

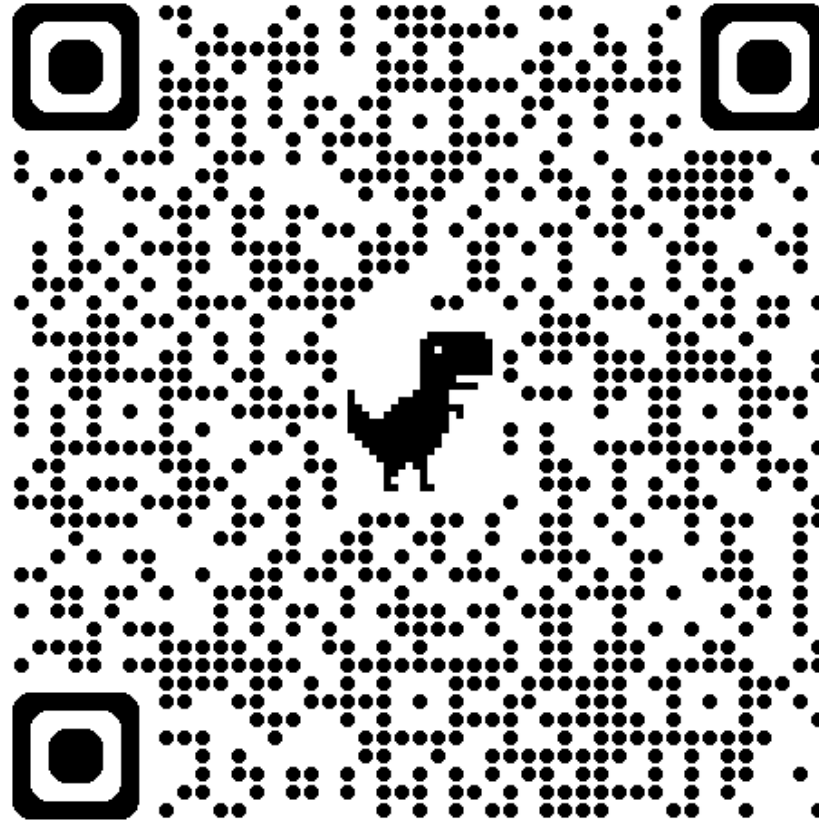


# Responsible AI with the WHI Data Resource

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A QR code for these slides



# Scope and Disclaimer

The recommendations that follow are intended as **high-level, general guidance** based on my experience working at the intersection of AI, statistics, and biomedical research.



## Individual Perspective

Reflects my perspective as a researcher in this space.



## Not Official WHI Guidance

Is not official guidance from the Women's Health Initiative.



## Not Fred Hutch Policy

Does not represent policy from the Fred Hutchinson Cancer Center.



## Not CDO Recommendations

Are not recommendations from the Office of the Chief Data Officer.

Appropriate use of AI in WHI-related research should always be evaluated **case by case**, in consultation with relevant data governance and institutional guidance.

*Any concepts or examples are meant to be **illustrative** rather than exhaustive and may not apply to every setting.*

