



# FROM THEORETICAL SCALE TO PRECISION ENGINEERING IN SUSTAINABILITY DATA

**Sangwon SUH, PhD**

Xinghua Chair Professor  
School of Environment, Tsinghua University

 TianGong Initiative

## 2 | Agenda

1. About TianGong
2. From automation to quality
3. Evaluating quality
4. Concluding remarks

# What is TianGong?



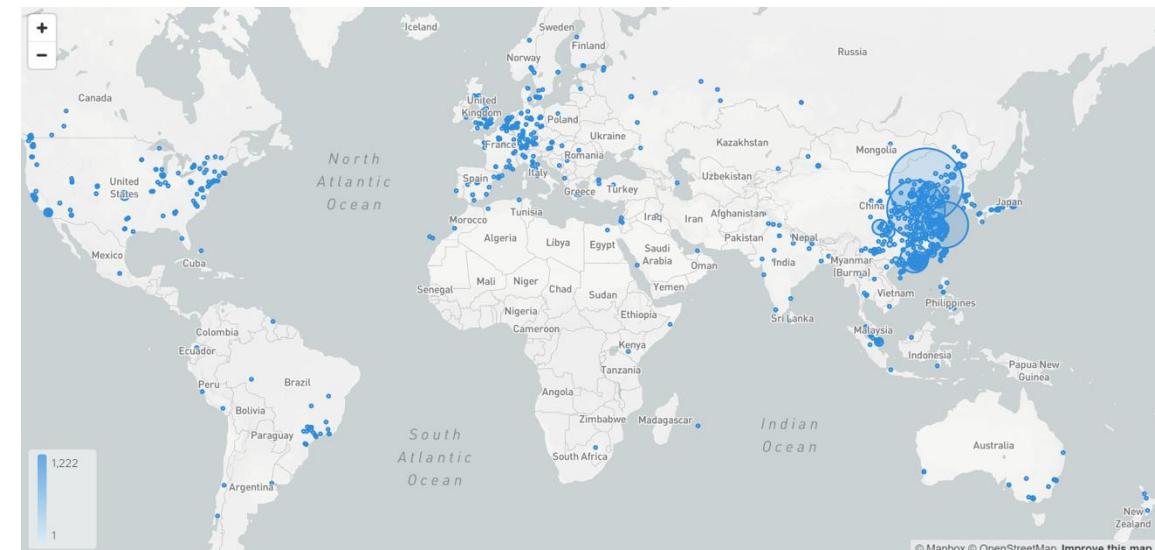
- A community-driven, AI-powered initiative to develop and maintain **open, transparent LCA background database**.
- Led by Tsinghua University with **43 investigators** and **200+ researchers**.



## Sample stats

Database	ecoinvent	GaBi	USLCI	TianGong Database
Unit process	~15,000	~17,000	~600	<b>4,315</b>
Geographical coverage	Primarily Europe	Primarily Europe	US	<b>China</b>
Time to develop	~20 years	~20 years	~10 years	<b>1 year</b>

## User locations



4

# TianGong Database (currently, based largely on the literature)

TianGong LCA Data Platform

Open Data

Models

Processes

Flows

Flow Properties

Unit Groups

Sources

Contacts

Commercial Data

My Data

Team Data

Full-text search: Enter one or more keywords.

Reference year

Location

Version

Updated at

Option

Index Name Classification

1 Remediated soil ; Cement addition ; Soil solidification and stabilization ; Soil remediation ; In situ Mining and quarrying / Mining support service activities / Support activities for other mining and quarrying / Support activities for other mining and quarrying

2 Remediated soil ; Lactate injection ; Stimulated biological degradation ; Soil remediation ; In-situ Water supply, sewerage, waste management and remediation activities / Remediation and other waste management service activities / Remediation and other waste management service activities / Remediation and other waste management service activities

3 Soil remediation; Chemical oxidation and soil vapor extraction combination; In-situ Water supply, sewerage, waste management and remediation activities / Remediation and other waste management service activities / Remediation and other waste management service activities /

