Towards Interactive AI-assisted Material Selection for Sustainable Building Design

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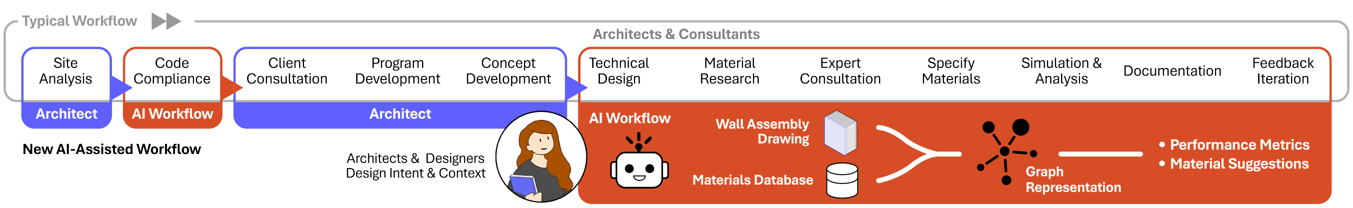

Figure 1: The proposed scope of our AI-assisted material selection workflow. Our prototype translates wall assembly sketches into graphs and supports sustainable material choices aligned with the architect's design intent.

Abstract

We present an AI-assisted workflow that supports architects in designing wall assemblies using sustainable materials. Material selection in architecture is a complex process involving multiple data points and trade-offs across environmental performance, cost, and constructability. Making this process more efficient is essential for encouraging sustainable design practices. Our approach uses artificial intelligence and large language models to streamline aspects of material analysis and information management. The workflow integrates into standard architectural practice by translating wall assembly sketches into graph representations that reflect components and their relationships. Through an interactive interface with graph visualisation, architects can explore material options, review properties and substitute components in line with their design intent. We contribute a prototype workflow and report findings from a preliminary study on the integration of AI tools in early design stages. The study highlights benefits such as reduced decision effort, increased confidence, and improved access to material information.

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CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**; Visualization application domains; • **Social and professional topics** → *Sustainability*; • **Computing methodologies** → **Artificial intelligence**.

Keywords

Architecture, Engineering, and Construction Industry; Sustainability; Net-Zero; Material Selection

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1 Introduction

The Architecture, Engineering, and Construction (AEC) industry contributes significantly to global carbon emissions, with embodied carbon projected to be nearly half of all emissions by 2050 [3, 9, 20]. Unlike operational carbon, which is emitted during the use of a building and is variable depending on how a building is used, embodied carbon is inherent in the materials and processes used during its construction, which means that material selection plays the most critical role in achieving lower carbon emissions for sustainable architecture [4, 16]. Despite increasing pressure to reduce carbon emissions, the adoption of low-carbon materials remains a challenge. Architects and building designers struggle with fragmented data, limited expertise, and balancing complex requirements such as cost, availability, aesthetics, performance, and sustainability [12, 19]. Architects often default to familiar materials and overlook low-carbon alternatives. However, the implementation of low-carbon materials in construction is hindered by a global shortage of the expertise needed to specify and apply them [19]. The AEC industry currently lacks effective tools to help architects select materials based on design and performance needs.

We explore the use of artificial intelligence (AI) for material selection, especially in wall assemblies. We introduce a novel AI-assisted workflow developed with architecture domain experts, offering material recommendations tailored to project goals and current market options. We studied 11 professional architects using our AI-assisted prototype to gain practical insights into choosing low-carbon materials in design scenarios. We collected feedback through questionnaires on themes like work demands, usability, decision-making support, and design flexibility. This research provides insights into architects' perceptions and interactions with the prototype. Our contributions include:

- We present a novel AI-assisted workflow to assist architects during the development of wall assembly designs, and provides material options evaluated against project goals (see Figure 1).
- We identify professional architects' typical workflows in architectural design and material selection (see Figure 5).
- We highlight lessons learned regarding the practical integration of AI tools in architectural design workflows in regard to (1) reducing effort, (2) building trust, and (3) navigating information.