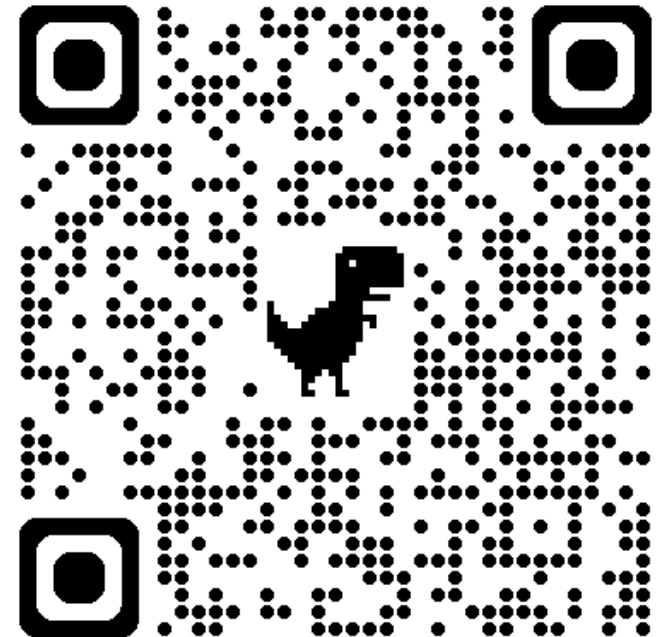
# WHI Data Use Agreement

## Statement on the Use of AI Tools ([www.whi.org/md/DUA](http://www.whi.org/md/DUA)):

“The use of AI tools (like ChatGPT, Google Bard, natural language processing (NLP) servers, and others) is increasing rapidly in the research sphere. One concern for WHI is how these tools protect the security and privacy of the information they collect. Many AI vendors state that they will use content entered into their services to train AI models, meaning data entered into the AI product could be accessed by subsequent users of the product or could be vulnerable to a data breach at the AI vendor. Additionally, many of these AI vendors are external service providers and therefore operate outside of the governance of institutional data policies and agreements.

When an investigator signs a data use agreement (DUA) to gain access to WHI data, they agree not to share data with commercial entities or anyone else without authorization from WHI. **Be aware that entering any individual-level WHI data (or unpublished summarized data) into an external AI tool could constitute a disclosure of data that is not compliant with your DUA and not consistent with participant consent.** The few exceptions to this would require a signed legal agreement between your institution and the AI vendor and would need WHI review.

Questions about usage of AI and machine-learning tools related to WHI data should be directed to the WHI Help Desk ([helpdesk@whi.org](mailto:helpdesk@whi.org)).”



# Why does this conversation matter now?

AI is already part of the *research pipeline*



Literature Search Assistants



Coding Copilots



Statistical Workflow Automation



Manuscript Editing/Drafting



Multimodal Modeling



Clinical Prediction Tools

**Question:** How do we use these responsibly with WHI data?

# What makes WHI different?

Thinking about the WHI data resources



## Longitudinal

Data spanning many collection periods.



## Clinically Rich

Deep medical and health insights.



## High-Impact for Policy

Informing critical public health decisions.



## Multi-Investigator

Collaborative and complex access needs.



## Sensitive

Requires strict privacy safeguards.



## Access-Restricted

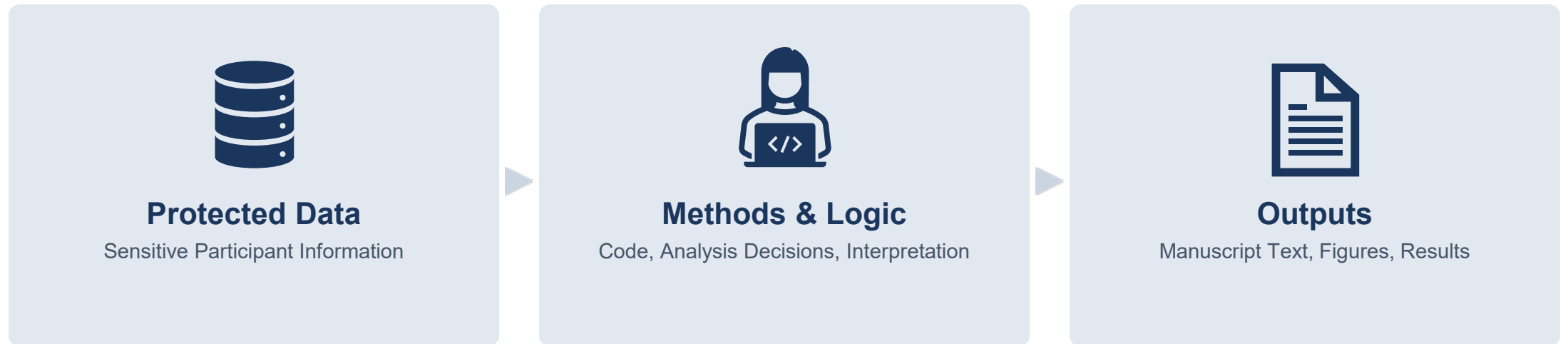
Controlled and authorized usage only.