2006 United Kingdom of Great Britain and Northern Ireland 01.01.000 2025-02-26 06:10:40

2019 Belgium 01.01.000 2025-02-26 06:10:09

2019 Belgium 01.01.000 2025-02-26 06:05:47

North Pacific Ocean

North Atlantic Ocean

Visitors 150,000+

Regions 88

Visits 2,300,000+

Downloads 21,000

## Data sources

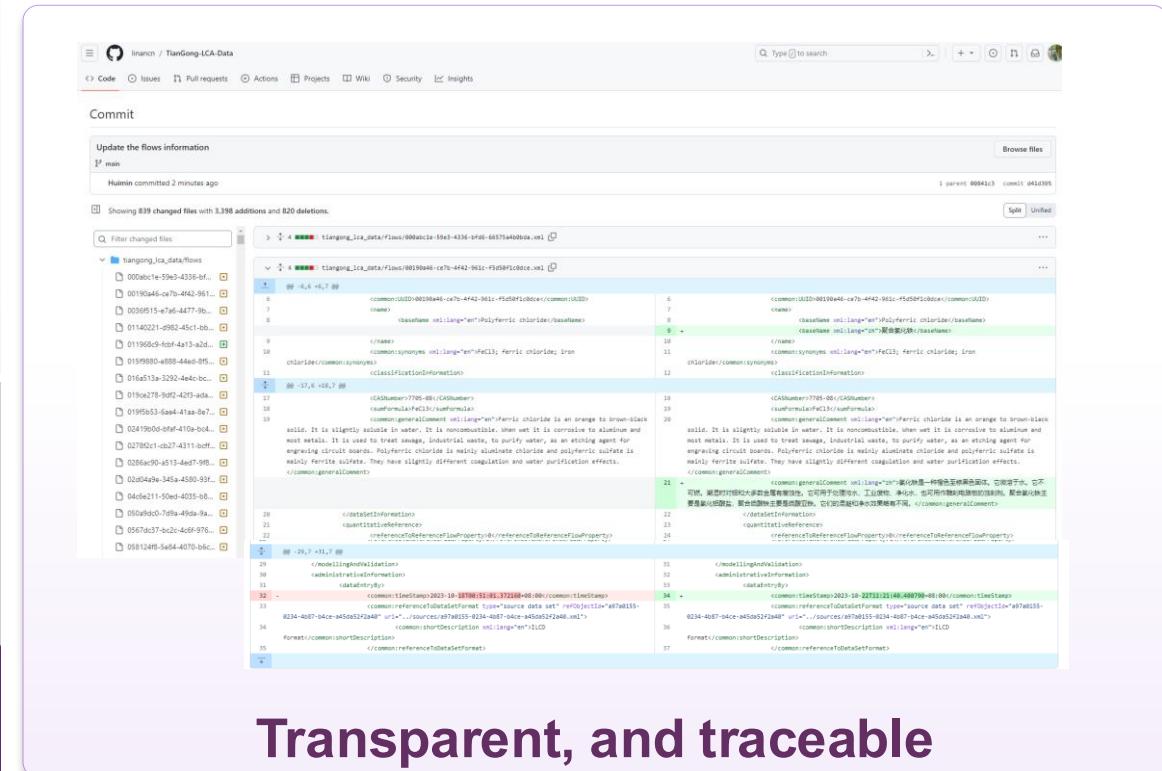
**1,188**

## Unit processes

**4,315**

# Flows

**96,518**



**Transparent, and traceable**

<https://lca.tianqong.earth/>

# 5 | TianGong Database

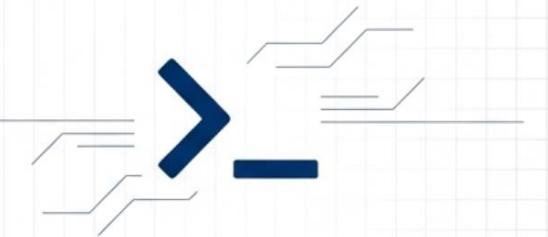
## Deployment Options



**SaaS / Online:** immediate access and collaboration

**Private Deployment:** Docker-based local deployment for enterprise security

## Developer Tools



**MCP:** Local/Remote servers for AI Agents

(<https://github.com/linancn/tiangong-lca-mcp>)

**Python SDK:** Data structures and validation for LCA workflows (*tidas-tools*)

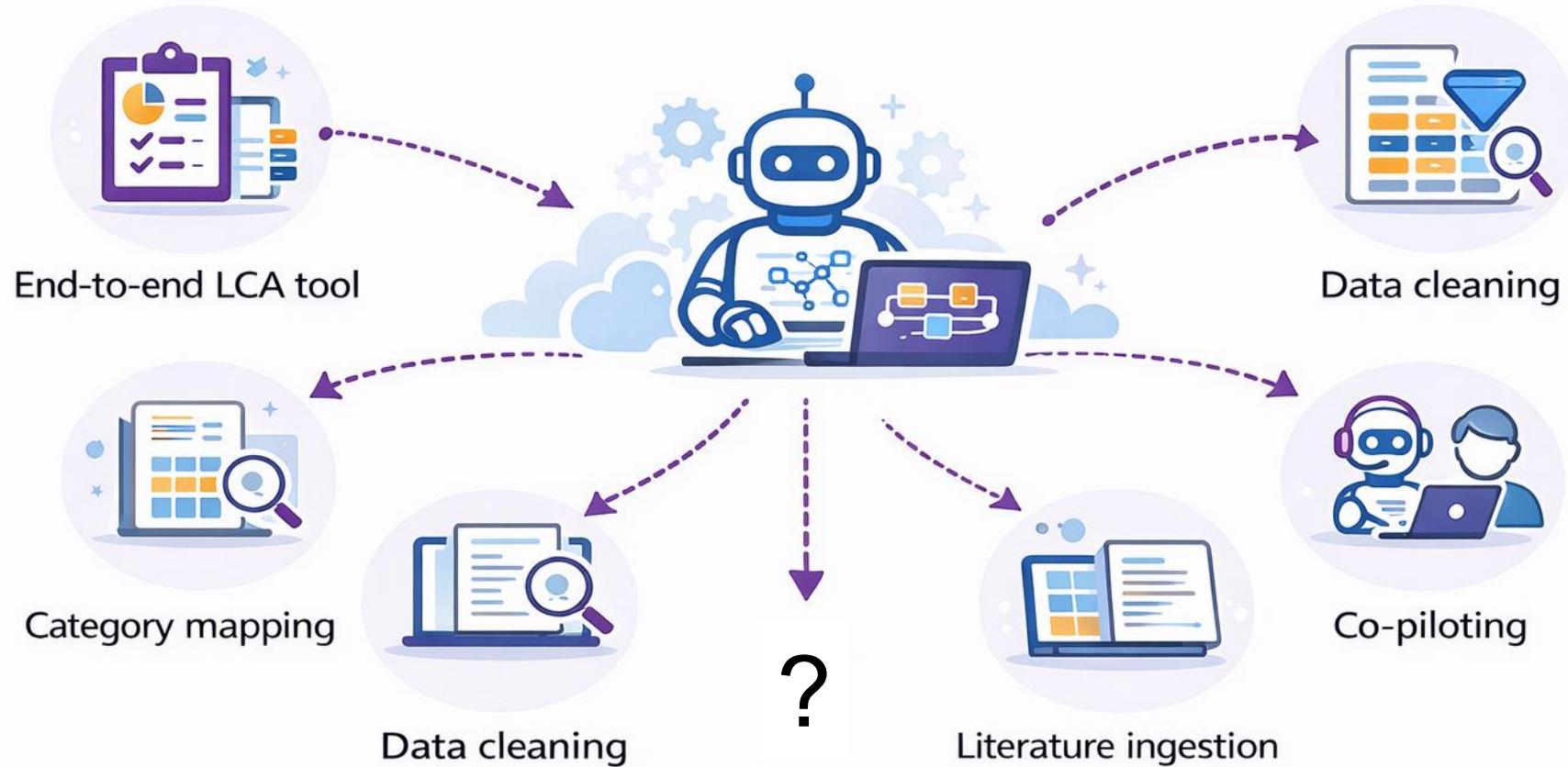
**Embedding model:** Trained on LCA datasets and process semantics, improving data understanding

