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BACKGROUND

- Network meta-analyses (NMA) enable the simultaneous comparison of multiple treatments across a connected evidence network.
- NMAs are an essential components of health technology assessment (HTA) submissions and the newly introduced European Union (EU) Joint Clinical Assessment (JCA) process.^{1,2}
- These analyses rely on repetitive and highly regimented tasks which must increasingly be performed within short timelines and using large, complex volumes of evidence.
- Advances in artificial intelligence (AI) and large language model (LLM) technologies can be leveraged to automate parts of the NMA process, enable more efficient analyses, and support comprehensive and timely final submissions to regulatory and HTA bodies.³

OBJECTIVE

- This study aimed to assess the potential applications of AI- and LLM-supported algorithms throughout the NMA process and develop an automated NMA framework aligned with existing best practices.

METHODS

- The conventional NMA workflow was separated into systematic modular components, allowing for granular examinations of each stage in the analytical pipeline.⁴
- Repetitive, regimented tasks which placed high burdens on analyst time and ability were found for potential automation as summarized in Table 1.
- A suite of automation algorithms was developed using R v4.5.1 for application to the NMA process. AI LLMs such as ChatGPT, Claude Opus & Llama were used to develop the LLM-assisted modules.
- Algorithms and AI were combined in a user-friendly interface with human-in-the-loop functions.
- Four NMA projects were used to confirm the benefits of this framework. Efficiency was measured in terms of time saved at the feasibility and execution/reporting stage compared to a standard non-AI supported process.

Table 1. Automation Potential Within the NMA Process

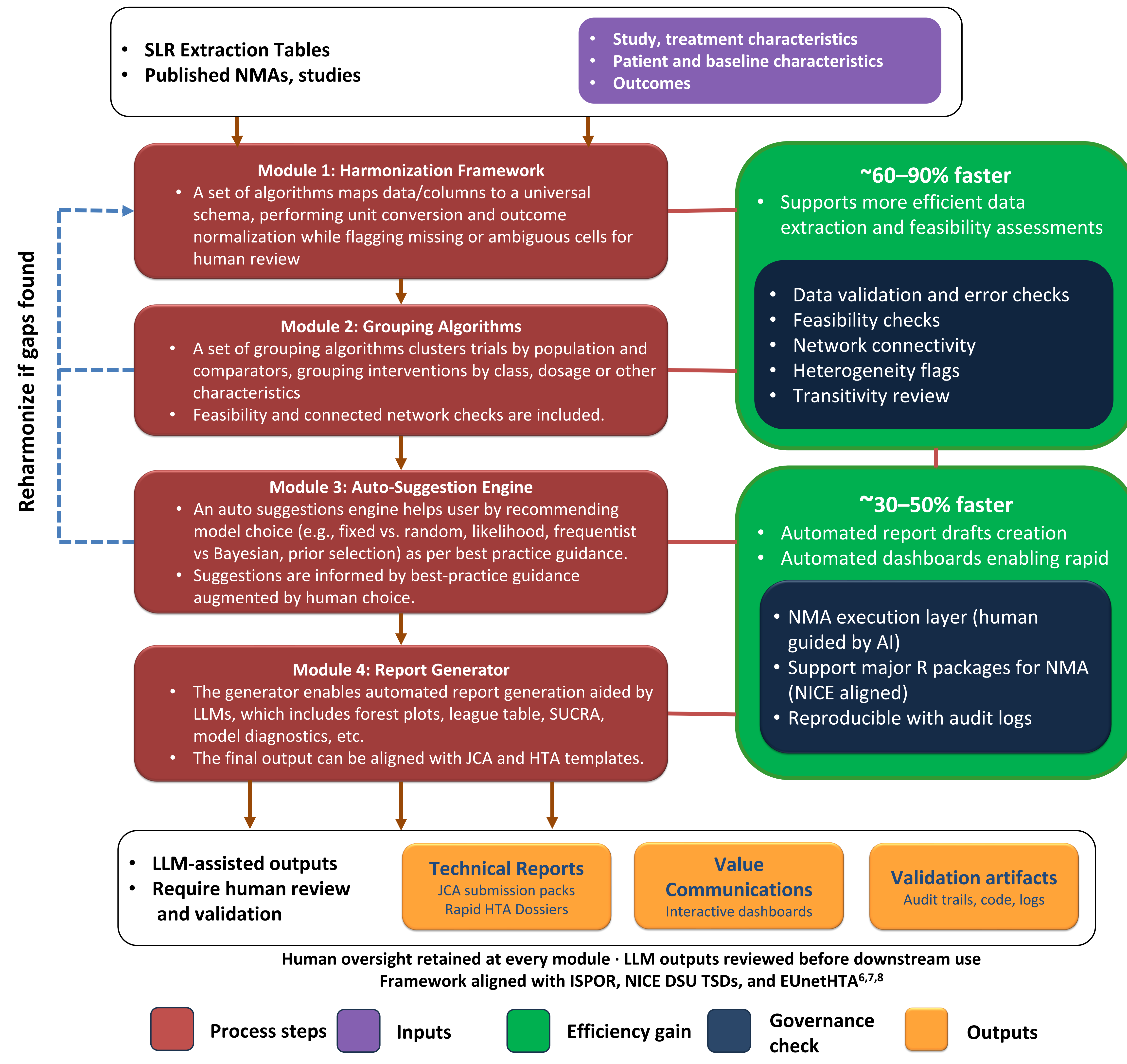
Step	Task	Automation Potential
1	Data extraction	<ul style="list-style-type: none"> • Automated data extraction into a common schema (either from an available data extraction grid or from published NMA or articles) • QC, validation, and edits by human reviewer in a user-friendly way
2	Study and intervention grouping ⁵	<ul style="list-style-type: none"> • Studies can be automatically grouped based on geography, PICOS, design, or other criteria • Treatment grouping can help to find connected networks and ease efficient class effect modelling • Algorithms/LLMs informed by clinical opinion and scientific reasoning support intervention grouping
3	Analysis	<ul style="list-style-type: none"> • Automated model and statistical suggestions can hasten the process of analysis • Code and methods standardization aided by LLMs/algorithms
4	Reporting	<ul style="list-style-type: none"> • Draft version of reports may be generated via LLM according to HTA and JCA requirements for human finalization and review • Interactive dashboards can be created with AI for dissemination of results • Audit and review logs, codes, etc. can be made available for transparency and reproducibility

RESULTS

- The automated NMA framework is presented in Figure 1.
- LLMs and AI algorithms can ease the greatest efficiency gains in the data extraction, feasibility, and reporting phases of the process, allowing analysts to work strategically instead of spending time on repetitive tasks.
- Predetermined prompts & validation checks can take best practices into account to minimize potential errors.
- Human review stays essential at every step to ensure data are appropriately protected and all relevant regulations are followed.

RESULTS (cont.)

Figure 1. Automated NMA Framework



CONCLUSION

- An AI-enabled NMA framework has the potential to meaningfully improve efficiency, transparency, and consistency in NMAs by automating time-consuming and repetitive tasks.
- Human-in-the-loop design enables validation at key steps such as data extraction and reporting results.
- Further development and validation is needed to fully evaluate and exploit the capabilities of this framework.

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