2 Background and Related Work

In the AEC industry, material selection is a critical factor in building performance, cost, and sustainability [22]. The process begins with gathering project requirements, such as client preferences, budget, and code compliance [11], followed by architects coordinating and developing design documents that propose materials. They use software tools to evaluate material properties and environmental impact, often relying on pre-designed assemblies to save resources [21]. Balancing cost, aesthetics, performance, feasibility, and sustainability is particularly challenging when working with unfamiliar materials [19]. While AI-driven material selection has been explored in manufacturing [13] and domain-specific sustainable agents [23], the AEC industry presents unique demands due to factors like aesthetics, cost, availability, and familiarity with the materials [13]. To address these challenges, we propose an AI-assisted workflow that simplifies material selection. Our research focuses on *building wall assemblies*, where architects have the flexibility to explore novel materials that may impact sustainability [18]. Wall

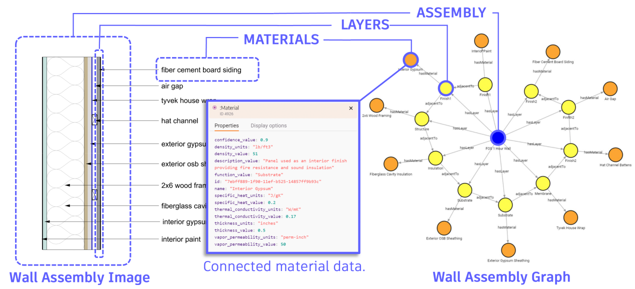

Figure 2: Wall assemblies are modeled as graphs, with nodes holding entity attributes and edges capturing relationships like adjacency.

assemblies can also be a precursor for scaling to other building parts like floors and roofs [14].

Data visualizations have long been used to support decision-making tasks by transforming complex datasets into intuitive and actionable insights [7]. They help decision-makers evaluate choices by presenting data that highlights relationships, trends, and trade-offs. For instance, in the software release planning domain, Aseniero et al. used a modified Sankey diagram and Parallel sets to illustrate the flow of resources like budget and time allocation into software features, allowing planners to track how resources can potentially be used, enabling comparisons between different solutions and facilitating informed decisions [6]. By simplifying complex information and emphasizing key differences, these visual tools empower users to analyse options effectively and select optimal outcomes. While prior work has applied AI to isolated tasks such as material property prediction or sustainability scoring, little research combines these algorithms with user-facing, interactive tools that fit architects' day-to-day workflows. Our study closes this gap by integrating retrieval-augmented LLM recommendations with a novel graph-based visualisation, enabling architects to explore, verify, and adapt sustainable wall-assembly options in a single interface. Thus, we assert that AI tools and data visualization could augment complex AEC workflows like sustainable material selection.

3 Graph-Based AI-Assisted Design Workflow Application

We present a novel AI-assisted workflow designed to support architects in finding, evaluating, and validating appropriate materials for building assembly. The workflow begins when architects define high-level sustainability goals and provide initial wall assembly sketches. For this study we used Vision-Language Models (VLMs), e.g. GPT-4o [10], to extract data from architectural drawings and transform them into computable Graph Representations (GR). We constructed a GR schema consisting of nodes (materials or layers) and edges (relationships such as adjacency), as illustrated in Figure 2. To our knowledge, this is the first instance of visualizing architectural wall assemblies and related material information through this novel graph-based approach.

