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# Large Language Models Based In-Context Learning for Early Stage Building Life Cycle Assessment

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- 1 Introduction
- 2 Methodology: building LCA dataset and methods
- 3 Results: LLM method comparative analysis
- 4 Conclusion

# Building Design Space is Complex



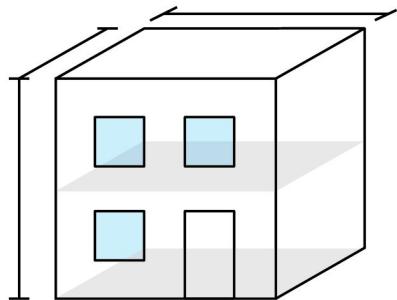
Design variables:

- 1) Number of buildings: 3 or 4
- 2) Orientation: 0-360°
- 3) Number of stories: 5-8
- 4) Footprint
- 5) Window-Wall-Ratio: 15-50%
- 6) Shading presence
- 7) Shading depth
- 8) Materials:  
Cladding (7), Substructure (2), Partition (5), Floor finish (8),  
Floor structure (12), Columns & beams (10), Windows (5), Wall  
structure (6), Wall finishes (2), Roof (10)
- 9) Dimensions:  
Cladding (4), Flooring surface (4), Ceiling (4), Wall finishes (4),  
Substructure (8)

**Design space size:  $5.73 \times 10^{23}$**

# Calculating Embodied Carbon in Buildings

Material amount  
From Building 3D Model



Global Warming Potential  
(GWP) per material  
from LCI Database

X

kg CO<sub>2</sub>e / unit of material

=

kg CO<sub>2</sub>e

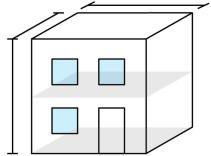
Assumptions

**Buildings have thousands of parameters**

# Facilitating LCA Quantitation using LLMs - Fast and Recursive

Current Practice

Architect



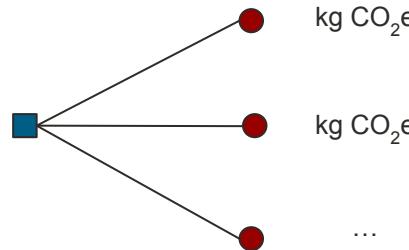
Few design options

Engineer

Several days

LCA tool

(One Click LCA, Tally,  
LC3, etc.)



Linear data transmission

Research Goal

Parameters	
Area	m <sup>2</sup>
Width	m
...	...

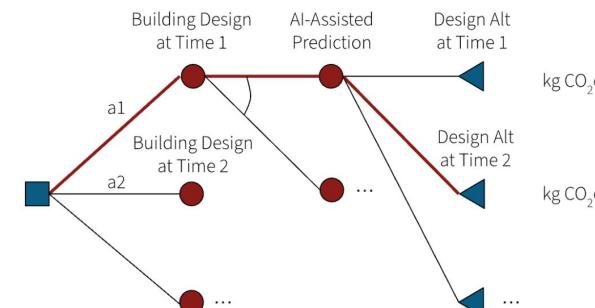
Set of parameters

Architect

Several hours

LLM tool

(ChatGPT, Claude, etc.)