**Open LCA database. Flexible deployment. Ready for AI.**



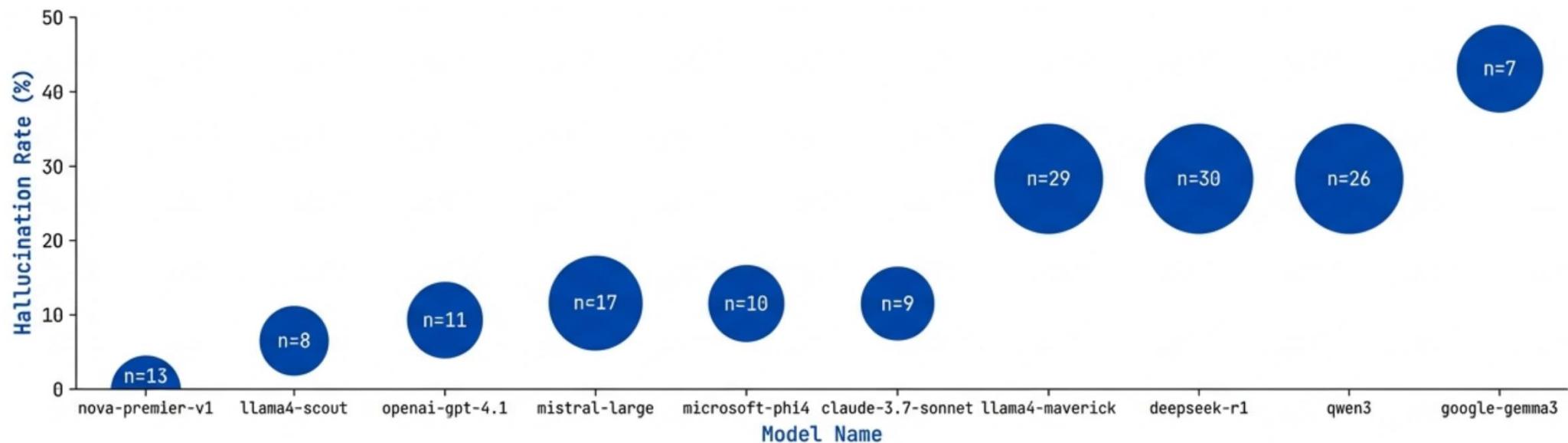
# FROM AUTOMATION TO QUALITY

# Proliferation of AI in LCA



## Reality check

- **37.2% of responses contained incorrect or misleading information**
- **Up to 40% hallucination on citation for some models**



Source: Donaldson, A., Balaji, B., Oriekezie, C., Kumar, M. & Patouillard, L. An Expert-grounded benchmark of General Purpose LLMs in LCA. 2025. <https://arxiv.org/abs/2510.19886>

## Quality concerns: 2025 ACLCA challenge session feedback

- “AI needs deep training by subject matter experts before being trusted to select appropriate technologies.”
- “AI needs more stringent, specific rubrics compared to human expert judgment.”
- “At least initially, human-inspection by sector-expert on technological representativeness is needed.”
- “AI should not both perform and validate allocation; needs clear documentation for human-verification.”
- “Currently don't trust AI fully for source credibility assessment; would require human checks initially”
- “Common conventions (e.g., medium voltage preference) can be used to flag unconventional AI choices for human review.”

# Approaches for improving the performance of AI

## PROMPT ENGINEERING



Crafting effective input prompts to guide AI responses.

**Good for:** Rapid prototyping, adjusting tone and formatting.

Giving **detailed instructions** on homework assignments

## RAG (RETRIEVAL AUGMENTED GENERATION)



Enhancing AI with access to external databases for better-informed answers.

**Good for:** Citations, factual accuracy, up-to-date information.

Giving the **references info to be cited** in their homework

## FINE-TUNING



Training AI on specific domain knowledge to improve expertise.

