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In reference to '*Directed acyclic graphs for clinical research: a tutorial*'

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Dear Editor,

I was interested to read the recent article by Byeon and Lee titled "*Directed acyclic graphs for clinical research: a tutorial*" [1], published in *the Journal of Minimally Invasive Surgery*. The authors provide a helpful overview of directed acyclic graphs (DAGs) and their utilization in confounder selection and identification of causal effects in clinical research. Articles such as this are essential for improving our understanding of the key concepts and principles of DAGs as their use becomes more widespread.

While the tutorial covers the fundamentals well, a few points should be clarified or expanded upon.

First, the fact that the validity of a DAG analysis depends entirely on the assumed causal structure encoded in the diagram requires further emphasis. DAGs per se do not identify causality or causal effects, rather they encode causal hypotheses defined by the researcher based on background knowledge. The inferred conditional independencies and adjustment sets are only valid if the hypothesized DAG structure accurately reflects reality [2,3]. This key point needs to be brought to the reader's attention, as incorrect causal assumptions will lead to biased effect estimates regardless of the DAG rules applied.

Secondly, the example of "M-bias" nicely illustrates the risk of conditioning on a collider. However, colliders are not always a problem. VanderWeele and Robins [4] point out that colliders only introduce bias if they open a path between the exposure and previously closed outcome. In many cases, conditioning on colliders has no deleterious effect [5]. A more balanced discussion of collider bias would improve the paper.

Finally, solely focusing on the DAGitty web tool may limit the reader's awareness of more flexible software options. For example, the R package dagitty includes several features lacking in the web interface, including the option of larger graph sizes, algorithm stability checks, and animated presentations to visualize d-separation rules [6]. The authors could point researchers toward these enhanced implementations as models become more complex.

Overall, this is a well-written, accessible introduction to DAGs. With minor clarifications, it will serve as a valuable reference for researchers looking to apply DAG methodology in clinical studies.

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Notes

Authors' contributions

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Writing–original draft: All authors
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All authors read and approved the final manuscript.

Conflict of Interest

All authors have no conflicts of interest to declare.

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Data availability

The data presented in this study are available on request from the corresponding author.

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