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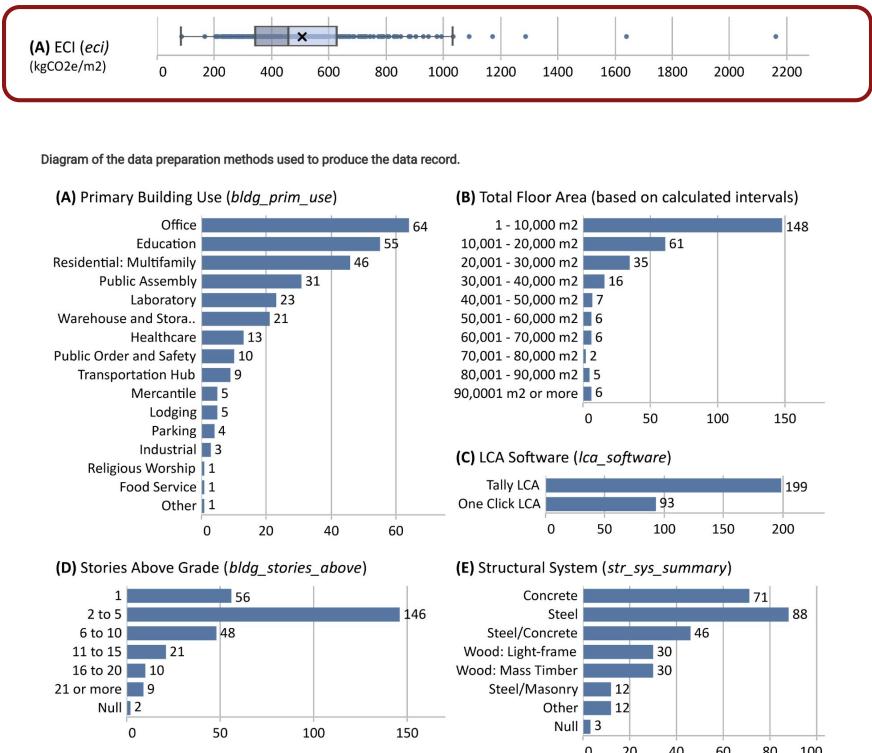
Results: LLM method comparative analysis