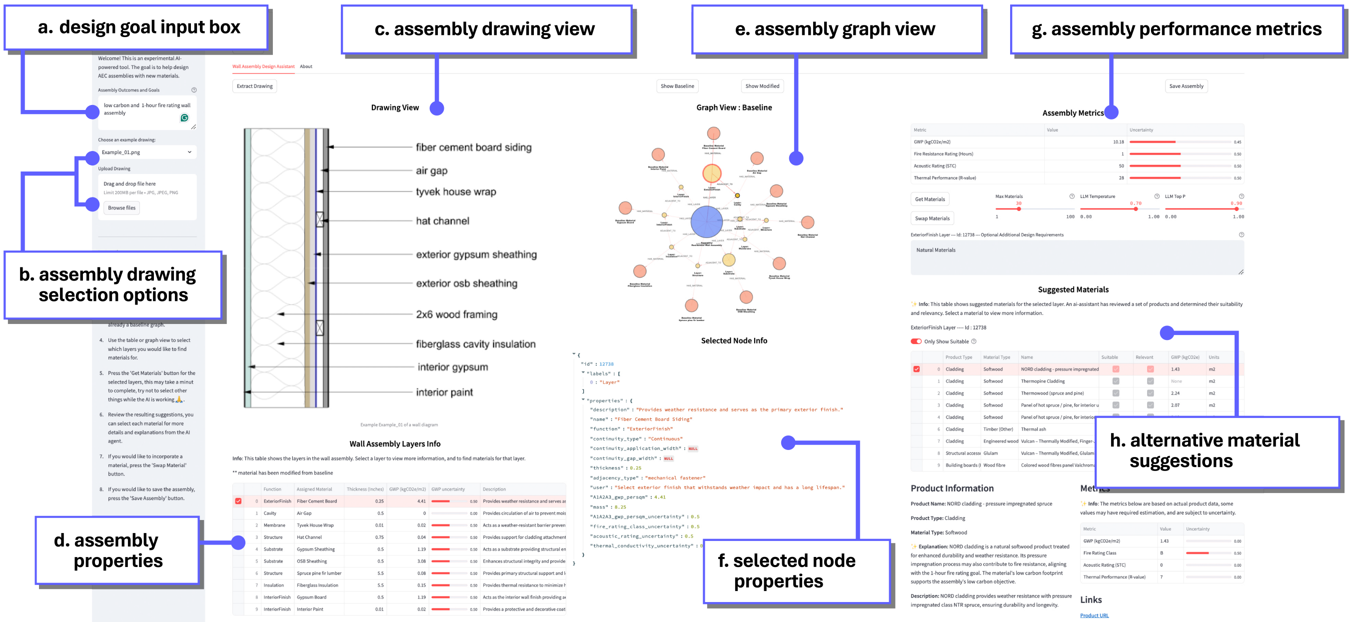

Figure 3: Architects begin by entering design intent (a) and selecting or uploading a wall assembly drawing (b). The assembly view (c) displays layers and materials, with their properties shown in (d). The graph view (e) visualises component relationships, and node details such as GWP and fire rating appear in (f). Performance metrics are shown in (g), with alternative material suggestions in (h).

The workflow further leverages Retrieval-Augmented Generation (RAG) [1] to enable LLMs to effectively incorporate external knowledge for domain-specific purpose, integrating real-world 2050 Materials database [1] into a specialised Materials Knowledge Graph (mKG). We use two RAG strategies with LLMs, vector-based and graph-based framework [8, 17], to quickly identify relevant sustainable materials. The retrieved material data is then ranked based on suitability and relevance. Each recommended material includes detailed descriptions, explanations, uncertainty metrics, and direct URL links to supplier documentation and certification details as shown in Figure 3.

The workflow maintains a Human-in-the-loop approach, users can interactively refine their material search queries by specifying assembly parts and target project metrics. The AI system then demonstrates how alternative materials impact overall performance metrics. Once suitable materials are identified, architects can incorporate them into the assemblies and compare metrics between the new and original designs. In our workflow, architects can easily compare new assemblies against original designs and quickly evaluate alternative options, significantly simplifying and enhancing the sustainable design decision-making process.

[1]RAG is a technique that improves LLMs' output by integrating external knowledge from databases or other sources [17].

4 Preliminary Study

4.1 Participants

We conducted a preliminary study with 11 professional architects to investigate their typical material selection workflows and explore how our AI-assisted prototype might influence their practices. Participants were recruited through an online screening survey targeting architecture designers with experience in material selection. The survey received 43 responses, from which we chose 11 participants ensuring diversity in expertise, gender, and age groups. All participants had at least two years of experience in architectural design and were familiar with the development process of new building assemblies and its required material selection practices (see Figure 4).

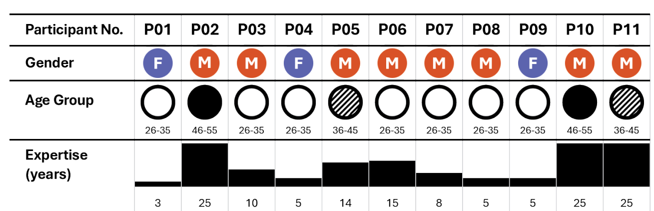

Figure 4: Figure summarizing our participant demographics. Expertise is measured in years of work in the AEC industry.