These unique characteristics drive the need for *responsible AI use!*

This means AI use must preserve  
*trust, privacy, and interpretability.*

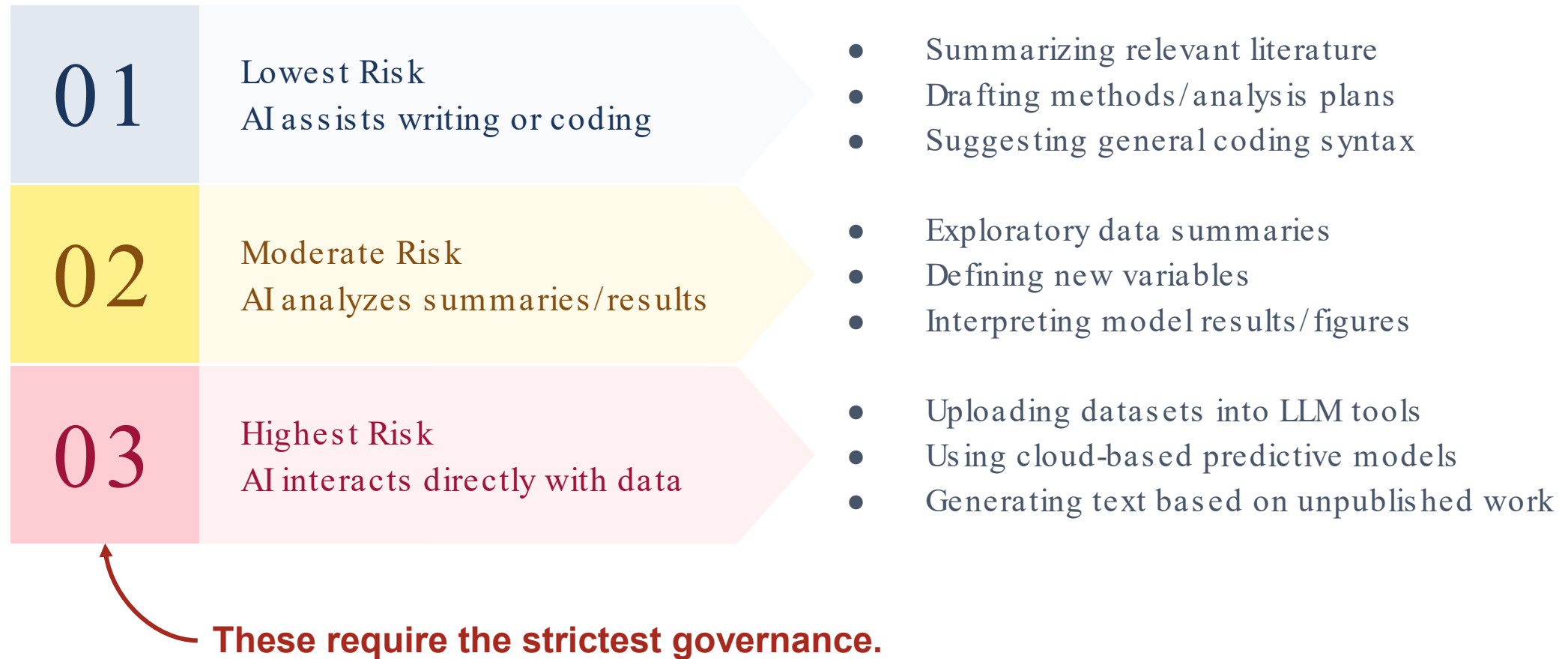
# Responsible AI use depends on *where* it enters the pipeline

AI for research can potentially be used to act on:



Each stage presents ***different risk levels.***

# We'll consider a simple, three-tier risk framework:



# Categories of AI Tools Researchers Use

Four major types:



## Closed LLMs

ChatGPT, Claude, Gemini

**Proprietary models hosted by external providers**



## Open LLMs

LLaMA, Mistral, Falcon

**Models with public weights that can be hosted locally**



## Coding Agents

Copilot, Cursor, Codex

**AI tools for code generation and workflow acceleration**



## Domain ML Models

Vision Models, Survival Nets

**Specialized tasks like computer vision or survival prediction**

Each behaves differently with respect to *privacy*.

