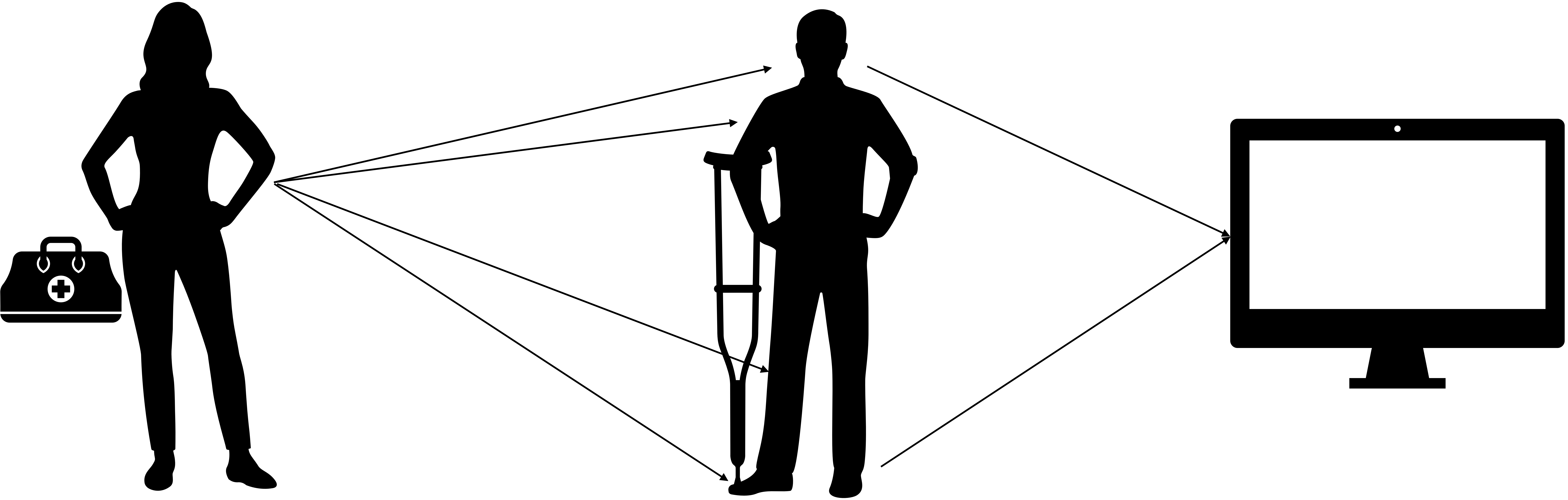
Clinical Data

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



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A Brief Introduction

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  - In essence, it is not “random” 🙄

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- **MAR** — Missing at Random
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  - In essence, it is not “random” 🙄
- **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	70.4	70.2	70.3	70.5	71.3
Women	64.0	64.2	64.1	64.2	65.4
Overall	67.0	67.2	67.1	66.3	68.4

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Simplified Example: Height Measurements

Sample of 200 men and 200 women

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25% of men and women
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50% of men
did not want to share their height

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Simplified Example: Height Measurements

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