**Good for:** Jargon, specific formats, internalized logic

Giving an **intensive review on a specific subject** before the exam

## AGENTIC WORKFLOWS

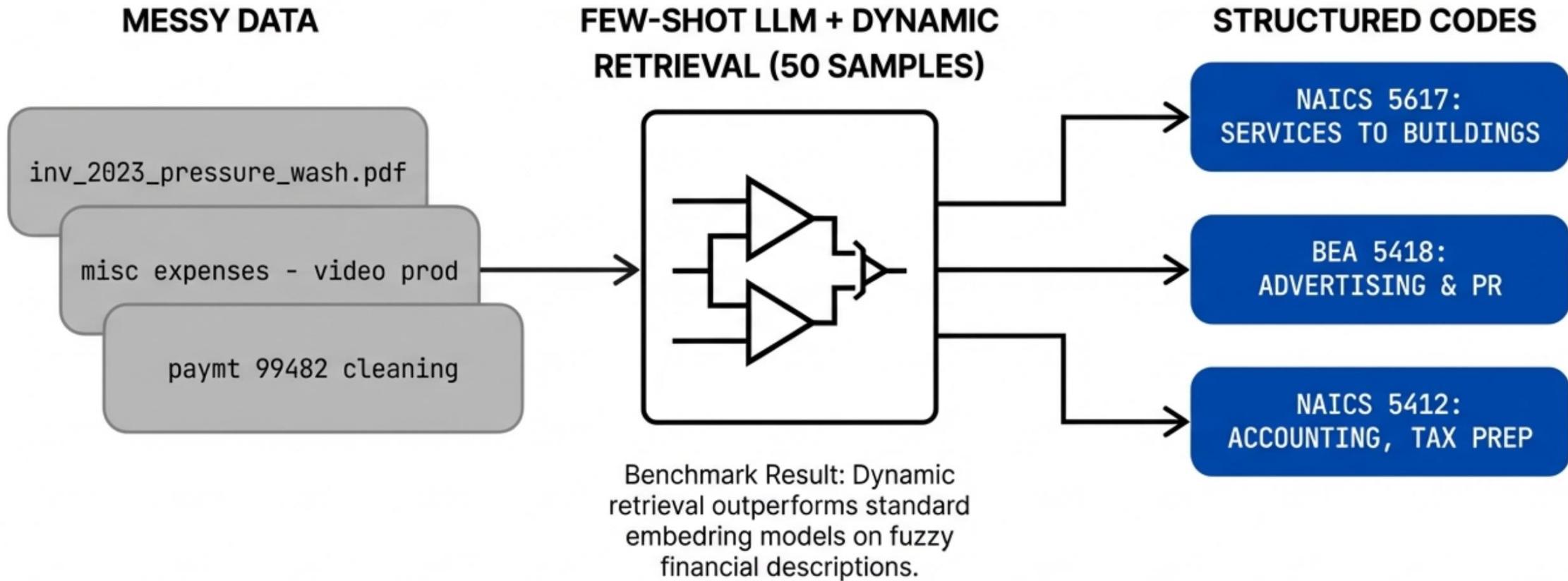


Developing AI agents capable of performing goal-oriented tasks autonomously.

**Good for:** Task automation, problem-solving, decision-making.

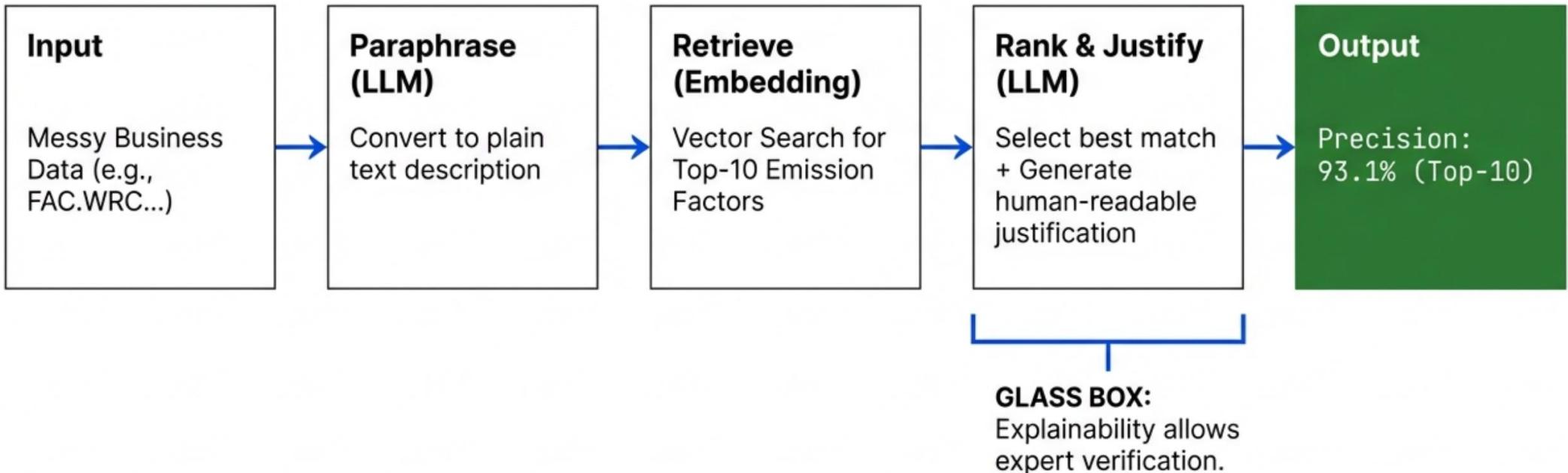
Allowing students to **work together** on a homework assignment

