AutoCriteria: A GENERALIZABLE CLINICAL TRIAL ELIGIBILITY CRITERIA EXTRACTION SYSTEM POWERED BY LARGE LANGUAGE MODELS

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MSR126

INTRODUCTION

- Eligibility criteria in clinical trials play a pivotal role in patient recruitment and in safety and treatment evaluation, resulting in improved patient care
- Natural language processing (NLP) techniques offer the potential to enhance the efficiency of clinical trial studies by automatically extracting eligibility criteria¹
- Existing NLP approaches face challenges in capturing fine-grained criteria within a given text and may lack applicability across various disease areas
- Recently, large language models such as ChatGPT and GPT-4 have gained traction in the open NLP domain as well as biomedical and clinical domains^{2,3}

ELIGIBILITY CRITERIA EXTRACTION RESULTS ON 180 TRIAL DOCUMENTS

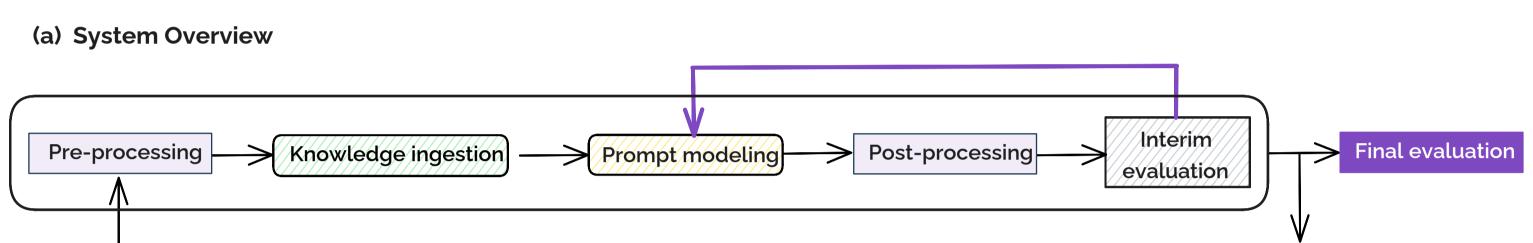
Table 1: AutoCriteria results in extracting criteria phrases.

Disease	Precision (%)	Recall (%)	F1
Breast Cancer	87.26	81.17	84.10
Multiple Myeloma	85.53	86.83	86.18
Alzheimer's	94.54	92.38	93.45
NASH	95.08	95.81	95.44
Crohn's	87.21	88.30	87.75

OBJECTIVE

Our aim is to develop a system that automatically extracts eligibility criteria, emphasizes contextual attributes, and can handle diverse diseases utilizing a cutting-edge large language model

AUTOCRITERIA: SYSTEM OVERVIEW AND COMPONENTS



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Inclusion Criteria:

- Have a diagnosis of probable Alzheimer's
- disease;Have an MMSE score of > or = 10 and < or = 24

Exclusion Criteria

- Have a current diagnosis or severe or unstable cardiovascular disease
- Have a history of myocardial infarction (MI) in the last six months
- Low folate or Vitamin B12

Trial document text (Input)