This study received institutional ethics approval. All participants provided written informed consent, were free to withdraw at any time, and their data were stored and reported in anonymised form in compliance with GDPR and ACM research-ethics guidelines.

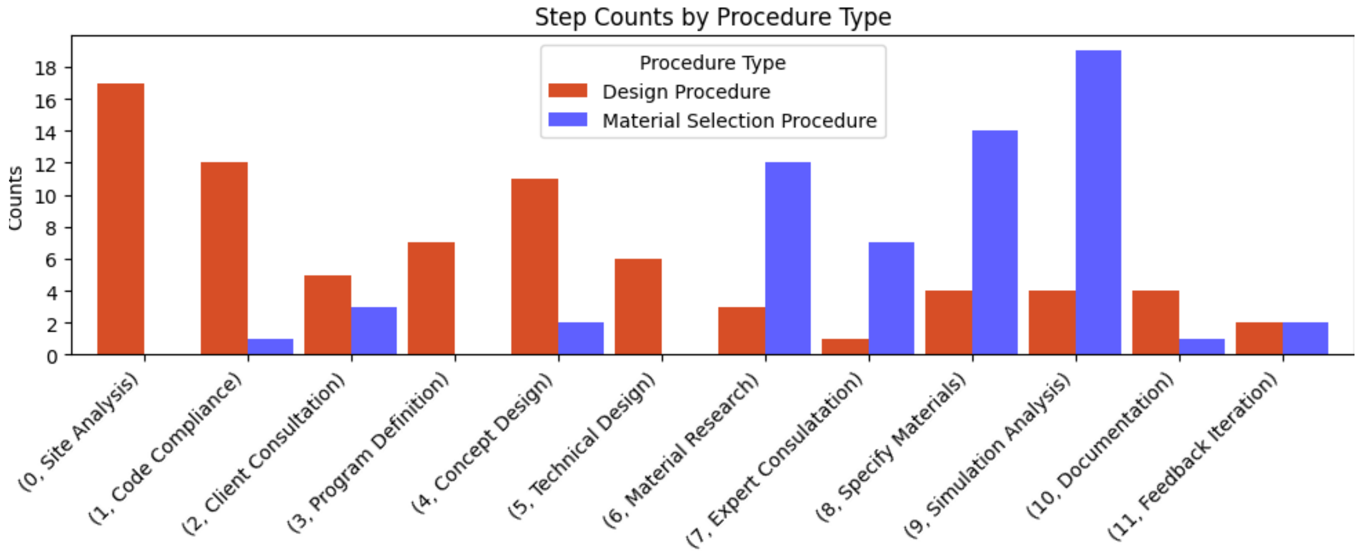

Figure 5: Comparison of the counts of participant responses relating to the high-level design task and material selection task. The step tags are ordered by their associated step IDs, highlighting their relative frequencies in the dataset.

4.2 Study Procedure & Data Analysis

Each participant took part in a 1-hour remote study conducted via virtual conferencing (Zoom), comparing typical and AI-assisted workflows through structured design tasks. The session began with a baseline task (20 mins), where participants described their typical design process under a design scenario in a think-aloud session (5 mins), followed by a practical material selection scenario using their typical workflow (15 mins). This scenario was presented on a virtual mural tool (Miro board), simulating a real-world situation where they needed to balance performance, aesthetics, and sustainability criteria to select materials for a wall assembly. Afterwards, participants evaluated their typical workflow via a questionnaire assessing trust, mental, physical, and temporal demand, as well as effort and frustration using a 5-point Likert scale.

Next, we introduced and demonstrated key features of our AI-assisted tool, such as automated material suggestions, performance comparisons, and a graph-based representation interface. Participants then repeated the design task using the AI-assisted workflow (20 mins), followed by completing a second questionnaire. This questionnaire included the previous measures plus additional questions to assess the tool's usability and their perception of the graph view. The session concluded with a semi-structured interview (5 mins) to gather qualitative insights.

