Enhancing Equity and Efficiency: AI-Powered Eligibility Assessment for Adult Complex Care

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Background:

- The Adult Complex Care (ACC) program provides coordinated, multidisciplinary support for adults with high medical, behavioral, and social complexity.
- These patients often have frequent hospital or emergency department (ED) visits and require intensive care coordination and chronic disease management.
- Current eligibility determination is based on a *manual chart review* of clinical notes.
    - *Challenges:* Labor-intensive, inconsistent across reviewers, delays enrollment, and may introduce inequities.
- Advances in artificial intelligence (AI) and large language models (LLMs) enable rapid synthesis of unstructured EHR data, reducing manual burden and variability.
- Inspired by successes in clinical trial matching and care coordination triage, we developed an LLM-powered eligibility assessment pipeline to improve efficiency, consistency, and equity in identifying eligible patients.

Figure 1. Manual vs. AI-assisted chart review

Objectives:

- Develop an LLM-driven workflow to streamline ACC program eligibility assessment.
- Evaluate its accuracy, speed, and transparency against manual chart reviews.

Methods:

- **Patient selection:** Identified via structured EHR filters based on number of admissions/ED visits in prior 6 months, age, and PCP type.
- **Note sampling:** Extracted all notes from the past 3 months and selected ED, H&P, and discharge summaries from 3–6 months prior.
- **Processing:** Deduplicated and date-filtered notes; passed through a HIPAA-compliant Azure OpenAI GPT-4o pipeline.
- **Prompt design:** Used explicit inclusion/exclusion criteria for ACC eligibility (e.g., pregnancy, substance use disorder, uncontrolled behavioral health, organ transplant, or enhanced care monitoring (ECM) enrollment.
- **Token monitoring:** Applied a tokenizer to count all tokens (including prompt) for cost and context tracking.
- **Evaluation:** Compared LLM outputs with manual chart review (n = 27) to assess sensitivity, specificity, and interpretability.
- **IRB:** Exempt quality improvement project.