# Closed LLMs

Proprietary models hosted by external providers

## Examples

- ChatGPT
- Claude
- Gemini
- Codex
- Copilot

## Strengths

- Strong reasoning capabilities
- Writing/editing assistance
- Advanced coding support
- Statistical/logical explanations

## Risks

- External inference servers/web exposure
- Unclear data use and retention policies
- Possible training reuse of data or data leakage

**Recommendation:** Never paste protected WHI data into closed LLMs.

# Open LLMs

Models with public weights that can be hosted locally

## Examples

- LLaMA (Meta)
- Mistral / Mixtral
- Gemma
- Falcon
- Private Deployments

## Strengths

- Potential secure hosting
- Reproducible pipelines
- HIPAA-style compatibility
- Auditable/version control
- Can customize cohort metadata/performance

## Risks

- Local infrastructure need
- Task-specific performance gaps
- Version tracking requirements
- Data exposure if misconfigured

**Recommendation:** Potentially viable for protected WHI data. Needs rigorous AI protection and data governance plans, version control, and approved environments.



# Coding Agents

AI tools for code generation and workflow acceleration

## Examples

- GitHub Copilot
- Cursor
- Codex

## Strengths

- Programming workflows
- Generate example code
- Assist with debugging
- Language translation
- Improve documentation
- Simulation study setup

## Risks

- Incorrect statistical code
- Hallucinates functions
- Non-standard shortcuts
- External prompt transmission
- Data exposure via prompts

**Recommendation:** Potentially lower risk for WHI projects when used for code generation strictly *without* data exposure. But always review code and output for accuracy.

# Domain ML Models

Specialized tasks like computer vision or survival prediction

## Examples

- Vision transformers
- CNNs for radiology
- Survival deep learning
- Genomic foundation
- Models for extracting text

## Strengths

- Enable analysis of complex modalities
- Scalable prediction from imaging and biosignals
- Integrate datasets
- Improve phenotyping
- Supports discovery

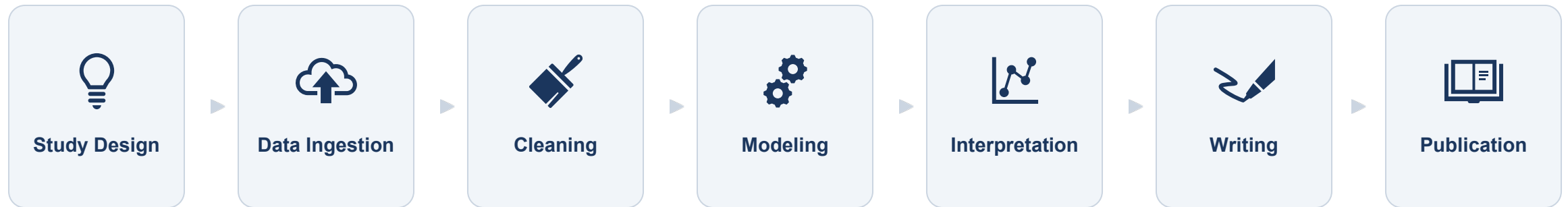
## Risks

- Encode unknown biases
- External checkpoints may violate governance rules
- May require cloud GPUs
- Limited interpretability or reproducibility
- Re-identification risks

**Recommendation:** Use only when approved and within approved secure compute environments. Document model source, checkpoints, preprocessing steps, and configurations.

# AI Can Enter the Pipeline at Many Stages

A typical research workflow:



Each stage has different ***governance*** needs.

# 💡 Study Design

Ideation, power calculations, literature review

## Examples

- Brainstorming research questions
- Drafting power calculations
- Summarizing public literature
- Generating dummy data structures

## Governance Context

- Typically involves no participant data, making it a potentially low risk entry point for AI
- Focus on using AI to speed up the methodological and structural planning

**Recommendation:** Can utilize general-purpose AI tools for administrative and structural tasks while ensuring no sensitive institutional or pre-publication proprietary data are shared.