Data from both phases were analysed quantitatively to assess perceptions of traditional versus AI-assisted workflows. Qualitative data from interviews were thematically analysed to explore participants' experiences, focusing on usability, and opportunities for integrating AI and graph representations/visualization into architectural design practices.

5 Results

We present our findings in three main sections: Participants' typical workflow, overall participants' perception across different workflows, and overall feedback.

5.1 Identified Typical Workflows

We first identified the participants' typical workflow illustrated in Figure 5. We compare the counts of participant responses relating to the high-level design task and material selection task. The analysis of the participant workflows revealed distinct emphases in the design and material selection procedures. Steps associated with conceptual and preparatory stages, such as *"Site Analysis"* and *"Concept Design"*, were predominantly reported in design workflows, while tasks like *"Simulation Analysis"* and *"Expert Consultation"* were more frequent in material selection processes. A detailed workflow description can be found in the appendix, and we highlighted the steps that can be powered by AI tools.

5.2 Workflows Comparison

We analysed user experience and graph representation insights, comparing participant perceptions between Group A (n=5, <8 years' experience) and Group B (n=6, ≥8 years' experience). Color gradients, ranging from -2 to 2, represent the scores for each metric, with blue indicating high scores and red denoting low scores. The scores are averaged for the two participant groups to highlight variations in perception and experience.

As shown in Figure 6, both groups generally viewed the AI-assisted workflow as reducing the temporal demand, effort required, and frustration levels when compared to the Typical Workflow. Notably, experienced architects in Group B reported significantly lower mental and temporal demand scores with the AI tools, highlighting their potential to reduce cognitive and time-related demand.

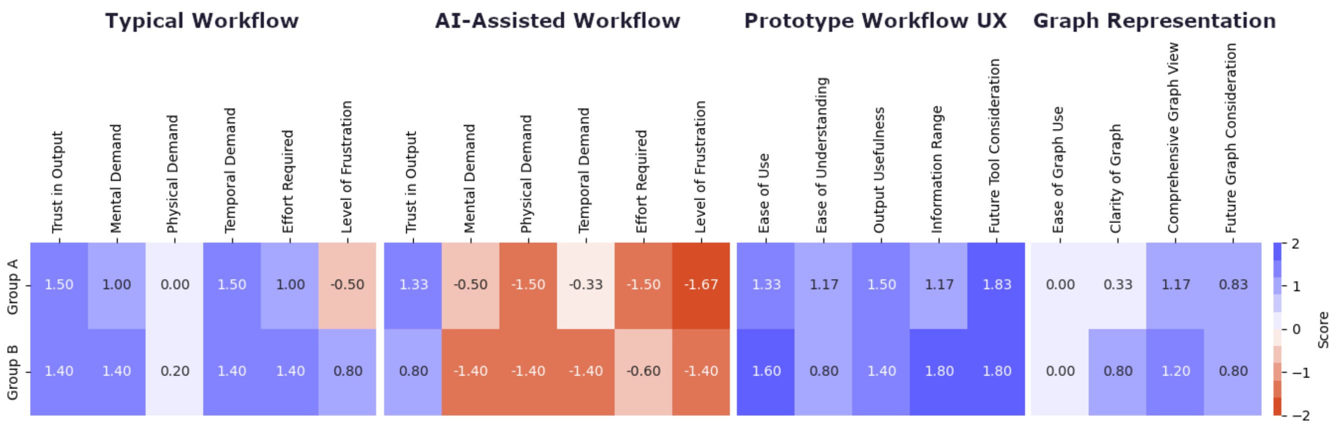

Figure 6: Heat-map of mean Likert-scale responses for early-career (Group A, n = 5) and expert (Group B, n = 6) architects. The diverging colour scale ranges from −2 (strong disagreement, red) to +2 (strong agreement, blue). Each row is a survey item phrased as "I [verb / object]", e.g., "I trust the output."

The UI was particularly well-received by both groups, scoring high on ease of understanding, output usefulness and future adoption, which indicates its potential to boost productivity among architects. In contrast, feedback on the proposed graph representation was mixed. Group B found the graph clarity to be satisfactory, suggesting that more experienced users adapt well to innovative data visualizations. However, Group B's lower scores indicate a need for simpler, more straightforward graph designs that emphasize clarity over complexity. Both groups gave moderate scores for comprehensiveness, pointing to a potential for more detailed or context-rich graph content.