4

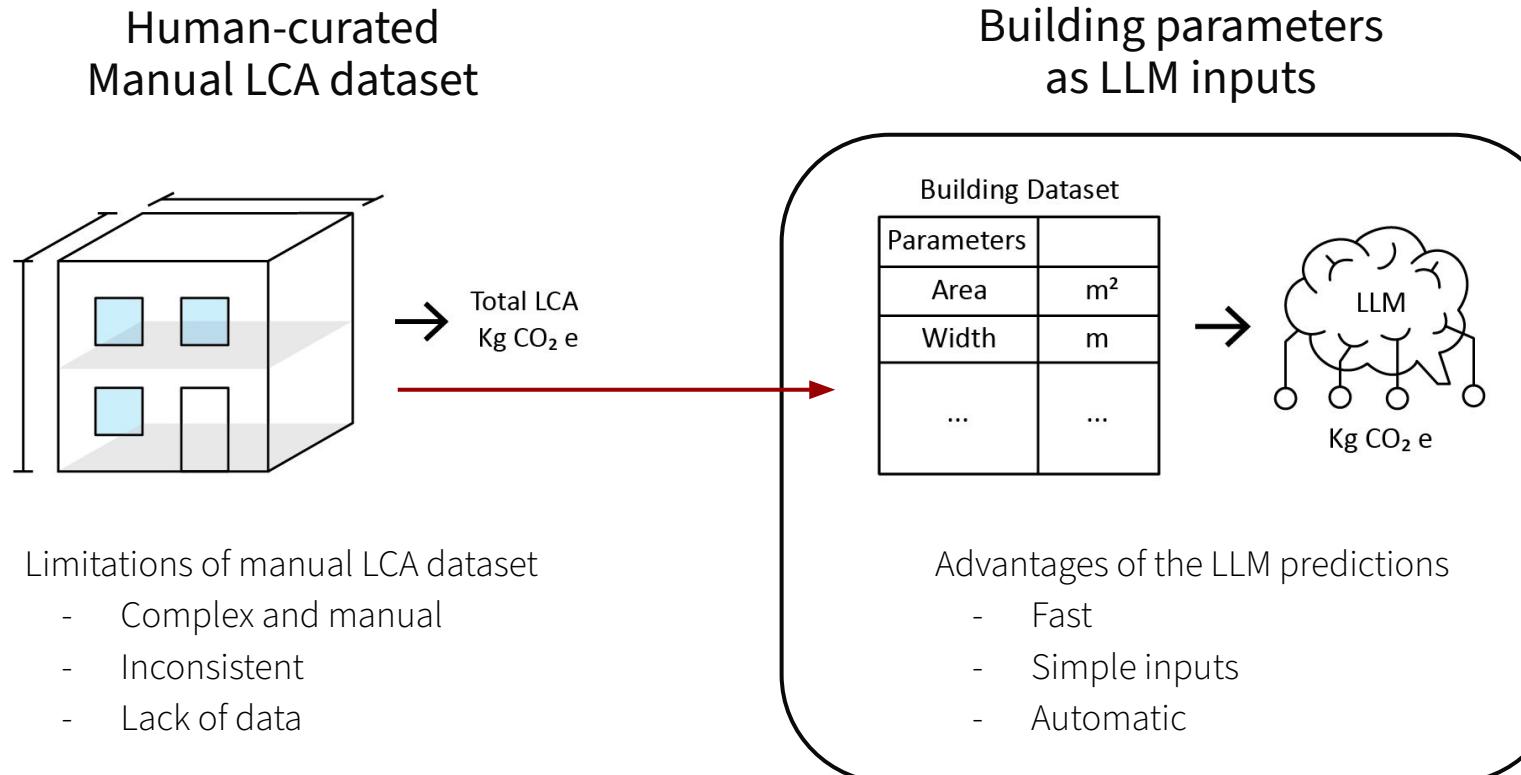
Conclusion

# Building LCA Dataset from Carbon Leadership Forum (CLF)

- 292 buildings contains 72 parameters with carbon intensity
- 30 contributors across North America
- LLM Inputs: **49 parameters** excluding carbon data e.g. region, climate, building type, area, height, structural system, foundation, mass total
- LLM Outputs: **range of kg CO<sub>2</sub>e/m<sup>2</sup>** for each building
  - Comparison with **eci\_a\_to\_c\_cfa**: Embodied carbon intensity (Sum of the project's total GWP for life cycle stages A-C normalized by conditioned floor area (CFA) for new construction projects)



# Transitioning Manual LCA dataset to LLM Input



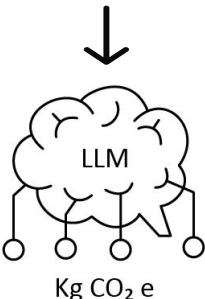
# In-context Learning Methods for LCA Prediction

LLM Innate Knowledge

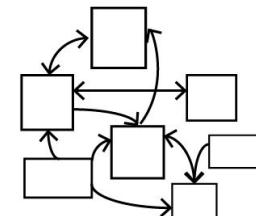
Domain Knowledge

Ontology-based Knowledge

Parameters	
Area	m <sup>2</sup>
Width	m
...	...



5 journal papers and report  
related to building LCA



**Building ontology:**  
Structured representation of building domain knowledge in each design step.  
Interconnections between building parameters and complexity are systematically captured.

Building LCA process documentation

# Detailed Claude 3-7-sonnet API Prompt Structure

LLM Innate Knowledge

(3)

Domain Knowledge

(1) + (3)

Ontology-based Knowledge

(1) + (2) + (3)