# ATLAS for mapping (prompt engineering w/ RAG)



Source: Watershed (<https://neurips.cc/virtual/2024/100600>)

# PARAKEET (prompt engineering w/ paraphrasing + RAG)



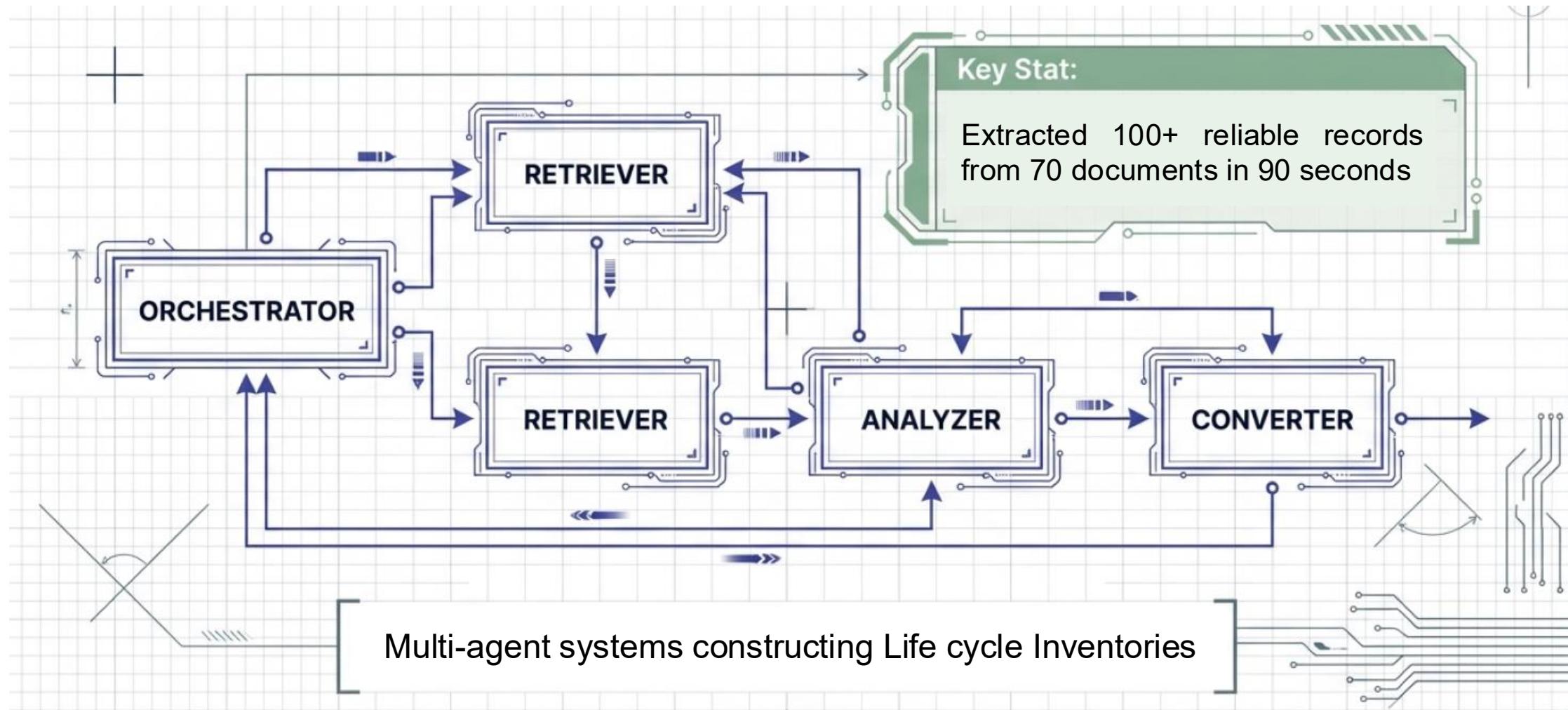
Source: Amazon (<https://www.amazon.science/publications/parakeet-emission-factor-recommendation-for-carbon-footprinting-with-generative-ai>)

## Fine Tunning using domain-specific knowledge: TianGong

Redacted (manuscript under preparation)

**LCA domain-specific embedding outperformed raw or generic embedding models at all cutoff-rank values ( $K$ )**  
Source: TianGong: manuscript under preparation

# Agentic workflow: High- LCA Data Extraction at Scale



Source: TianGong from Tsinghua University (see Jinliang's presentation later today)