5.3 Qualitative Analysis and Findings

We conducted a thematic qualitative analysis on our participant feedback, using a transcription analysis software tool (Dovetail) to auto-transcribe the video recordings of each participant and tag relevant statements using open coding. Four of the authors performed the coding independently and iteratively reconvened to discuss the codes and achieve agreement. We present four high-level *emergent themes* (E.T.) that we observed.

- **E.T.1 Material Selection Complexity.** Participants highlighted the complexity and importance of the architectural design process. Key facets included detailed site analysis, design development, and expert consultations. An early career respondent noted, *"We need to brainstorm the project and conduct surveys on the area to anticipate future developments."* (P08) While AI integration was seen as beneficial for providing comprehensive data, significant effort was still needed to research alternative designs and ensure compliance with local standards. One participant remarked, *"we must consider safety... consult with experts to choose environmentally friendly materials."* (P05).
- **E.T.2 Workflow Demands and Verification.** The design workflow demands significant effort and time, being both comprehensive and mentally taxing. An early career participant stated, *"mentally exhausting"* (P03). Material selection, writing specifications, and stakeholder coordination were particularly challenging, with verification of materials adding to the workload. An experienced architect noted, *"Writing specifications is one of the most time-consuming tasks."* (P07). Despite these challenges, The AI-assisted workflow's ability to provide detailed verification data was highly valued. An early career respondent remarked, *"A tool that can measure and identify the most cost-effective material is very helpful."* (P02). However, managing and verifying the extensive data remained mentally demanding, highlighting the need for reliable and comprehensive information for accuracy and compliance.
- **E.T.3 Uncertainty and Trust.** Participants expressed concerns about the trustworthiness of AI recommendations and desired transparency *"there might be underlying factors influencing the outputs .. we need complete transparency."* (P10). Managing large volumes of information added to these concerns. *"I would like to experiment with it further to see the accuracy of its outputs."* (P11).
- **E.T.4 Interface Usability.** The AI-assisted workflow's interface received mixed reviews. Participants appreciated detailed data visualization but found the interface challenging to navigate. *"The information is available, but the presentation is confusing."* (P06). Suggestions included simplifying the interface and organizing data intuitively. *"The graph contains a lot of information. I wish it could be easily broken down into parts."* (P07).

6 Discussion and Future Work

In this work, we introduced a novel AI-assisted workflow for material selection in wall assembly, followed by a mixed-method study involving 11 architectural designers. Based on a preliminary analysis of our findings, we found several key lessons about integrating AI tools to support material selection workflows. Survey results indicate that while our AI-assisted workflow offers significant benefits in terms of detailed insights and comprehensive data, some areas require improvement. The mental and temporal demands of the process, the need for greater transparency in AI-assisted recommendations, and the interface's usability are key concerns that need to be addressed.

Reducing Effort By centralizing material data into highly queryable formats such as Graphs and associating that data to an architect's construction documentation, our findings suggest that we can reduce the time it takes to consider different material options while architects design assemblies (**??**, **??**). Furthermore, by utilizing LLMs, Knowledge Graphs, and AI-agent techniques to find and evaluate material options for an architect's project goals, our results show the reduction of mental demand needed to consider new material options. We find that combining these techniques reduces the effort to develop higher-performing, lower-carbon assemblies compared to the typical architect workflow.
Recommendation: Additional example data of code-compliant assemblies are needed for the AI-assisted workflow to compare and recommend how to bring novel designs into building code compliance.

Building Trust Trust in AI-assisted recommendations is a major concern among participants (**??**, **??**) and it has been a main focus in recent research on human-AI interaction and decision-making systems [2, 5, 15]. The need for greater transparency and explainability in how the AI system selects and evaluates materials was frequently expressed. Participants emphasized the importance of reliable and comprehensive information to ensure accuracy and compliance, particularly when managing large volumes of data.
Recommendation: Provide explanations for how the AI system selects and evaluates materials, including details on algorithms and data sources used. Offer a comprehensive view of the material properties and performance metrics to easily compare different options. Allow users to trace back the data to its source, offering a way to explore and verify information. Incorporate ways for users to report discrepancies or inaccuracies in the AI recommendations.