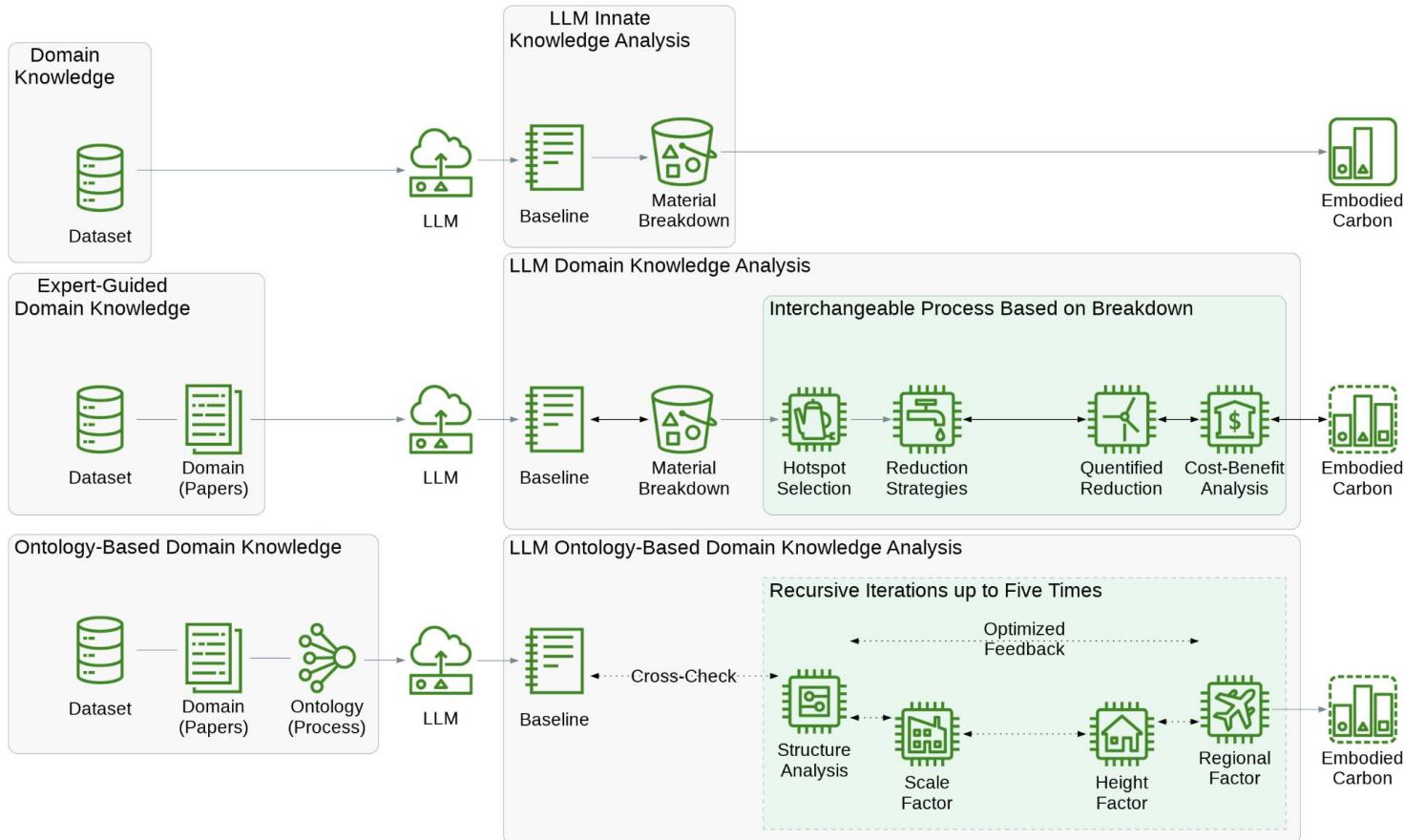
- (1) These five journal papers (.pdf) contain background information about early building LCA process.
- (2) This document (.txt) contains a detailed practice guide on the life cycle assessment of buildings focused on implementation. Use this guideline for LCA estimation.
- (3) Forget the information from previous sessions and calculate everything from the beginning. **data\_glossary\_LLM** (.xlsx) contains feature names and descriptions for the data. Reference the given feature information above. Estimate the embodied carbon value of (x) buildings **in the Excel file** (.xlsx). Each row represents different building data. Provide each range for each data in units of kgCO<sub>2</sub>e/m<sup>2</sup>. For floor area, you need to use bldg\_cfa. Update the ranges. If cfa is not provided, you can use bldg\_renovated\_cfa + bldg\_renovated\_gfa for renovated buildings. Include life cycle stages A-C. Show results in a table with the range with cfa. If it does not converge: Can you provide a plausible range for each building given the information in units of kg CO<sub>2</sub>e/m<sup>2</sup>?