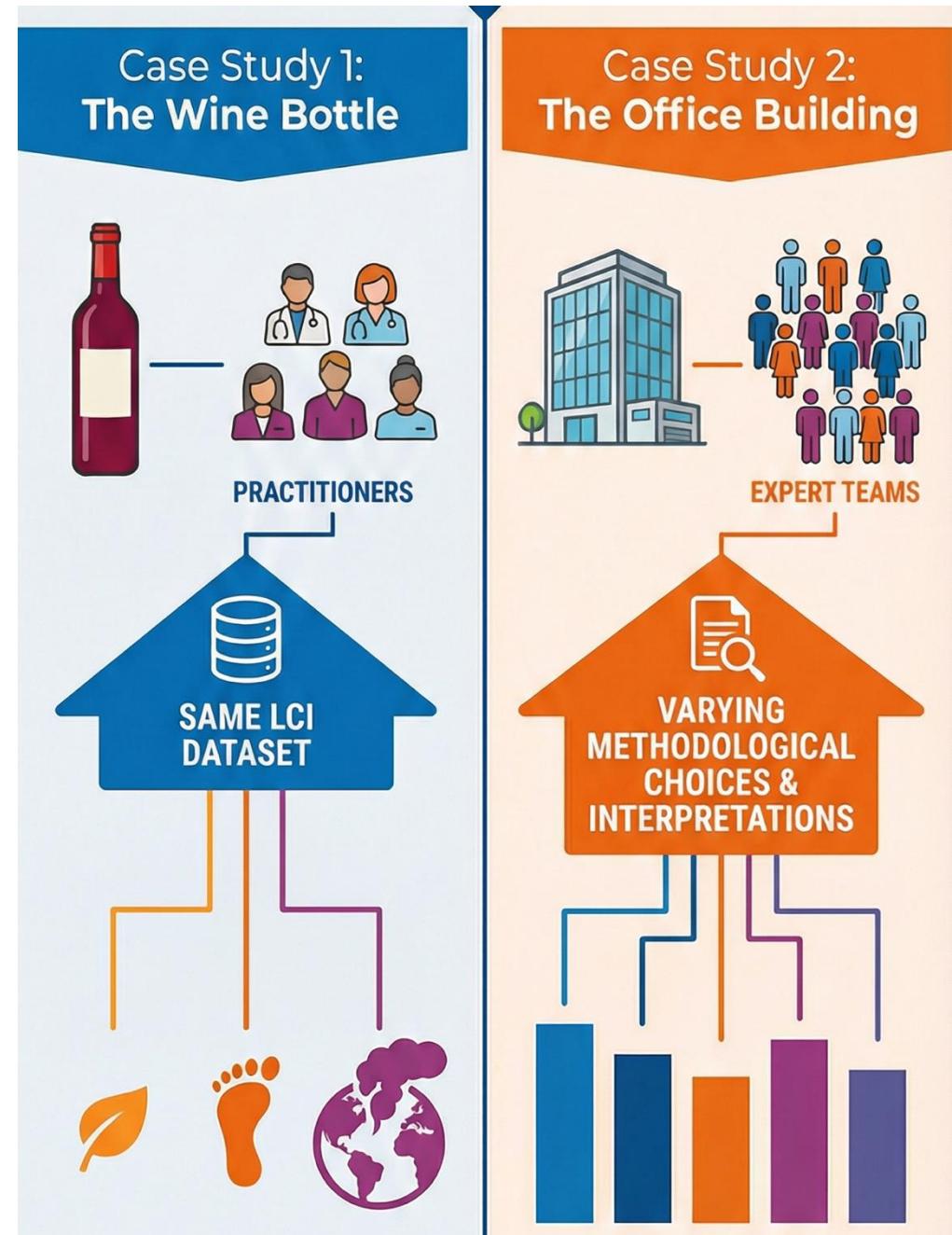
# EVALUATING QUALITY

## 16 | Challenges

- **The "Ground Truth" Paradox:** High-quality labeled LCA datasets are scarce, and experts often don't agree with each other.

# The "Ground Truth" Paradox

- Practitioner Effect (Literature):
  - Independent practitioners produce **+ - 20% difference** on a simple product w/ same LCI dataset (Scrucca et al., 2020).
  - Round-robin study shows a **X 7 variation** (10 v.s. 71 kg CO<sub>2</sub>-eq m<sup>-2</sup> yr<sup>-1</sup>) on the same building with different (process) LCI datasets.
  - AI cannot simply "predict" the expert's consensus, because often there is none.



## 18 | Challenges

- **The "Ground Truth" Paradox:** High-quality labeled LCA datasets are scarce, and experts often don't agree with each other.
- **Goal & Scope Dependency:** Quality is not absolute; it depends on the study's context.

# The “Ground Truth” Paradox: from ACLCA 2025

How do you model voltage?

Top Answer:  
**It Depends**

59 votes

Allocation Method?

It Depends

59 votes

LCA is not binary. Decisions on **Allocation (Economic vs Mass)** and **System Boundaries** are **subjective** and **context-dependent**.

## 20 | Challenges

- **The "Ground Truth" Paradox:** Not only that high-quality labeled LCA datasets are scarce, but also that experts often don't agree with each other.
- **Goal & Scope Dependency:** Quality is not absolute; it depends on the study's context.
- **Hallucination:** Studies show that LLMs are rather lazy; they would gladly make things up rather than laboring to find the truth.
- **Traceability in Agentic Swarms:** Tracing the root cause of an error is becoming increasingly complex as multiple agents interact with each other.