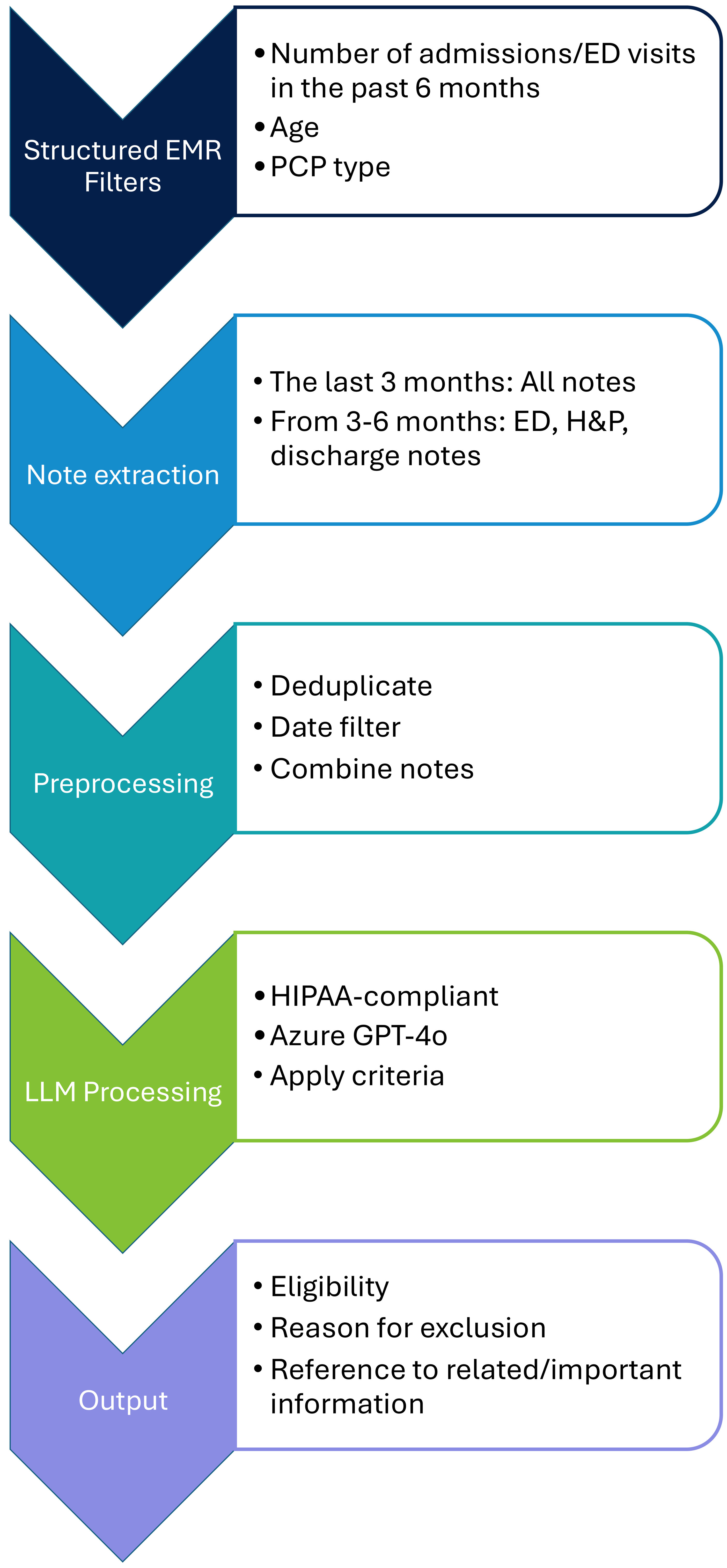

Figure 2. Overview of the LLM-based pipeline

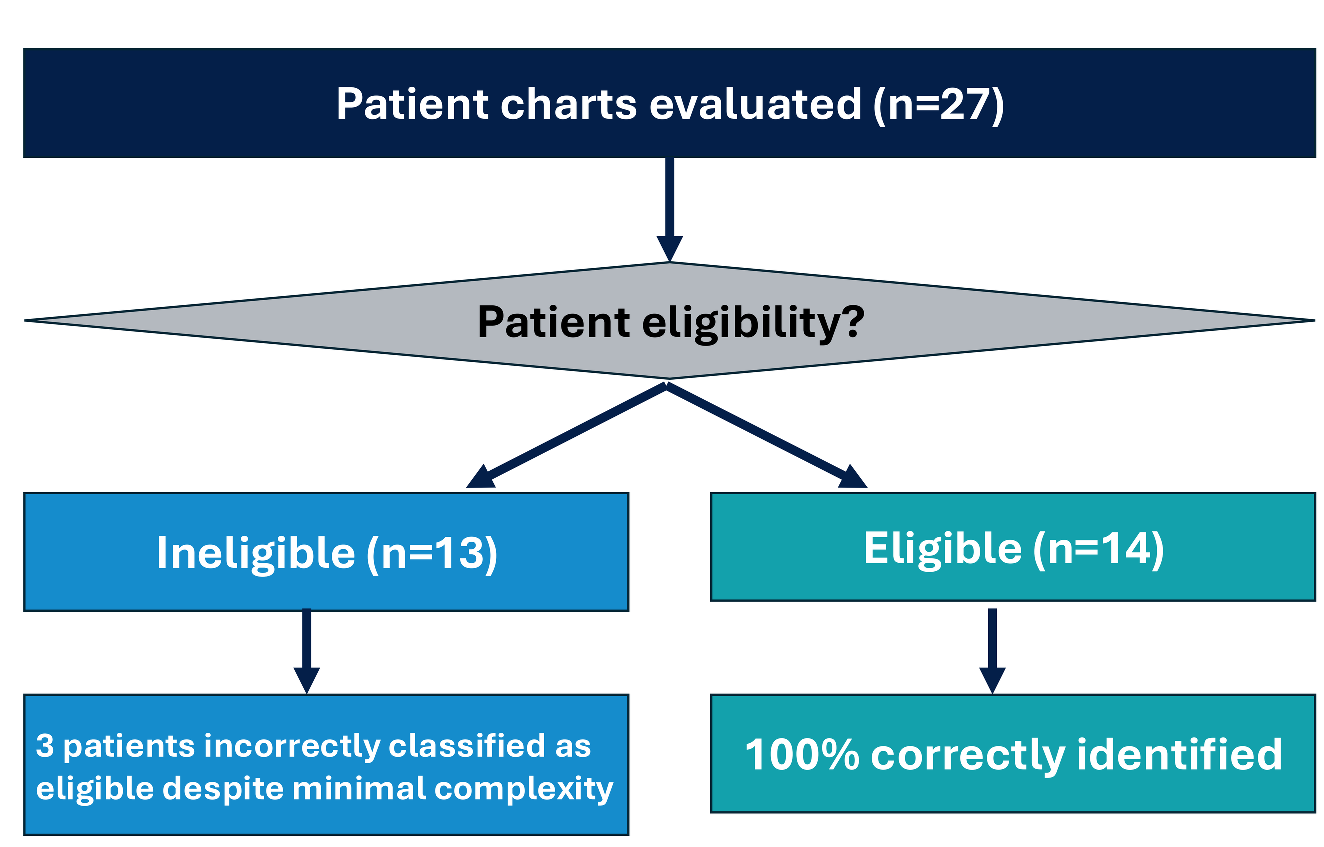

Figure 3. AI-based eligibility assessment performance

Results:

- Processed 27 patient charts, producing structured CSV outputs with eligibility status, rationale, and utilization counts.
- **Performance metrics:**
    - **Sensitivity: 100 %**
    - **Specificity: 77 %**
    - Average processing time: ~15 seconds per chart
    - Estimated monthly cost: ~$30 per 100 patients
- Lower specificity reflected over-inclusion of patients with limited complexity.
- The LLM outperformed individual human reviewers in 3 cases, correctly matching the multidisciplinary consensus when one reviewer's judgment was incorrect.
- Each output included concise reasoning and referenced supporting notes, allowing transparent and verifiable review by clinicians.

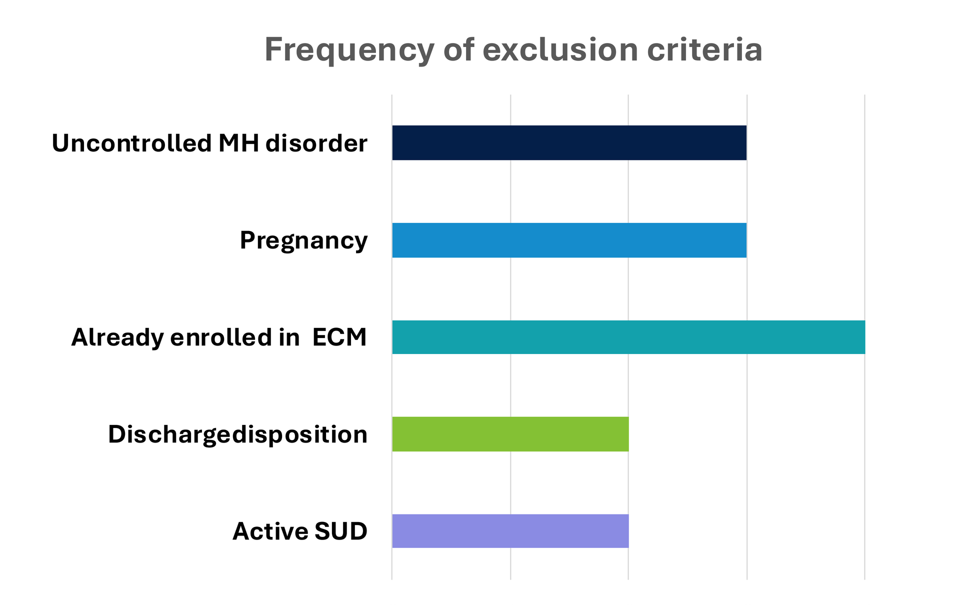

Figure 4. Exclusion criteria detected by the LLM

Conclusions:

- LLMs can streamline eligibility assessments traditionally reliant on manual chart review.
- The pipeline showed *high sensitivity*, *reasonable specificity, and interpretable structured outputs at low cost*.
- Supports equitable, reproducible decision-making in ECM programs.
- **Limitations:** small sample size and single-institution scope may limit generalizability.
- **Areas for improvement:** refine prompt logic and social/behavioral complexity recognition to enhance specificity.
- **Next steps:** large-scale validation, workflow integration, and continuous tuning to sustain accuracy.

Take Home Messages:

- LLMs can streamline complex eligibility reviews with transparent reasoning.
- Structured outputs enable equitable, reproducible workflows across care programs.

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