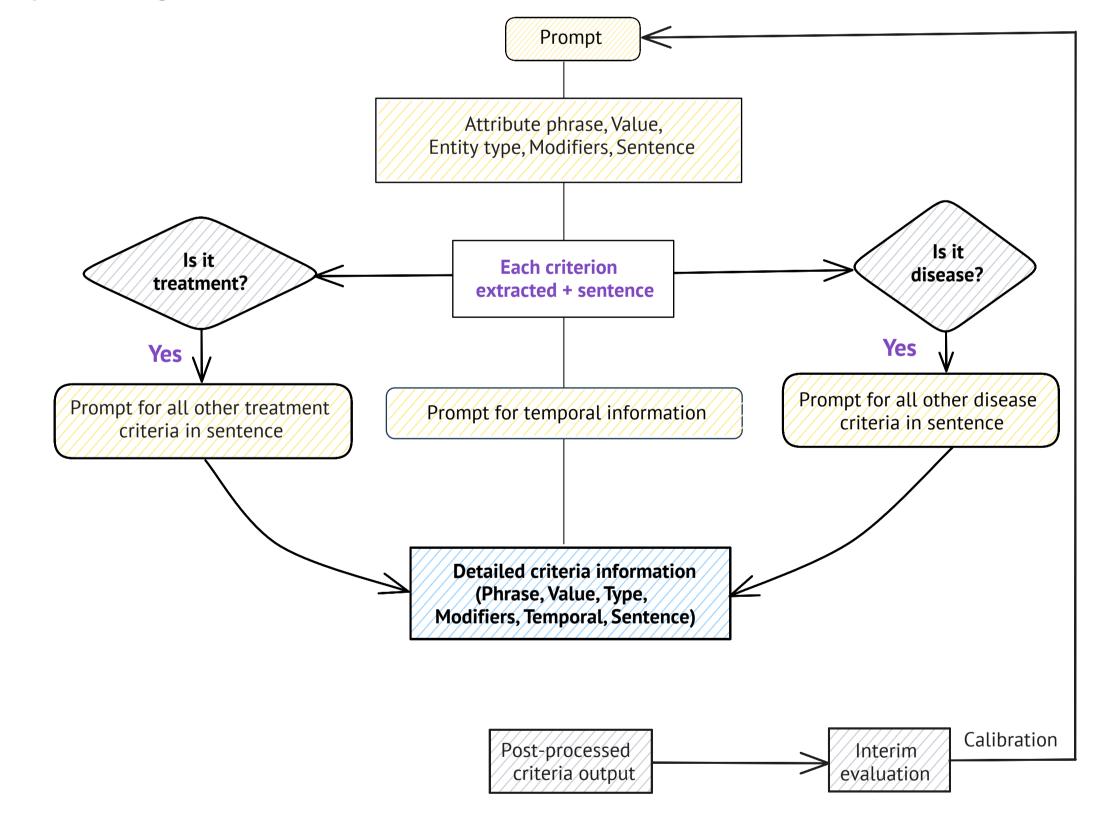
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Criteria Type	Entity Type	Attribute	Value	Modifier	Temporal	Source Sentence
Inclusion	Diagnosis	Alzheimer's Disease	Yes	Probable	NA	Have a diagnosis of probable Alzheimer's disease
Inclusion	Score	MMSE	>=10 and <= 24	NA	NA	Have an MMSE score of > of = 10 and < or = 24
Exclusion	Comorbidity	Severe or unstable cardiovascular disease	Yes	Current diagnosis	NA	Have a current diagnosis of severe or unstable cardiovascular disease
Exclusion	Comorbidity	Myocardial infarction (MI)	Yes	NA	In the last six months	Have a history of myocardial infarction (MI) in the last six months
Exclusion	Lab test	Low folate or Vitamin B12	Yes	NA	NA	Low folate or Vitamin B12
Extracted criteria information (Output)						

	Ulcerative Colitis	91.85	92.99	92.42
	SCD	90.46	90.15	90.30
	HPAH	87.39	90.23	88.79
	HoFH	90.38	88.01	89.18
	All	89.62	89.23	89.42

Table 2: AutoCriteria accuracy (%) in extracting contextual details.

Disease	Attribute + Value	Entity type + Attribute + Value	Entity type + Attribute + Value + Temporal	Entity type +Attribute +Value +Temporal + Modifier
Breast Cancer	76.86	74.09	71.51	67.21
Multiple Myeloma	81.68	73.96	68.74	66.54
Alzheimer's	91.05	90.67	88.00	85.14
NASH	91.87	91.61	88.56	86.28
Crohn's	85.10	83.43	81.20	78.83
Ulcerative Colitis	88.01	86.76	86.29	83.64
SCD	87.10	85.91	85.91	83.36
HPAH	90.00	89.42	89.19	86.05
HoFH	86.70	84.83	84.27	82.21
All	85.90	83.37	81.09	78.95

(b) Prompt Modeling



Pre-processing

• We split the raw criteria text for each trial document into two parts - Inclusion and Exclusion, we then split each of these parts into smaller chunks and run AutoCriteria on each chunk

Knowledge ingestion

 We identified the ontology of key criteria entities and attributes for each disease with the help of knowledge experts. This knowledge is also leveraged in prompt modeling
Prompt modeling

DISCUSSION

- AutoCriteria system not only identifies key criteria but also extracts contextual details including negation/temporal information and classifies entity types
- Our system is highly adaptable to various diseases, including Cancers, Autoimmune diseases, Alzheimer's, NAS, and other rare diseases, highlighting its generalizability
- Strengths of AutoCriteria include:
 - $\checkmark\,$ understands context including exceptions or "if" condition
 - ✓ captures different arm/cohort information
 - \checkmark handles the same criteria entity extraction with different values and modifiers
- Limitations of AutoCriteria include:
 - ✓ does not handle sophisticated criteria conditions such as "at least one of these criteria"
 - ✓ sometimes makes mistakes in differentiating the main criteria entities from modifier entities

CONCLUSION

- We have developed a generalizable GPT-based system that can identify granular eligibility criteria information from clinical trial documents across a variety of disease domains without requiring manual annotations
- Our adaptable prompts allow easy customization for new diseases without manual training data, facilitating large-scale criteria analysis
- We created two separate comprehensive prompts, one for Inclusion and another for Exclusion
- Each prompt consists of three main components 1) a general instruction, 2) the Inclusion or Exclusion criteria text, and 3) the query that asks about criteria attributes (phrases), their corresponding values, modifier information, entity types, and source sentences

Post-processing

• We processed the GPT-4 responses to handle any inconsistencies in the model output

Interim evaluation

- We evaluated the prompts manually, and iteratively calibrated them using expert feedback for every disease
- With enhanced granularity, improved accuracy and generalizability, AutoCriteria has the potential to significantly streamline the clinical trial initiation and conduct process, ultimately reducing time requirements

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