DAGLive: An AI-Augmented Interactive Application for Living Causal Diagrams

MSR298

Tushar Srivastava[1], Paridhi Sharma[2], Hugo Pedder[3], Hanan Irfan[1]

[1]ConnectHEOR, London, UK; [2]ConnectHEOR, Delhi, India; [3]University of Bristol; ConnectHEOR Limited, Bristol, UK

Email: tushar.srivastava@connectheor.com

KEY MESSAGE

DAGLive is a human-in-the-loop web application in which an LLM proposes candidate causal relationships from a research question or study PDFs, and researchers review them, link evidence to each pathway and version the diagram as evidence changes

1 BACKGROUND

Directed acyclic graphs (DAGs) are central to transparent causal inference in real-world evidence and health outcomes research. They are an increasingly popular approach for identifying confounding variables that require conditioning when estimating causal effects [1], and HTA-facing real-world evidence guidance such as the NICE RWE framework expects confounder selection to be explicit and justified. In practice, the evidence behind each arrow sits in separate documents and the diagram is not updated when the evidence changes.
However, developing and maintaining evidence-informed DAGs presents practical challenges:

- **Time-intensive development:** Constructing evidence-informed DAGs requires considerable time and effort to identify relevant variables and specify causal relationships, often relying on manual input and domain knowledge.[2,3]
- **Limited integrated functionality:** Existing tools such as DAGitty support DAG drawing and analysing [4] but are not primarily designed for AI-assisted evidence extraction, evidence annotation or version-controlled collaboration.

GAP: As evidence evolves, causal assumptions require reassessment, highlighting the need for an integrated, evidence-linked and version-controlled DAG development platform.

2 OBJECTIVES

DAGLive was developed as an AI-augmented, human-in-the-loop (HITL), evidence-linked and version-controlled DAG platform, designed to support:

1. **Multiple input pathways** to start a DAG
2. **AI-assisted extraction** of causal information
3. **Human review** and editing of generated DAGs
4. **Evidence documentation** for each causal pathway
5. **Iterative refinement** via versions and comparison
6. **Interactive visualisation** of selected pathways

3 METHODS

DAGLive is a cloud-based, interactive web application that integrates a large language model (LLM) to support AI-assisted extraction and structuring of causal information.

- **Multiple development pathways:** Four input mechanisms were integrated to support AI-assisted and researcher-defined DAG construction (Figure 1).
- **HITL by design:** AI output is a set of candidate relationships, not a final causal model; researchers review and edit.
- **Iterative refinement:** Evidence annotation, version history and comparison were incorporated to support ongoing DAG refinement.

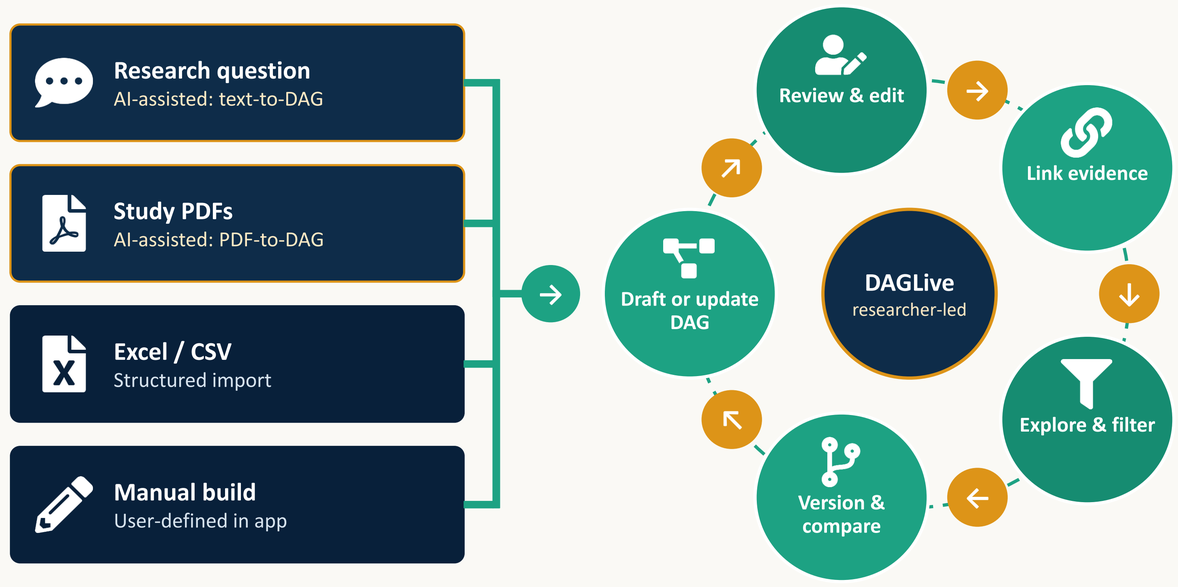


Figure 1: Overview of DAGLive's four input pathways and iterative, researcher-led DAG development workflow.

4 RESULTS

The implemented DAGLive application supports four DAG development pathways (Table 1), with login-based authentication and project-level organisation.
Its integrated functionalities include:

- **Interactive visualisation:** Colour-coded node and pathway types facilitate visual identification of variables and causal relationships (Figure 2).
- **Node and pathway information:** Provides access to variable attributes and supporting evidence, enabling traceability of causal assumptions (Figure 3).
- **Grouped variable views:** Enable navigation between grouped and individual variables to explore DAGs at different levels of detail (Figure 4).
- **Scenario-based filtering:** Enables focused examination of selected causal pathways by isolating relevant pathway subsets (Figure 5).
- **Version management:** Maintains version history and enables comparison of DAG revisions to track changes in causal assumptions.