# Interactive LLM Sessions Reveal LCA Prediction Analysis

Innate  
Knowledge

Domain  
Knowledge

Ontology-Based  
Knowledge





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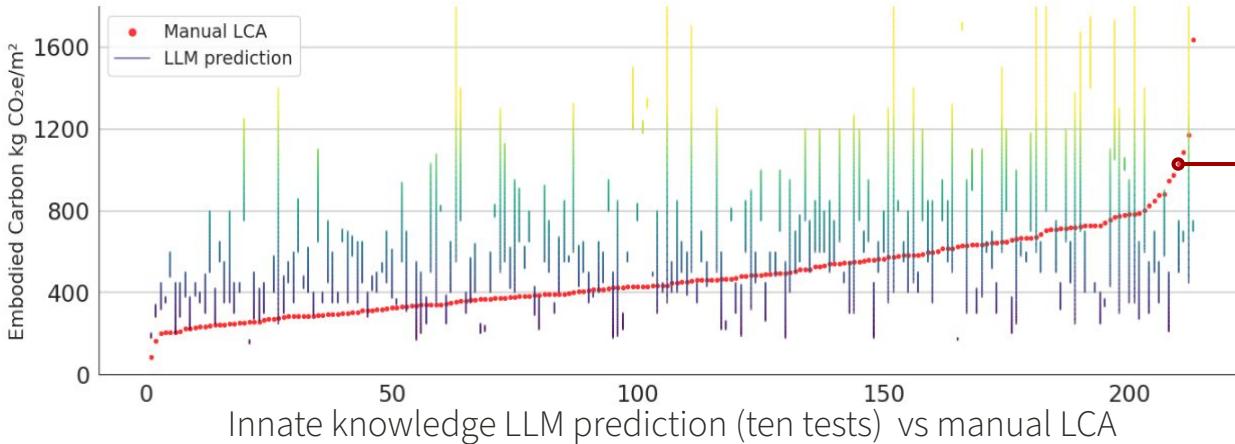
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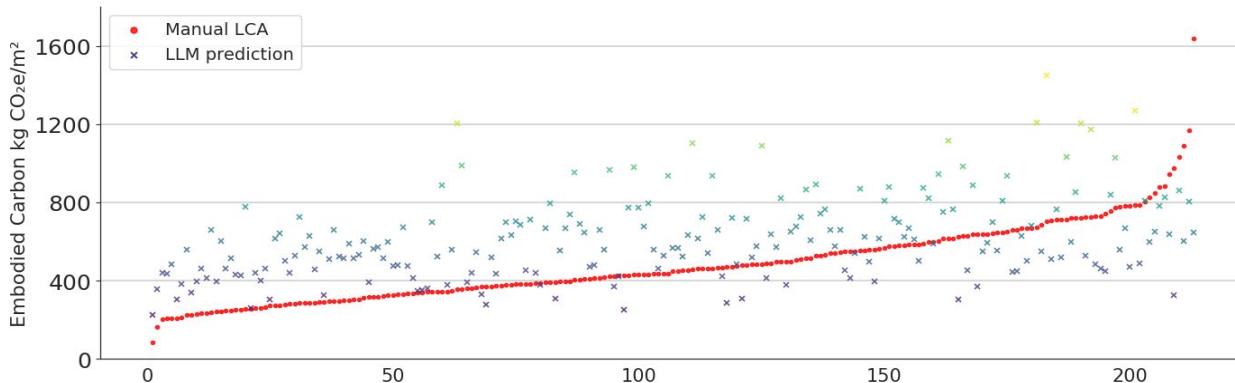
# Comparing Manual LCA vs Innate Knowledge

