MSR28

Evaluating the Performance of GPT-4o and Retrieval-Augmented Generation in Extracting Data from Journal Articles: A Comparative Study

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Background

- Systematic reviews are essential for evidence-based research as synthesized published data can inform clinical practice and policy
- However, manual data extraction from scientific articles is time-consuming, labor-intensive, and prone to errors, potentially affecting review quality[1,2]
- Advancements in natural language processing (NLP) and artificial intelligence (AI), particularly large language models, offer a solution[3]

Objective

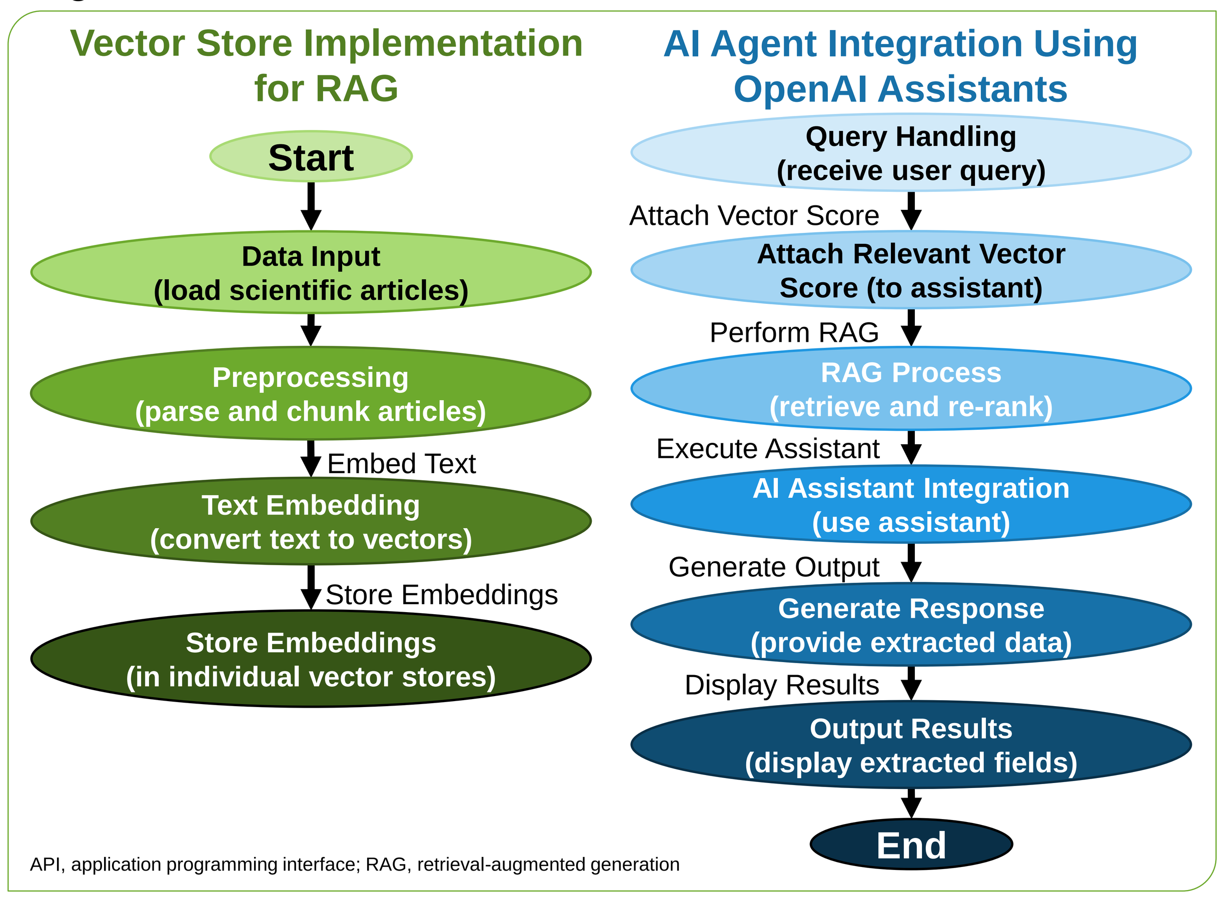
- To evaluate the performance of a custom-designed system utilizing GPT-4o and retrieval-augmented generation (RAG) for extracting specific fields from scientific journal articles, compared with domain expert extraction