Table 1: DAG development pathways, corresponding input formats and AI-assistance capabilities.

Pathway	Input	AI-assisted
Text-to-DAG	Natural-language research question	Yes
PDF-to-DAG	Uploaded study PDFs	Yes
Spreadsheet import	Excel/CSV in variable and pathway schemas	No
Manual construction	Built directly in the app	No

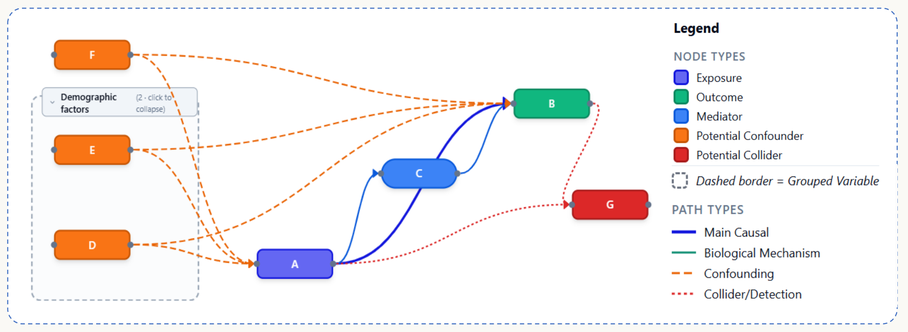


Figure 2. Colour-coded node and pathway types in the DAGLive interface, with corresponding legends.

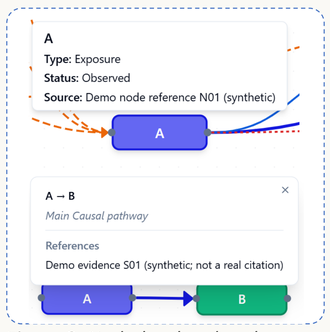


Figure 3: Node-level and pathway-level information

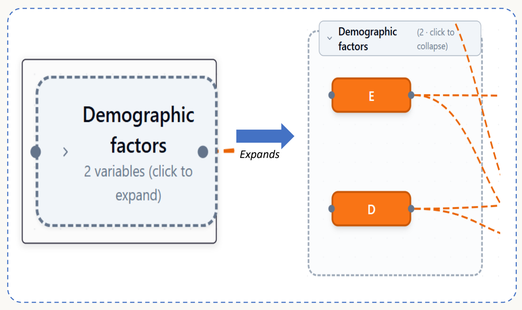


Figure 4. Grouped versus individual variable views

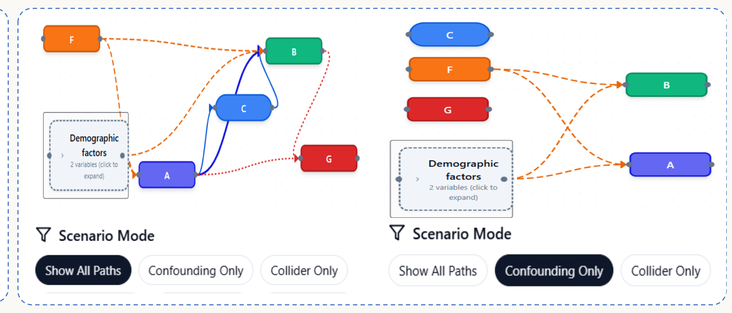


Figure 5: Scenario-based DAG filtering comparing the complete network with a view restricted to confounding pathways.

Note: Figures 2–5 illustrate DAGLive functionalities using synthetic variables and evidence references.

5 DISCUSSION

DAGLive turns a DAG from a one-off drawing into a maintained record of causal assumptions. AI-generated causal relationships remain provisional and require researcher review and refinement. Not yet evaluated: the accuracy of LLM extraction against expert-built DAGs.

Table 2: DAGLive's gain is continuity: evidence and versions travel with the diagram.

	DAGitty with manual documentation	DAGLive
Starting point	Variables and pathways specified by hand	**Question, PDFs, spreadsheet or manual**
Evidence	Documented manually across sources	**Attached to each causal pathway**
Updates	Revisions managed outside the tool	**Versions saved and compared**
Role of AI	Not integrated	**Proposes candidates; researcher decides**

Evolving tool: functionality is in place; continued development will refine its capabilities and usability. Ask authors for demonstration of working tool.

6 CONCLUSION

- **One environment:** AI-assisted extraction, import, manual build, evidence annotation, versioning and visualisation.
- **Supports, not replaces, expert judgement:** researchers assess and refine every AI-assisted DAG.
- **Not yet evaluated:** extraction accuracy and efficiency.
- **Next:** **an open-source release is planned.**

Living, evidence-linked DAGs may support more transparent and updateable causal inference workflows; efficiency and extraction accuracy have not yet been evaluated.

REFERENCES

1. Tennant PWG, et al. Int J Epidemiol. 2021;50(2):620–32.
2. Poppe L, et al. Health Psychol Rev. 2025;19(1):45–65.
3. Ankan A, Textor J. Proc Mach Learn Res. 2025;286:172–83.
4. Textor J, et al. Epidemiology. 2011;22(5):745.

Financial disclosure: Authors are employees of ConnectHEOR Limited. No external funding received to conduct this research and no conflict of interest to declare.

Poster presented at ISPOR Europe 2026 in Vienna, Austria, 8–11 November 2026