Ethics of Data Collection, Use, and Responsibility of Artificial Intelligence in Skeletal Biology

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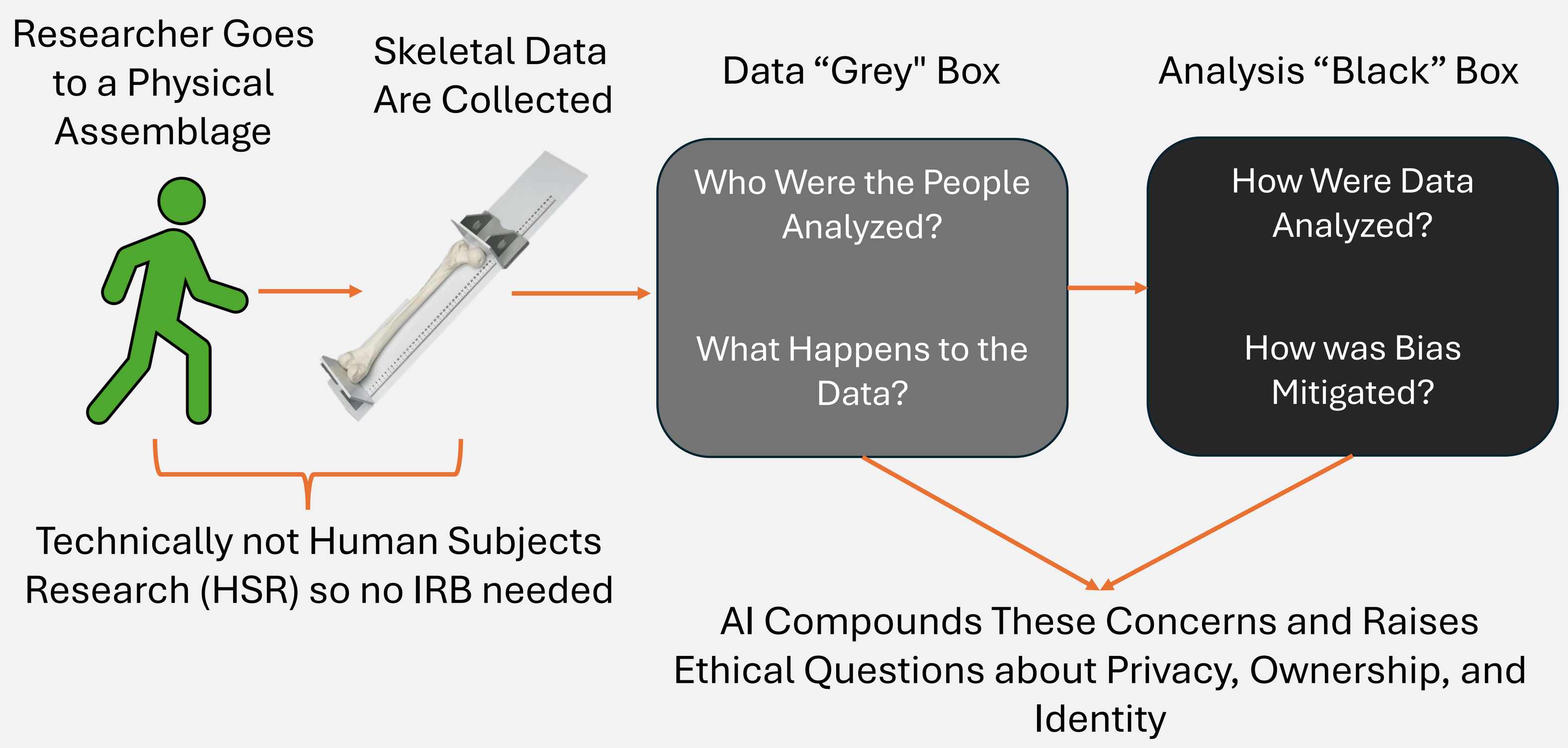
The Need for AI Guidelines in Skeletal Biology



- **Ethical guidelines** for the study of human remains are fundamental to scientific integrity and the welfare/dignity of those we study – but **are limited for digital datasets**[21, 27]
- AI and ML analysis of digital data facilitates the computational detection of complex/nuanced patterning in skeletal data
  - **Pros:** efficient, works well with "big data," detects patterns and mechanisms that are not easily recognized
  - **Cons:** Inconsistent understanding of limitations, model overfitting (accuracy inflation), "black box" methodology, concerns with data privacy
- **We present an overview of ethical principles and a guiding praxis for use of AI in skeletal biology** – particularly as it relates to:
  - Informed consent
  - Community consultation
  - Contextualized datasets that meaningfully represent their history

Operational Definitions

Data: A collection of facts, numbers, words, observations, or other useful information that can be transformed to provide insights into the world[14]

Skeletal Data: Digital values characterizing human skeletal remains, capturing the description, metrics, morphology, image, geospatial relationship, or other information pertaining to their overall character

Physical Assemblage: Any curated repository of materials that that exists in physical rather than digital space (e.g., a documented skeletal assemblage)

Artificial Intelligence (AI): The application of intelligent machines where intelligence is both the computational application and the ability of the computer to take actions that maximize performance[23]. Typically engaged in learning, reasoning, perception, and problem-solving where the goal is output not internal validation.