# Data Ingestion

Extracting, summarizing, and modeling raw or derived data

## Examples

- Summarizing participant-level tables
- Extracting signals from imaging
- Embedding clinical text
- Multimodal integration

## Concerns

- PHI Exposure
- Re-identification risk
- Cloud storage leakage
- Vendor retraining risk

**Recommendation:** Only use with a pre-approved plan, within approved secure compute environments, and employ local inference models and institutionally managed containers.



# Writing Code

## Syntax generation, templates, and example frameworks

### Safe Uses

- Generating regression syntax
- Producing visualization templates
- Developing simulation frameworks
- Documenting human-written code

### Example Prompts

*“Write an R script that demonstrates fitting a Cox model with interaction terms.”*

This is generally safe, as no participant-level data is required for AI to generate this code.

*“Write an R script that analyzes the data in `./phi_data.csv` using a Cox model with interaction terms.”*

This is not safe, as protected data are given as context for AI to generate this code.

**Recommendation:** Do not give data as context. AI for code generation is typically appropriate when working with public libraries, syntax structures, and non-PHI simulation parameters.

# Statistical Modeling Decisions

Variable selection, hyperparameters, and analysis planning

## Examples of AI Use

- Variable selection suggestions
- Hyperparameter tuning advice
- Model comparisons
- Simulation planning

## Potential Risks

- Hidden assumptions in model logic
- Overconfidence in specific methods
- Hallucinated or incorrect references

**Recommendation:** Treat AI as another collaborator, not an authority (and seek humans who are authorities). Always verify outputs through independent statistical validation.

# Interpreting Results

Summarizing outputs, interpreting the meaning of statistical measures

## Examples of AI Use

- Summarizing regression outputs
- Translating concepts like hazard ratios
- Generating figure captions

## Potential Risks

- Incorrect inference claims
- Causal misinterpretation
- Exaggeration of certainty

**Recommendation:** Do not put unpublished results from analysis of protected data into LLMs. General AI interpretations must be investigator-reviewed to ensure accuracy and validity.

# Writing Assistance (*Lower Risk if Used Properly*)

High-level guidelines for safe and appropriate usage

## Safe Uses

- Editing grammar
- Formatting methods
- Restructuring paragraphs
- Summarizing literature

## Not Appropriate

- Generating new/first drafts of text
- Uploading data to write conclusions
- Fabricating citations
- Drafting undisclosed analyses

**Recommendation:** Do not use to generate text or to write conclusions for unpublished results. Always check journal/institutional AI policies for writing assistance and disclose the use of AI when allowed.

# A Special Case: Training AI Models

When AI model development is itself the research objective

## Common Examples

Increasingly, new research is being proposed that seeks to:

- Train prediction models on tabular data
- Integrate biomarkers into existing ML workflows
- Use free text narratives with structured data

## Workflow Requirements

Specialized infrastructure is often necessary for model training:

- GPU-enabled compute
- Pretrained checkpoints or open-weight models
- Containerized workflows
- Reproducible pipelines and version tracking

## Governance Expectations

Projects that propose to train AI models typically require:

- Formal analysis plan and model documentation
- Specification of compute and storage locations
- Confirmation that training occurs within secure institutional infrastructure





**Recommendation:** Work within approved secure environments using locally hosted, open-weight models and institutionally approved containers. Have detailed AI protection, infrastructure, model training, and data governance plans before proposing these types of projects.

# Reproducibility Concerns with LLMs

LLMs introduce additional challenges:

- **Non-Deterministic Outputs:** Identical prompts can yield different results with no way of ‘seeding’ a response.
- **Version Drift:** Model updates are irregular and can change behavior and quality over time.
- **Undocumented Reasoning:** Internal logic for arriving at a result is often opaque and cannot be replicated.
- **Hidden Training Data:** Exact data sources are rarely disclosed and can leak information/lead to potential plagiarism.