Navigating Information Looking at the emergent themes of **??**, **??** and **??**, we observed that presenting the wall assembly data in a graph representation may be challenging to our participants initially, but once learned, it can be beneficial to see more information at-a-glance. Making sustainability metrics more salient in the visualization (e.g., the node size) also enabled our participants to assess certain materials and find alternatives quickly.
Recommendation: Explore transitions between novel and familiar data visualization representations. For example, the force-directed graph in our prototype for the wall assembly can transition into a more familiar layout, such as a linear wall assembly layout or a tree layout. Future research can also explore the design and study of novel representations that specifically highlight sustainability metrics to learn about their effects on designing for sustainability.

6.1 Future Work and Limitations

Future work will concentrate on refining the UI prototype to improve usability, interactivity and on rigorously evaluating the reliability of the overall workflow. We will also explore alternative visualization and presentation layouts to support a wider range of decision-making scenarios. Finally, conducting further studies with larger and more diverse participant groups will provide deeper insights and improve the generalisability of the findings.

As the workflow relies on LLMs, there is an inherent risk of hallucinated or outdated content. We mitigate this risk through RAG anchored to a curated materials database and by surfacing provenance links for every recommendation. Future versions will incorporate automatic uncertainty estimates and mandatory human-in-the-loop verification before any specification is adopted.

7 Conclusion

This study has demonstrated that integrating AI-assisted workflows can enhance the material selection process in architectural design, supporting the hypothesis that AI tools can reduce cognitive load and improve decision-making efficiency based on the sample group in this study. By examining participants' responses to typical and AI-assisted workflows, our research highlights the importance of transparency, data verification, and user interface usability in building trust and acceptance of AI-assisted recommendations. While the AI-assisted workflow showed promise in reducing the time and mental effort required for material selection, participants underscored the need for greater explainability and accuracy to enhance trust. Enhancing these aspects would likely lead to greater acceptance and more effective use of ai-assisted workflows like the one used in this study in broader design applications among both early-career and experienced architects. Future work should involve expanding participant diversity and advancing the scope of the AI-assisted workflow. Development should focus on more extensive recommender systems and visualisations on uncertainty associated with metrics associated with sustainable architecture. Overall, our findings underscore AI's transformative potential on architectural workflows to accelerate sustainable design practices and most importantly, the openness of professionals at all levels to new approaches to design.

References

[1] 2025. 2050 Materials. https://2050-materials.com/

[2] Sayed Fayaz Ahmad, Heesup Han, Muhammad Mansoor Alam, Mohd Rehmat, Muhammad Irshad, Marcelo Arraño-Muñoz, Antonio Ariza-Montes, et al. 2023. Impact of Artificial Intelligence on Human Loss in Decision Making, Laziness and Safety in Education. *Humanities and Social Sciences Communications* 10, 1 (2023), 1–14. doi:10.1057/s41599-023-01787-8

[3] Mahmure Övül Arıoğlu Akan, Dileep G Dhavale, and Joseph Sarkis. 2017. Greenhouse Gas Emissions in the Construction Industry: An Analysis and Evaluation of a Concrete Supply Chain. *Journal of Cleaner Production* 167 (2017), 1195–1207.

[4] Ali Akbarnezhad and Jianzhuang Xiao. 2017. Estimation and Minimization of Embodied Carbon of Buildings: A Review. *Buildings* 7, 1 (2017), 5. doi:10.1016/j.jclepro.2017.07.225

[5] Theo Araujo, Natali Helberger, Sanne Kruikemeier, and Claes H De Vreese. 2020. In AI We Trust? Perceptions About Automated Decision-Making by Artificial Intelligence. *AI & Society* 35, 3 (2020), 611–623. doi:10.1007/s00146-019-00931-w

[6] Bon Adriel Aseniero, Tiffany Wun, David Ledo, Guenther Ruhe, Anthony Tang, and Sheelagh Carpendale. 2015. STRATOS: Using Visualization to Support Decisions in Strategic Software Release Planning. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1479–1488. doi:10.1145/2702123.2702426

[7] Evanthia Dimara and John Stasko. 2022. A Critical Reflection on Visualization Research: Where Do Decision Making Tasks Hide? *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (Jan. 2022), 1128–1138. doi:10.1109/TVCG.2021.3114813 Conference Name: IEEE Transactions on Visualization and Computer Graphics.