Innate knowledge LLM prediction (one test) vs manual LCA



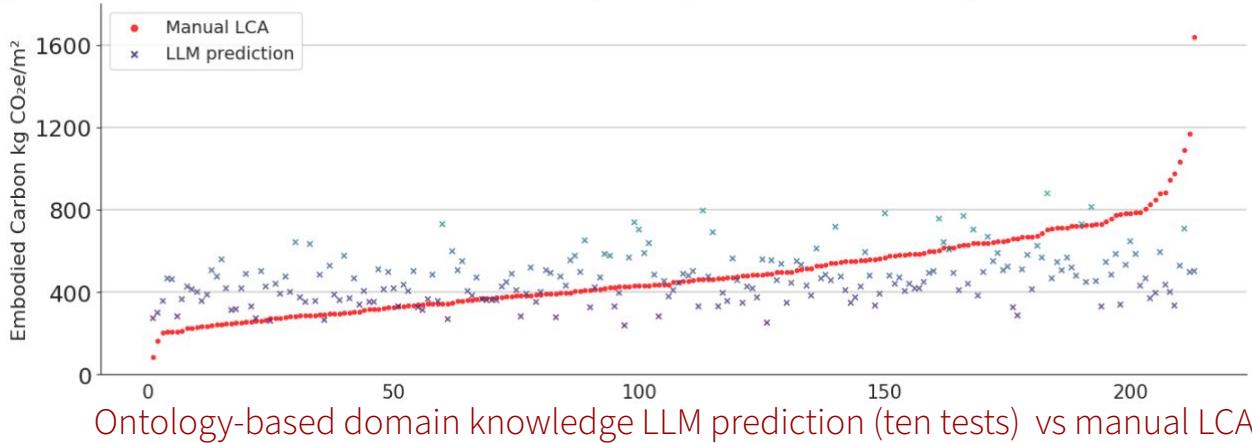
Building ID: 152  
Location: WA  
Size: 4,350 ft<sup>2</sup>  
Typology: Education  
Stories: 2 to 5  
Structure: Concrete