Methods

SYSTEM DEVELOPMENT

- A system using OpenAI's GPT-4o model[4] integrated with RAG capabilities was developed to automate the extraction of key data fields for both straightforward and nuanced data with accuracy comparable to that of domain experts
- System architecture consisted of 2 primary components (**Figure 1**):
  1. **Vector Store Implementation for RAG**
     - Journal articles were parsed, chunked, and embedded into vector stores
  2. **AI Agent Integration Using OpenAI Assistants**
     - OpenAI assistant was tailored to perform data extraction tasks
     - System leveraged the File Search tool to retrieve and extract relevant data from Vector Stores, enabling multi-step, context-aware searches

Figure 1: Workflow for Automated Data Extraction



API, application programming interface; RAG, retrieval-augmented generation

EVALUATION PROCESS

Study Selection

- To evaluate system performance, 4 unpublished systematic reviews including 36 published clinical trials and observational studies across diverse medical fields were selected
  - **Systematic review 1:** 10 full-text studies on prognostic value of sentinel lymph node biopsy in melanoma (9 cohort studies, 1 cross-sectional study)
  - **Systematic review 2:** 10 full-text studies on humanistic burden of systemic lupus (8 cross-sectional studies, 1 cohort study, 1 case-control study)
  - **Systematic review 3:** 8 full-text studies on indicators of symptomatic progression in oncology (7 randomized controlled trials [RCTs], 1 post-hoc analysis of an RCT)
  - **Systematic review 4:** 8 full-text studies on humanistic burden of kidney transplant rejection (5 cross-sectional studies, 2 cohort studies, 1 RCT)

Data Extraction and Analysis

- System tasked with extracting 6 data fields from full-text articles
  - Study design, location, setting, sample size, trial phase, blinding
  - Fields were chosen to test system's ability to handle extractions that were considered straightforward (information typically explicitly reported in articles; e.g., "Location", "Sample Size"), and those that were complex (varied reporting styles and terminologies in articles; e.g., "Study Design")

Comparative Analysis

- AI-extracted data were compared with those of domain experts by a third reviewer to determine if the AI-extracted data were "consistent" with domain experts. Two elements were considered:
  - **Similarity**: How closely AI's extractions matched those of experts in terms of both content and format
  - **Completeness**: System's ability to accurately capture all relevant data points that domain experts captured
- If both metrics were satisfied, the data field would be considered as "consistent" against the expert's extraction. The overall consistency rate was then calculated by using the following formula:
  - Consistency Rate = ((Number of Correct Extractions by AI) / (Total Number of Extractions of the Same Field by Expert)) × 100
  - Consistency was categorized as high (consistency >90%), moderate (75–90%), or low (<75%)

Results

GPT-4o and RAG-based system achieved an average consistency rate of 84% across diverse data types compared with extractions from domain experts