## 21 | How to navigate?

- **The "Ground Truth" Paradox:** the goal is to set the boundaries for acceptable options (and their quality hierarchies, if any).
  - For procedural quality: synthetic Q&As based on smart chunking + human validation

# Example: synthetic Q&A pair

## Category 1: Goal & Scope Definition

*Testing the AI's ability to detect ambiguity and enforce definition requirements.*

- **Example: Functional Unit Sufficiency**
  - **Scenario/Prompt:** "A study compares two beverage packaging options (Glass vs. PET) and reports results in 'kg CO<sub>2</sub>e per bottle produced.' Is this functional unit sufficient for a comparative assertion intended for public disclosure?"
  - **Reference Anchor:** ISO 14044, Clause 5.2.3 (Functional Unit Requirements).
  - **Expected "Gold" Answer: No.** The functional unit is insufficient.
- **Required Reasoning:**
  1. "Per bottle" describes a reference flow, not a functional unit.
  2. It fails to define the **performance characteristics** (e.g., volume delivered: 500ml) and **duration/quality** (e.g., shelf life or carbonation retention).
  3. Without equating the service provided, the comparison is invalid under ISO standards.
- **Critical Failure Flag:** If the AI answers "Yes" or proceeds to compare the materials without flagging the ambiguity.,

## 23 | How to navigate?

- The "Ground Truth" Paradox: the goal is to set the boundaries for acceptable options (and their quality hierarchies, if any).
  - For procedural quality: synthetic Q&As based on smart chunking + human validation
  - For empirical validity: property eval + key ground truth ranges (e.g., electricity)

# Empirical validity: Property Eval as the First Line of Defense

## FORMULA VALIDITY

$(A * B) / C$   CHECKED

Detect flipped multiplication/division signs.

## PHYSICAL PLAUSIBILITY

Output Mass  
> Input Mass



Impossible mass balance.  
Flag immediately.

## FAITHFULNESS



Verify cited sources exist in retrieved context.

Source: Parikh and Dumit (2025). *A practical framework for LLM system evaluations for multi-step processes*, Watershed (<https://watershed.com/blog/a-practical-framework-for-lm-system-evaluations-for-multi-step-processes>)

## 25 | How to navigate?

- **The "Ground Truth" Paradox:** the goal is to set the boundaries for acceptable options (and their quality hierarchies, if any).
  - For procedural quality: synthetic Q&As based on smart chunking + human validation
  - For empirical validity: property eval + key ground truth ranges (e.g., electricity)
- **Goal & Scope Dependency:** Machine-readable G&S template

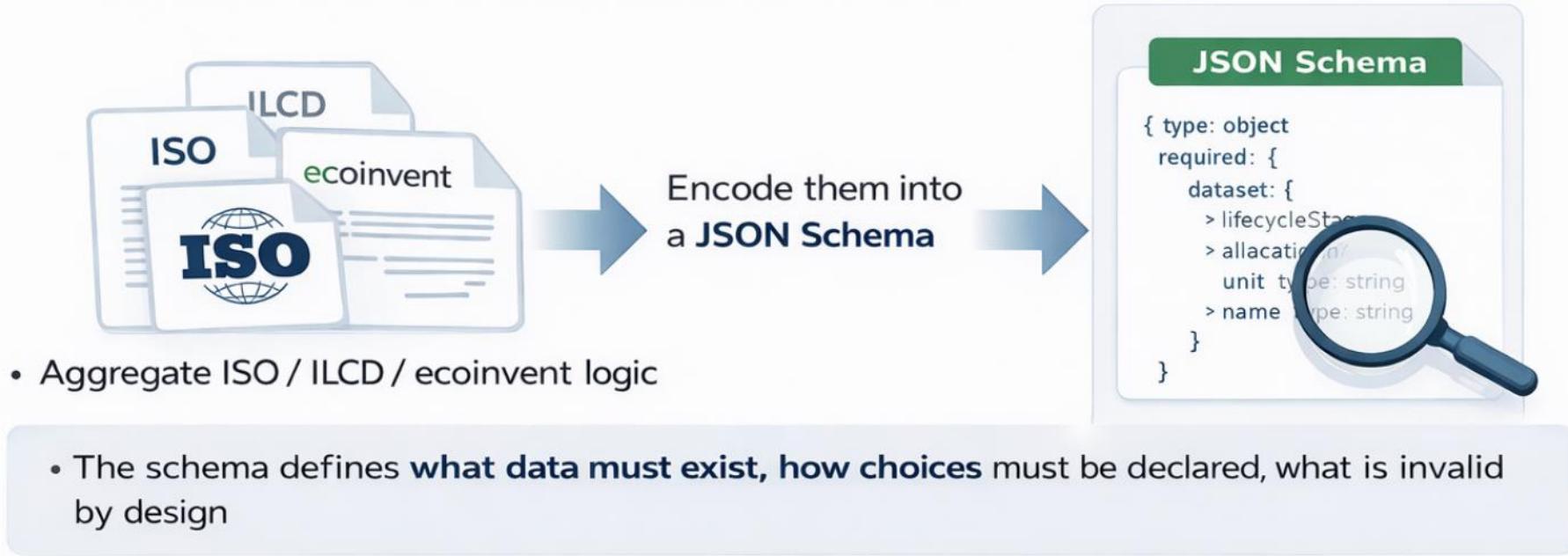
# Context-awareness: machine-readable G&S template

- Addresses “it depends” problem by constraining the choice of method and data based on the context.

```
{  
  "GOAL_DEFINITION": {  
    "intended_application": "comparative_assertion",  
    "intended_audience": "public_consumer",  
    "comparative_assertion_public": true, ← TRIGGER: Must enforce sensitivity analysis & critical review.  
    "regional_context": "US-NA", ← CONSTRAINT: Triggers specific PCRs and Grid Mixes.  
    "methodology_trigger": "ISO_14044_Clause_5.3"  
  }  
}
```

# Example: TIDAS—procedural quality via schema-as-context

We treat LCA standards not as documents for humans, but as **machine-enforceable context for AI**.