Innate knowledge LLM prediction (ten tests) vs manual LCA

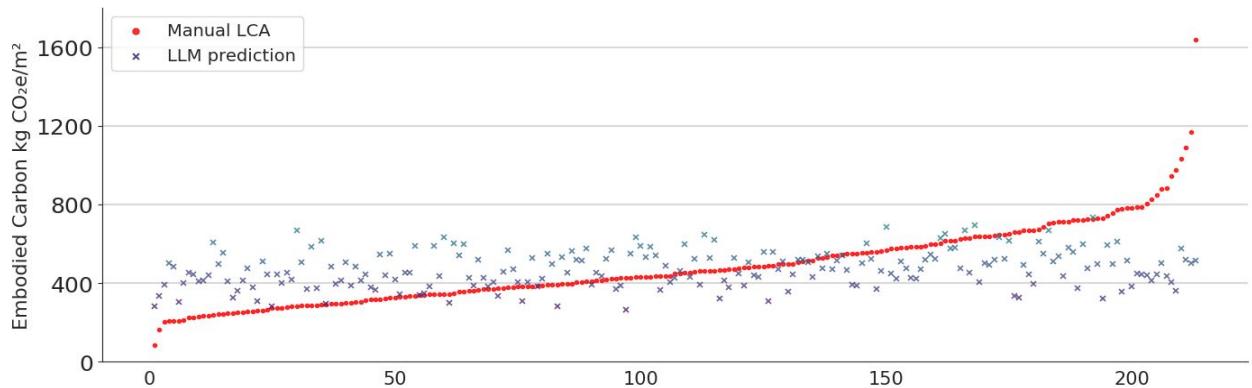


# Comparing Domain vs Ontology-Based Knowledge

Domain knowledge LLM prediction (ten tests) vs manual LCA



Ontology-based domain knowledge LLM prediction (ten tests) vs manual LCA



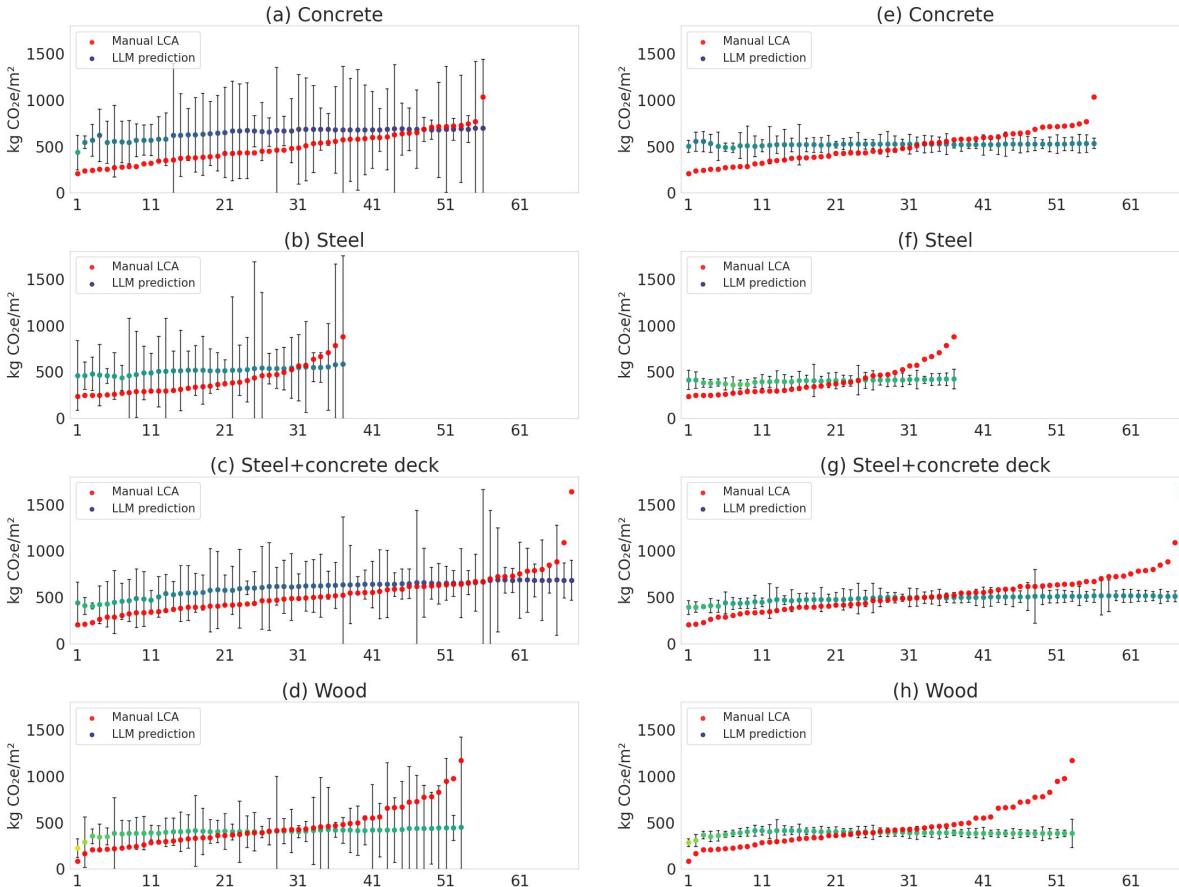
# Error Reduction: Innate vs Ontology-Based

	Baseline manual	1. Innate	2. Domain	3. Ontology	Reduction (Innate vs Ontology)
<b>RMSD*</b>		392.4	244.3	230.9	<b>41%</b>
Distance		219.0	152.0	150.7	31%
Median	446.9	574.5	452.0	466.0	
Mean	482.5	613.3	464.4	471.8	
<b>SD**</b>		218.5	78.6	51.6	<b>76%</b>