## Best Practices:

-  Record Model Name
-  Record Version
-  Record Prompts
-  Record Date

Treat prompts as ***analytic parameters*** in research documentation.

# Some Final Recommendations for WHI Projects

To maintain data integrity and research transparency, ensure the appropriate:

- ❑ **Data Privacy:** Never upload participant-level data to external LLM APIs.
- ❑ **Infrastructure:** Prefer local inference models for sensitive workflows.
- ❑ **Documentation:** Log AI-assisted steps in analysis documentation.
- ❑ **Reproducibility:** Treat prompts as part of reproducible research.
- ❑ **Disclosure:** Disclose AI assistance in manuscripts.

Prioritize *data security* and *methodological rigor* in all AI implementations.

# Documentation Expectations for AI-Assisted Research

## Some minimum reporting standards



### Model Identity

Specify the exact model name and version number used.



### Intended Purpose

Define the specific role of AI within your research workflow.



### Data Privacy

Note if any protected or sensitive participant data were involved.



### Human Oversight

Confirm that all AI outputs underwent human verification.



### Analytical Impact

Describe how AI influenced the final research conclusions.



### Reproducibility Log

Provide a log of all prompts used to ensure analysis can be replicated.

Think of this as your ***“AI Methods Section”***

# Practical Safe-Use Checklist for WHI Investigators

Some critical questions to ask before using AI:

- Does this tool see protected data?
- Does this tool store prompts externally?
- Can this step be reproduced later?
- Would I disclose this in a methods section?

***If unsure***, consult WHI and the appropriate data governance officials at your institution.

# Opportunities for WHI in Responsible AI

WHI is uniquely positioned to:



## Governance Standards

Set cohort-level AI governance standards



## Reproducible Workflows

Develop reproducible AI workflows



## Reporting Norms

Define reporting norms for AI-driven research



## Multimodal Modeling

Enable privacy-preserving multimodal modeling

Exciting time to be thinking nationally about ***ethical*** cohort-scale AI use

# AI as a Scientific Exposure

## Recognizing its influence

- It is spreading rapidly across science and society
- It spans individuals, institutions, and populations
- It influences public health research and practice
- It has the capacity to do good or harm

**Source:** <https://arxiv.org/abs/2604.14086>

### The Epidemiology of Artificial Intelligence

Harsh Parikh<sup>1</sup>, Tyler McCormick<sup>2</sup>, Emily Johnson<sup>3</sup>,  
Leo Hickey<sup>4</sup>, Megan Ranney<sup>1</sup>, Bhramar Mukherjee<sup>1</sup>

<sup>1</sup>Yale University <sup>2</sup>University of Washington <sup>3</sup>University of Southern Denmark <sup>4</sup>Vassar College

#### Abstract

Artificial intelligence (AI) systems increasingly shape how people access health information, make medical decisions, and receive care—yet epidemiology lacks frameworks for measuring AI exposure or studying its health effects at the population level. Here we argue that AI now functions as a determinant of health and propose a conceptual framework, borrowed from environmental epidemiology, for studying it. We distinguish *ambient AI exposure*—algorithmic curation and AI-mediated institutional decisions that affect populations regardless of individual choice—from *personal AI exposure*—direct, volitional use of AI tools. We characterize AI’s possible causal roles in epidemiological models, show that existing experimental approaches are inadequate for capturing chronic, population-level effects, and illustrate these ideas with nationally representative US survey data. We discuss implications for study design, health equity, and AI governance.