Figure 2: Overall Distribution of Consistent Extractions

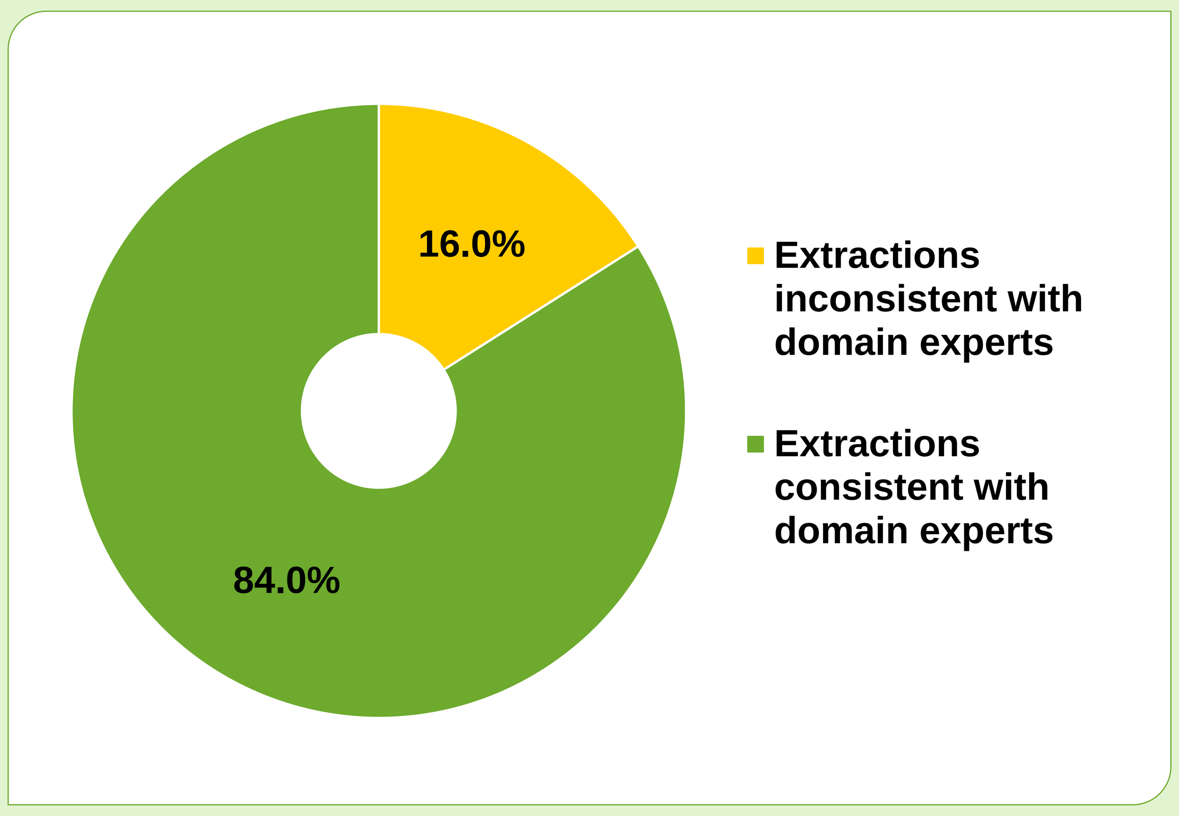
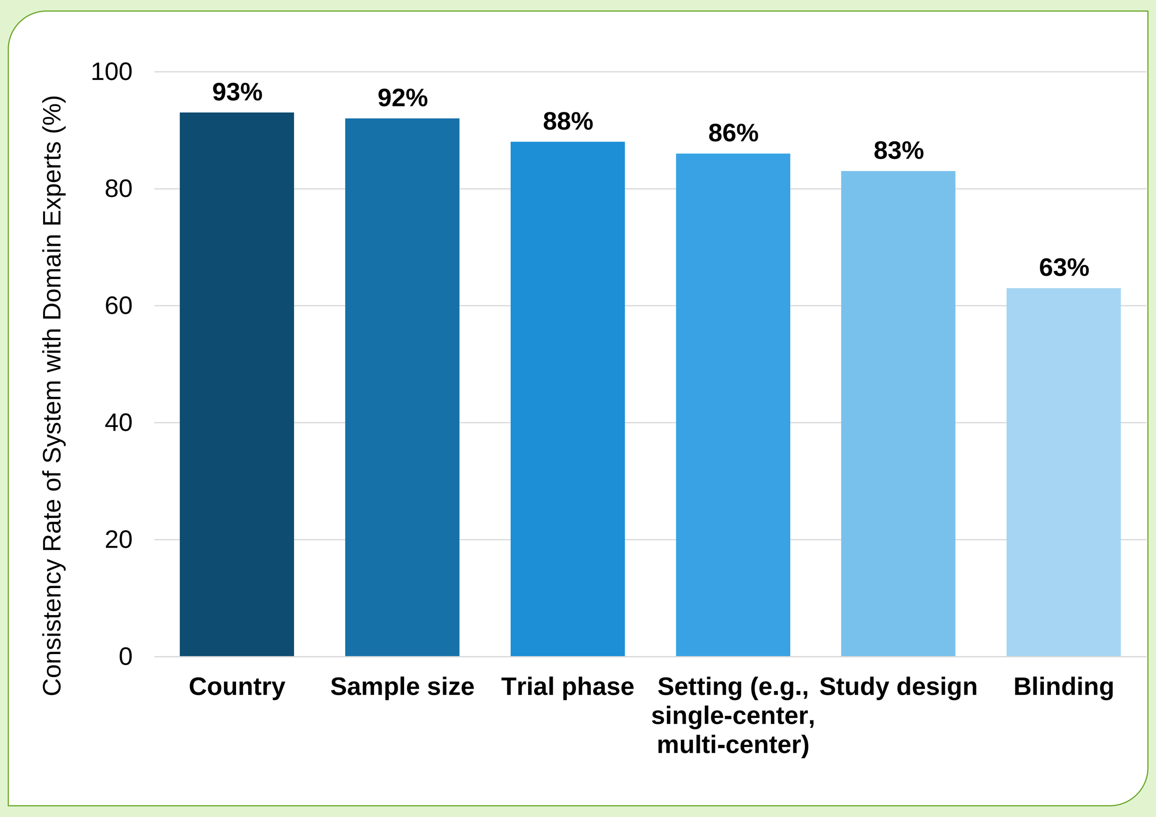