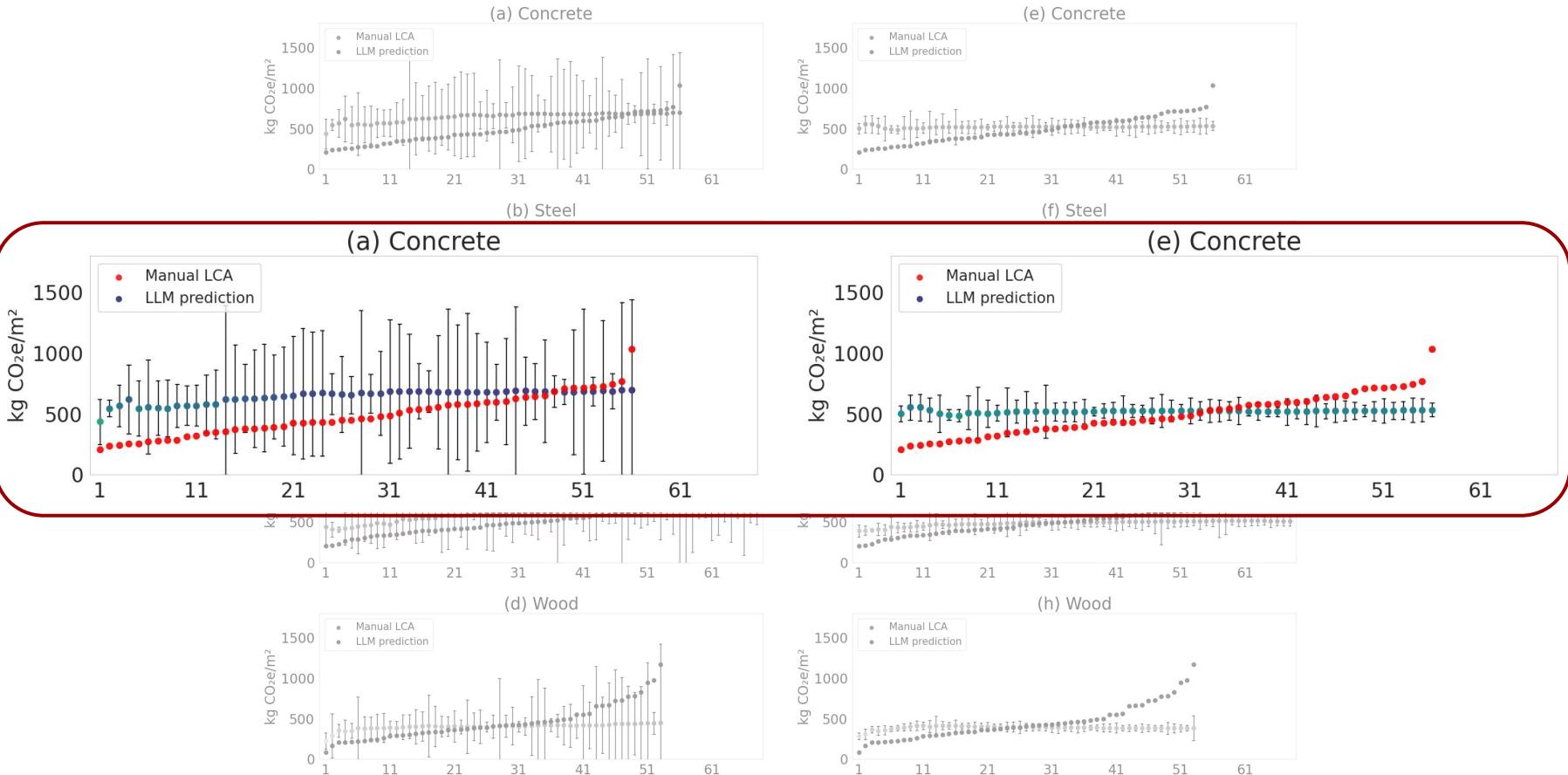
\*Root Mean Square Error (RMSD)

\*\*Standard deviation (SD)

# Structural System Comparison: Innate vs Ontology-Based



# Structural System Comparison: Innate vs Ontology-Based





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# Conclusion

- The study evaluated three LLM methods for early building LCA, finding the **ontology-based approach** achieved **41% reduction in RMSE and 76% reduction in standard deviation** compared to using only innate knowledge.
- LLMs demonstrate **self-retrospective learning capabilities** where predictions gravitate toward mean values, resulting in underestimation of high carbon values and overestimation of low carbon values.
- The ontology-based approach transforms LLMs from simple pattern-matching to **iterative refinement through multiple feedback cycles**, enabling more accurate predictions when proper domain knowledge is provided.
- Future work will focus on developing **systematic human-LLM interaction frameworks** that integrate supervised learning, non-monotonic reasoning, and prompt engineering for practical industrial LCA applications, with potential extension to similar engineering problems like **clusters of buildings with similar features**.

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Paper

Thank you!

Questions?

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