[8] Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, and Jonathan Larson. 2024. From Local to Global: A Graph

Rag Approach to Query-Focused Summarization. *arXiv preprint arXiv:2404.16130* (2024).

[9] Luisa F. Cabeza et al. 2021. Embodied energy and embodied carbon of structural building materials: Worldwide progress and barriers through literature map analysis. *Energy and Buildings* 231 (2021), 110612. doi:10.1016/j.enbuild.2020.110612

[10] OpenAI et al. 2024. GPT-4o System Card. arXiv:2410.21276 [cs.CL] https://arxiv.org/abs/2410.21276

[11] Karoline Figueiredo, Rodrigo Pierott, Ahmed WA Hammad, and Assed Haddad. 2021. Sustainable Material Choice for Construction Projects: A Life Cycle Sustainability Assessment Framework Based on BIM and Fuzzy-AHP. *Building and Environment* 196 (2021), 107805. doi:10.1016/j.buildenv.2021.107805

[12] George D Gann, Tein McDonald, Bethanie Walder, James Aronson, Cara R Nelson, Justin Jonson, James G Hallett, Cristina Eisenberg, Manuel R Guariguata, Junguo Liu, et al. 2019. International Principles and Standards for the Practice of Ecological Restoration. *Restoration Ecology* 27, S1 (2019), S1–S46. doi:10.1111/rec.13035

[13] Daniele Grandi, Yash Patawari Jain, Allin Groom, Brandon Cramer, and Christopher McComb. 2025. Evaluating large language models for material selection. *Journal of Computing and Information Science in Engineering* 25, 2 (2025), 021004.

[14] Lisa Iwamoto. 2013. *Digital Fabrications: Architectural and Material techniques.* Princeton Architectural Press.

[15] Vivian Lai, Chacha Chen, Alison Smith-Renner, Q Vera Liao, and Chenhao Tan. 2023. Towards a Science of Human-AI Decision Making: An Overview of Design Space in Empirical Human-Subject Studies. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 1369–1385. doi:10.1145/3593013.3594087

[16] Norbert Lechner. 2014. *Heating, Cooling, Lighting: Sustainable Design Methods for Architects.* John wiley & sons.

[17] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. 2020. Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. *Advances in Neural Information Processing Systems* 33 (2020), 9459–9474.

[18] Ricardo Mateus, Sara Neiva, Luís Bragança, Paulo Mendonça, and Mónica Macieira. 2013. Sustainability Assessment of an Innovative Lightweight Building Technology for Partition Walls–Comparison with Conventional Technologies. *Building and Environment* 67 (2013), 147–159. doi:10.1016/j.buildenv.2013.05.012

[19] Patrik Söderholm. 2020. The Green Economy Transition: The Challenges of Technological Change for Sustainability. *Sustainable Earth* 3, 1 (2020), 6. doi:10.1186/s42055-020-00029-y

[20] United Nations Environment Programme (UNEP). 2022. 2022 Global Status Report for Buildings and Construction: Towards a Zero-emission, Efficient and Resilient Buildings and Construction Sector. https://www.unep.org/resources/publication/2022-global-status-report-buildings-and-construction. Accessed: Dec. 16, 2023.

[21] Lisa Wastiels and Ine Wouters. 2008. Material Considerations in Architectural Design: A Study of the Aspects Identified by Architects for Selecting Materials. (2008).

[22] Johnny Kwok Wai Wong and Jason Zhou. 2015. Enhancing Environmental Sustainability Over Building Life Cycles Through Green BIM: A Review. *Automation in Construction* 57 (2015), 156–165. doi:10.1016/j.autcon.2015.06.003

[23] Shu Zhong, Elia Gatti, James Hardwick, Miriam Ribul, Youngjun Cho, and Marianna Obrist. 2025. LLM-mediated domain-specific voice agents: the case of TextileBot. *Behaviour & Information Technology* (2025), 1–33.