Figure 3: Consistency Rates by Data Field Type



OVERALL PERFORMANCE

Consistency

- System successfully extracted 168 data points from 36 studies, with 141 (84%) extractions considered consistent with those of domain experts (**Figure 2**)
- Consistency rate of the system varied across different data types, reflecting diversity and complexity of information reported in scientific literature (**Figures 3** and **4**)
- Performance of the system was categorized into three levels:

1. **High Consistency**
   - **Study Location:** Extracted 26/28 data points correctly (93% consistency)
     - High accuracy reflects the consistent way in which study location was reported across studies
   - **Sample Size:** Extracted 33/36 data points correctly (92% consistency)
     - This data type is often clearly stated, allowing more precise extraction
2. **Moderate Consistency**
   - **Trial Phase:** Extracted 7/8 data points correctly (88% consistency)
     - Occasional misidentifications occurred when there were subtle differences in the way phases were reported across studies
   - **Setting:** Extracted 31/36 data points correctly (86% consistency)
   - **Study design:** Extracted 30/36 data points correctly (83% consistency)
     - Most difficult field to extract due to the complexity and variability of study design descriptions
3. **Low Consistency**
   - **Blinding:** Extracted 5/8 data points correctly (63% consistency)
     - Inconsistencies in how blinding information was reported across studies led to lower extraction performance

ERROR ANALYSIS

Contextual Misinterpretations

- Errors typically occurred due to the system misinterpreting context, especially for complex fields (e.g., Study Design)
  - E.g., in studies that included multiple designs or exploratory sub-studies, the system sometimes incorrectly identified the primary design

Incomplete Extractions

- Some fields were partially extracted correctly, but had missing data
  - E.g., For "Location", the system sometimes only extracted one country when the study was conducted across multiple counties.