# Summary

AI has the potential to safely accelerate research if we are always thinking critically about



## Protecting Our Data

Protected data stay protected



## Reproducibility

Methods stay reproducible



## Investigator-Led Interpretation

Interpretation stays investigator-led



## Transparency

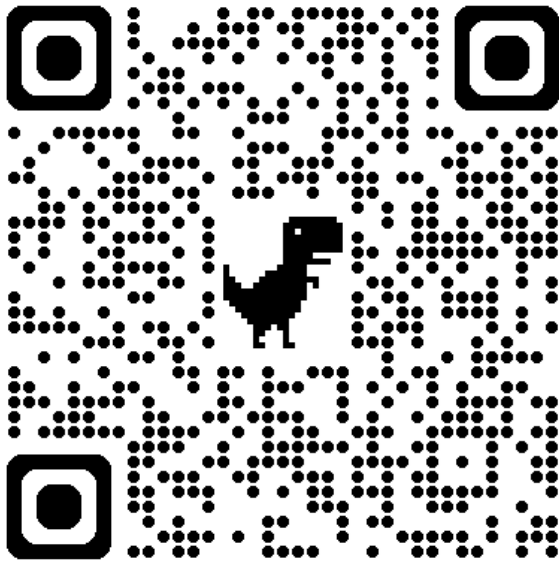
Documentation stays transparent

Responsible AI use is not about ***restriction***, it is about ***scientific integrity***.

# Additional Helpful Resources

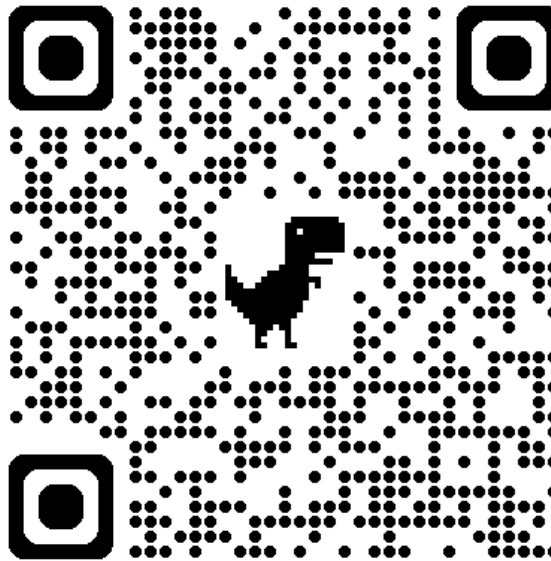
Courtesy of Dr. Carrie Wright

## AI Attribution Toolkit



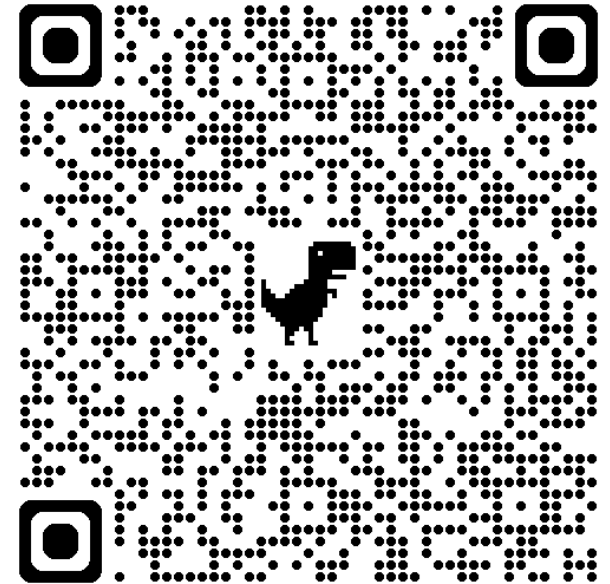
<https://aiattribution.github.io/>

## OTTR AI Use Cheatsheet



[https://www.ottrproject.org/cheatsheets/ai\\_everyday\\_uses.html](https://www.ottrproject.org/cheatsheets/ai_everyday_uses.html)

## Presentation on AI Ethics



[https://docs.google.com/presentation/d/15RmlGNAontc07VF4EdtQFeaOI\\_1QKc1TVMCb79vKKz0/edit?slide=id.g39de1049851\\_0\\_188#slide=id.g39de1049851\\_0\\_188](https://docs.google.com/presentation/d/15RmlGNAontc07VF4EdtQFeaOI_1QKc1TVMCb79vKKz0/edit?slide=id.g39de1049851_0_188#slide=id.g39de1049851_0_188)



# Thank You!

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