Leveraging Generative Artificial Intelligence for Assessing the Quality of Network Meta-Analysis: Methodological Considerations and Early Findings

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INTRODUCTION

- In recent years, we have seen the rise of **large language models** (LLMs), such as the Generative Pre-trained Transformer 4 omni (GPT-4o), which complement human efforts across a wide range of scientific tasks.
- Recent studies have evaluated the use of generative artificial intelligence (AI) in conducting and assessing **literature reviews**.(1,2)
- This approach could also be expanded to support the critical review of statistical manuscripts, including **network meta-analyses** (NMAs).

OBJECTIVES

- This study aimed to **evaluate the ability of GPT-4o to critically assess the quality of NMAs and compare the assessment to experts' conclusions**.

METHODS

- **A checklist** was developed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) - NMA guidelines (3) and Pacou *et al.,*(4) to **assess the robustness of published NMAs**. The checklist is presented in Table 1 below.
- This checklist was provided to GPT-4o with a **generic zero-shot prompt** requesting a response to each item, along with a global assessment.
- The **performance of the LLM was evaluated based on its level of agreement** with experts' assessment as follows: "*agreement*" was defined when expert and GPT-4o provided similar answers, "*some agreement*" when overall assessment were aligned but details in responses were different, and "*disagreement*" when experts and GPT-4o were not aligned.

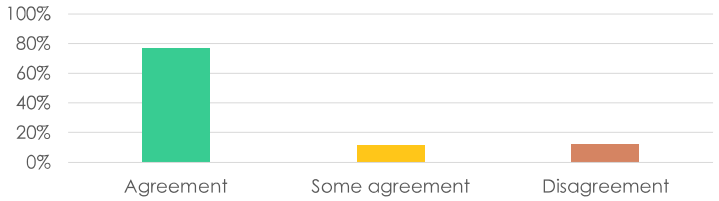
Table 1. *Checklist assessing the quality of published NMAs*

Checklist	Importance
Methods	
Q1. Is the protocol registered in PROSPERO?	**Low**
Q2. Was a systematic literature review (SLR) conducted to inform the indirect treatment comparison (ITC)?	**High**
Q3. Are the PICOS (population, intervention, comparator, outcome, study design) detailed?	**High**
Q4. Was any risk of bias assessment conducted?	**Low**
Q5. Were the population characteristics at baseline compared across trials?	**High**
Q6. Were heterogeneity and inconsistency assessed from both a statistical and clinical standpoint?	**High**
Q7. Were treatment effect modifiers identified and how? Was their distribution assessed across trials?	**High**
Q8. Was the statistical method for the ITC a non-naïve method?	**High**
Q9. Was the rule to select a fixed- vs. random-effect model reported?	**Medium**
Q10. Was a sensitivity analysis conducted?	**Medium**
Q11. Is the software reported?	**Low**
Q12. Are the codes available?	**Low**
Results	
Q13. Are the number of studies screened, assessed for eligibility, and included in the review reported? Is the PRISMA diagram reported?	**Low**
Q14. Is there at least one reference for each included trial?	**Low**
Q15. Are the data inputs presented?	**Medium**
Q16. Is there the same number of trials in data inputs and in the network?	**Medium**
Q17. Is there any heterogeneity detected? If yes, are results from sensitivity analyses or adjustment methods reported?	**High**
Q18. Is there any loop in the network? If yes, is there any inconsistency detected? If yes, are results from sensitivity analyses or adjustment methods reported?	**High**
Q19. Is the risk of bias reported? If yes, is there any bias detected?	**Medium**
Q20. If a Bayesian network is used, was the convergence assessed?	**High**
Q21. Were results of the meta-analysis presented as point estimate with 95% CrI/CI?	**Low**
Discussion	
Q22. Are the results compared to published NMAs?	**High**
Q23. Are there any comments on the validity of the assumptions (transitivity, consistency)?	**High**
Q24. Are there any comments or any concerns regarding network geometry or convergence?	**High**

RESULTS

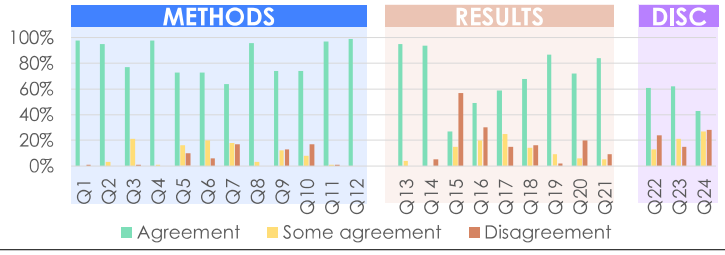
- **100 published NMAs** from 2016 to 2021 identified in a previous work (5) were independently assessed according to the checklist by GPT-4o and by four independent ITC experts.
- Overall, we obtained **77% of agreement** between GPT-4o and experts, 11% of partial agreement, and 12% of disagreement (see Figure 1). Those results showed a benefit in using LLM for review.

Figure 1. *Overall agreement results between GPT-4o and ITC experts*



- To understand GPT-4o performance, agreements are summarized by item (see Figure 2). **GPT-4o was found to perform well on closed and straight-forward questions** such as Q1, Q2, Q4, Q12, Q13 and Q14. However, **difficulties were observed** for Q15, Q16, Q17 and discussion points which are open questions or referring to figures.
- Moreover, it was observed that GPT-4 **struggled to identify low-quality NMA**, which was characterized by the absence of heterogeneity assessment, inconsistency checks, and sensitivity analyses. In 14 cases where experts marked heterogeneity assessment as "not reported," GPT-4 consistently reported an assessment.
- Experts also warn that GPT-4o can display **excessive confidence** in its responses, even when providing incorrect information. This can lead to overconfidence in reviews generated by LLMs and may diminish users' perspective and critical insight.

Figure 2. *Agreement results between GPT-4o and ITC experts per question*



CONCLUSIONS

- The current work aimed to evaluate the quality for LLM in the quality assessment of published NMA following a checklist.
- Overall, **results were aligned** between ITC experts and GPT-4o. However, **limitations** of assessment were exhibited when the points were associated with an open question in the provided checklist.
- The study currently uses zero-shot prompting, but exploring other **prompt engineering strategies** could improve the performance of the experiment by better customizing the LLM to cover the limitations found.
- For example, **few-shot prompting** could provide the model with examples to increase accuracy, and **chain-of-thought prompting** could enhance reasoning capabilities by guiding the AI step-by-step.

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DISCLOSURES

AN, GF, KP, PLN and AG are employees of Amaris Consulting. Authors have no conflict of interest to declare.

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