**The schema itself is the context.**

Not prompt, not system message, but structural constraint

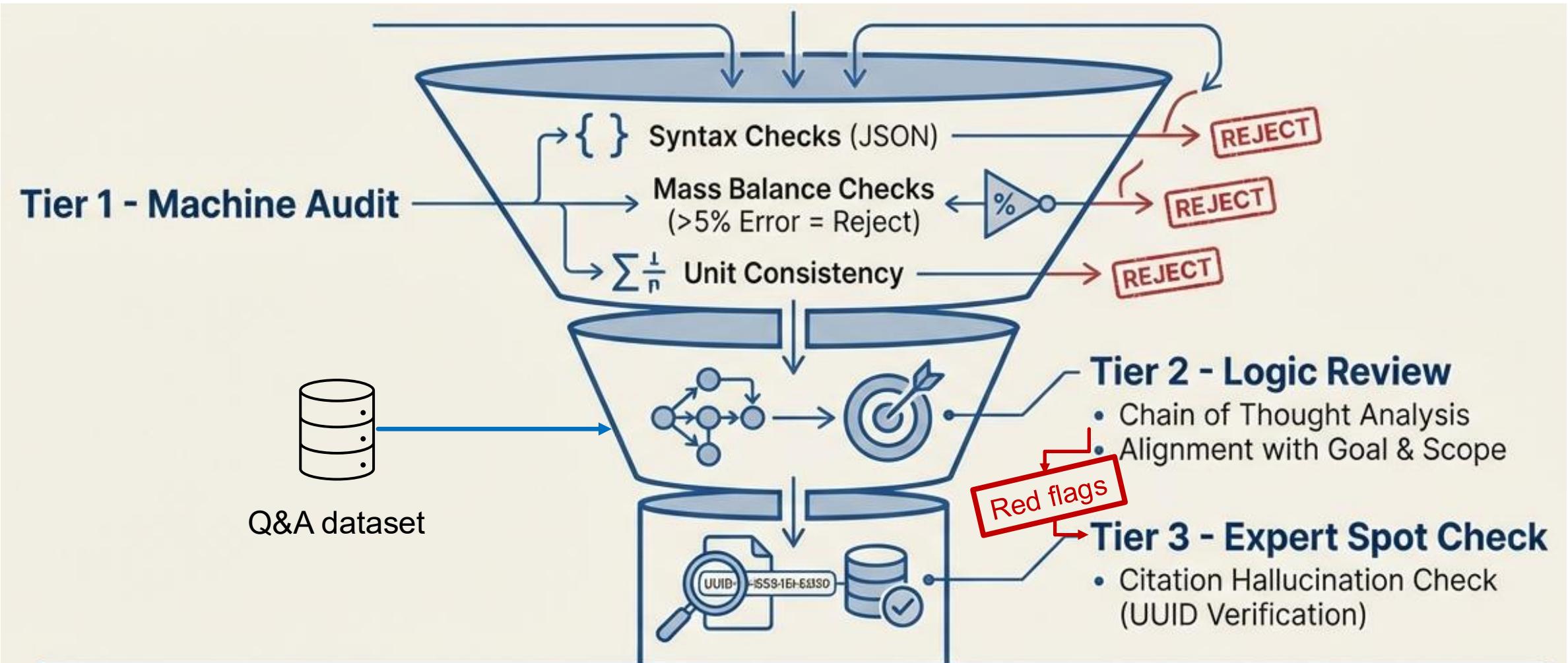
## 28 | How to navigate?

- **The "Ground Truth" Paradox:** the goal is to set the boundaries for acceptable options (and their quality hierarchies, if any).
  - For procedural quality: synthetic Q&As based on smart chunking + human validation
  - For empirical validity: property eval + key ground truth ranges (e.g., electricity)
- **Goal & Scope Dependency:** Machine-readable G&S template
- **Hallucination & Faithfulness:** Hallucination check—does *the reference exist?*
- **Traceability in Agentic Swarms:** Minimum documentation requirement including the documentation of key “reasoning” or “chain-of-thought”.

# Standardizing Minimum Documentation Requirement

- A. **System Provenance:** Model version, exact prompt log, and timestamp to trace hallucinations.
- B. **The "Context Key" (Goal & Scope).**
- C. **The "Chain of Thought" (Logic):** A log of decision hierarchies (e.g.,  
*"Attempted System Expansion → Failed → Economic Allocation*)
- D. **Data Integrity:** Secondary data must link to unique **UUIDs/DOIs** (check citation hallucination)
- E. **Automated audit trails:** Generated mass/energy balance checks and unit consistency flags.

# Overall Evaluation Protocol: a tiered approach



"Automation does not replace the expert; it elevates them to an auditor."



# CONCLUDING REMARKS

## Concluding remarks: Toward Trustworthy AI for LCA

- **Automation to precision:** The field is moving from *automation* with questionable quality to *precision engineering*.
- **Solving "It Depends" problem is crucial:** a choice should be evaluated against machine readable goal & scope context.
- **Scale Eval:** Synthetic Q&As + Property Eval + selective numerical validation would be the first line of defense.
- **Traceability and Documentation:** Unified provenance models and standardized documentation requirement.
- **Human-in-the-loop:** The goal is to making human audits more effective at scale.

**“As LCA grows more intelligent and scalable, so must the way we evaluate it.”**



**Sangwon SUH, PhD**

Xinghua Chair Professor  
School of Environment, Tsinghua University