Machine Learning (ML): A subset of AI that relies on the detection of patterns in a dataset to "teach" a computer to predict outcomes, recognize trends, and make classifications from prior knowledge (e.g., linear regression, random forest).

Deep Learning (DL): A subset of ML that utilizes ANNs as its base architecture, applications typically use pre-trained foundation models to analyze a large number of parameters.

Artificial Neural Networks (ANNs): Algorithms premised on the structure of a biological neuron, where inputs are iteratively passed through multiple layers of weighted statistical nodes to provide outputs.

Large Language Models (LLMs): A suite of DL models that build upon foundation architecture to analyze billions of parameters (e.g., GPT3's 175B) to generate a synthesis of information via predictive text.

Key Concerns

Data "Grey" Box

Who Were the People Analyzed?

- What is the Consent Process?
  - Informed v Implied v Dynamic
- What is the Duration of Consent?
  - Limited v Infinite
- What is Their Vulnerability Status?
  - Vulnerable v Secure
- Who "Owns" Their Data?

What Happens to the Data?

- Are Data Disseminated?
  - Repository v Local Storage
- Who Curates the Data?
  - Institutional v Individual
  - Academic v Community Institutions
- How Accessible are the Data?
  - Open v Limited v Closed

Analysis "Black" Box

How Were Data Analyzed?

- Is the Model Logic Interpretable?
  - "Glass" v "Black" Box Methods
- Is the Analysis Approach Transparent?
- How Were Results Validated?
- Are the Model's Results Reproducible?

How Was Bias Mitigated?

- What is the Inherent Composition of the Dataset?
  - Diverse v Limited Population
- What Parameters Were Most Useful?
- Were Data Pre-Labeled and How?
  - Supervised v Unsupervised Learning

Interdisciplinary Concerns of HSR

- **Ethics & oversight must be flexible:** IRBs and research teams need to think across disciplines, legal systems, and cultural norms.
- **Dynamic consent & communication:** Ongoing updates to participants regarding data usage.
- **Power & coercion are everywhere:** Teaching, policy, and mixed methods research all involve participants who may feel pressure or cannot fully opt out.
- **Policy & AI-informed research affect whole communities,** not just participants; can result in generational impacts without generational consent. Firm policies must be established for continued secure storage.
- **Accountability and acknowledgement:** the provenance, biases, and limits of datasets must be acknowledged repeatedly

Potential Recommendations

Situational Ethics Model – Recognize Unique Needs and Contexts

Standard for Data **Input**

"Data are people" — Latanya Sweeney

Recognize Humanity

Informed Consent

- Descendants and Families Should:
  - Know what research themes they are consenting to (e.g., genetics, skeletal synthesis, AI synthesis)
  - Have defined timelines for that consent
  - Be allowed to opt-out of specific research themes

Community Collaboration

- Jointly establish who "owns" data and who curates it

Advocate for Skeletal Data to be Considered HSR

Establish Data Provenance

Explicitly State Data Origins

- Researchers Should State:
  - Upon whom data were collected and their lived history
  - Where data were collected and by whom
  - Rationale for data collection

Facilitate Data Curation and Dissemination

- Standardization of commonly generated datasets (e.g., skeletal metrics)
- Establish preferred data repositories or institutional hosting with controlled access

"Be careful that your use of AI does not limit your true human growth. Use it in such a way that, if it disappeared tomorrow, you would still know how to think, create, and act on your own." — Leo XIV

Standard for Data **Output**

Develop Training and Understanding

Ensure Transparency

- Researchers Should State:
  - Exact model(s) used and rationale
  - Design for model training, testing, and validation
  - Performance metrics and rationale

Pedagogy Development

- Incorporation of AI Approaches In:
  - Department-level statistics and methods courses
  - Graduate seminars

Digital Version Tracking

Metadata Development

- Metadata Should Contain:
  - Record of management and technical participants
  - Software and hardware used for collection, curation, and analysis

Data Histories

- Datasets should be curated with live version tracking enabled (e.g., Git, Zenodo)
- Hosts should incorporate a public record of access and use

One Code, Many Things

- Provide Feedback!
- Contact Information
- References