Discussion

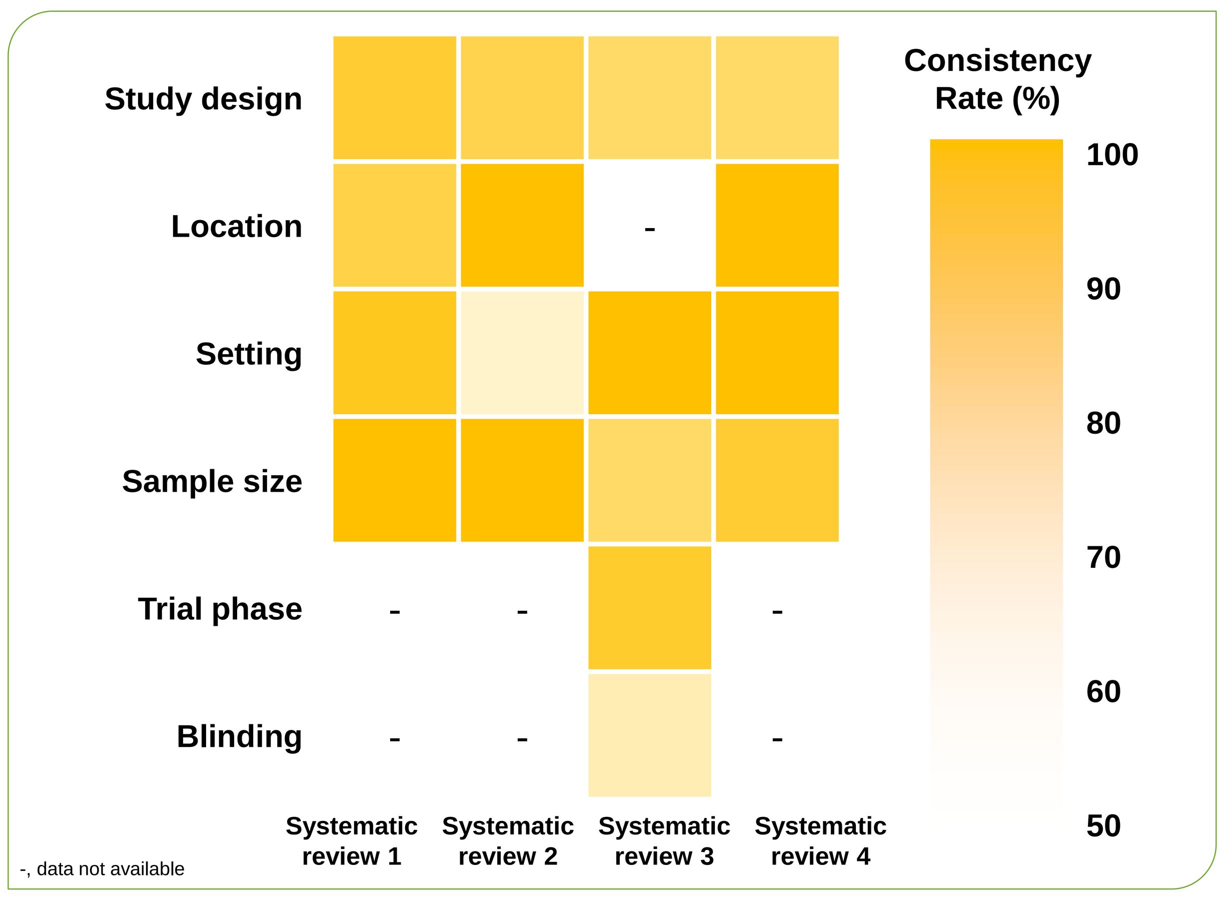
STRENGTHS

- System excelled at extracting simple, well-defined fields (e.g., study location, sample size) with consistency rates over 90%
  - This demonstrates the system's robustness when handling standardized data that is uniformly reported across scientific studies, suggesting strong potential for use in structured data environments

AREAS FOR IMPROVEMENT

- Contextual understanding
  - Fields such as "Blinding" and "Study Design" require the system to better understand and interpret complex, nuanced information
  - Enhancing model's contextual recognition could significantly improve accuracy in these more challenging fields
- Handling synonym variations
  - Performance could also be improved by refining the system's ability to handle varied phrasing and synonyms
    - Particularly in fields such as "Trial Phase", in which minor wording differences impact extraction
- Advanced NLP techniques
  - Incorporating more sophisticated NLP models for semantic understanding could help the system navigate the complexity of unstructured data
    - E.g., variable formats of study design reporting

Figure 4: Heatmap of Consistency Rates Across Different Systematic Reviews and Fields



Conclusions

- GPT-4o and RAG-based system shows high level of accuracy for certain measures of data extraction from published articles, although variability in performance across different fields indicates the need for further refinement
- Future development will focus on enhancing contextual understanding for complex fields, improving synonym recognition/semantic analysis, expanding/fine-tuning the system using broader datasets, and improving data extraction accuracy for additional fields, such as efficacy and safety measures
  - These improvements aim to create a more robust and comprehensive tool for data extraction and evidence synthesis

References

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