# Real-World Data Large Language Model Assistive SQL Coding System

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## Objectives

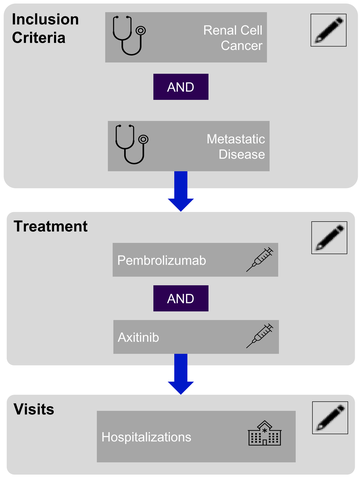
- To develop and evaluate a Large Language Model (LLM)-enabled text-to-SQL assistive programming system that accelerates and standardizes SQL generation for real-world data (RWD) analysis
- To characterize its methodological components and early performance on representative RWD tasks

**Takeaway**
An analyst-facing, metadata-aware SQL assistant can accelerate query drafting for claims and EHR data, but robust evaluation and human review remain essential for decision-grade evidence generation.

## Background

### The Challenge of Preserving Scientific Intent Across RWD Sources

- Real-world databases are heterogeneous, high-dimensional, and vendor-specific
- Common data models can simplify structure but may omit useful source-specific variables
- Cohort and treatment logic often depends on validated code lists and careful event timing
- Analysts need a faster path from natural-language questions to executable, reviewable SQL




**Typical analytic building blocks**

- Visits and care settings
- Inclusion / exclusion criteria
- Diagnoses, procedures, and treatment exposure
- Temporal relationships (before, after, during)
- Reusable validated code lists

## Methods

- Web-based assistant integrates foundation LLMs with retrieval-augmented generation (RAG) for including few-shot examples as question-SQL code pairs
- Retrieves verified few-shot “Golden Examples” based on semantic similarity to the user prompt.
- Prompts combine user question, metadata (see schematic), retrieved examples, and session context to generate SQL plus explanation; early deployment includes multiple commercial claims and EHR datasets
- Benchmark: 40 DE-SynPUF Medicare claims questions composed by reviewing SQL from historical RWE studies
- Benchmark SQL answers were developed with a combinations of two data scientists and LLM outputs. Evaluations were produced from a data scientist with LLM assistance.

**HEOR Efficiency Gains**

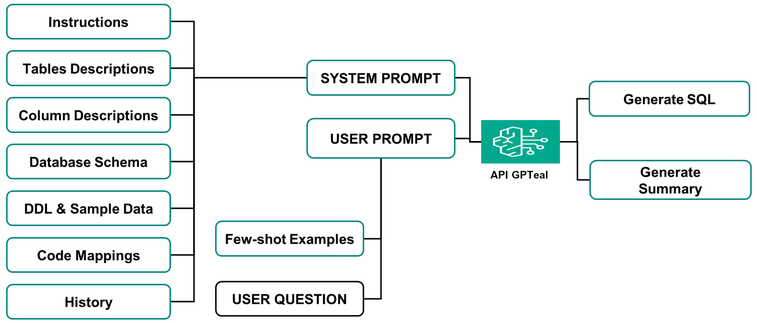
- Reduces time from analytic question to reviewable SQL draft
- Promotes more standardized use of metadata and prior validated query patterns
- Supports reproducible analyst-in-the-loop RWD workflows.

**Human oversight remains essential**

- Natural-language prompts can be ambiguous
- Correct SQL does not guarantee correct HEOR interpretation
- Final analyst review is still required for cohort validity, temporal logic, and code-list appropriateness.

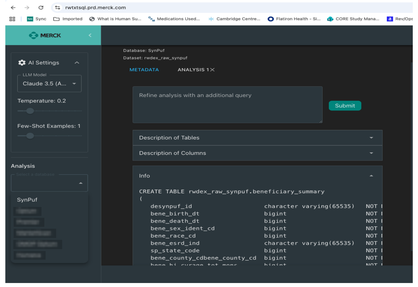
## Methods (continued)

### RWDEx AI SQL Assistant Architecture

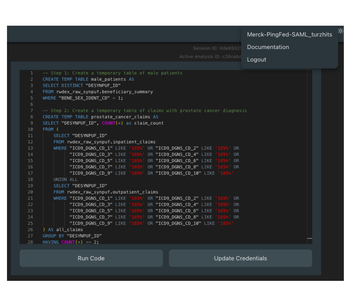



### Software Interface

**Settings and Database Metadata**




**Output SQL example**




### Initial benchmark results reported in abstract (Claude Sonnet 3.5)

- DE-SynPUF benchmark reported in abstract: 82.5% first-attempt accuracy and 97.5% within two attempts
- These results preceded the standardized difficulty and evaluation framework shown below, evaluating on a single difficulty dimension.

**Abstract-linked benchmark**

- Easy (N=5): 80% first attempt, 100% within two
- Medium (N=14): 86% first attempt, 100% within two
- Hard (N=21): 81% first attempt, 95% within two

### Two Dimensions of SQL Question Difficulty

**Orthogonality Concept**
SQL Difficulty and RWD Reasoning measure separate cognitive challenges and should remain independent.

**SQL Difficulty**
Assumes the intended domain concept is already understood.
Measures only how hard it is to express the logic correctly in SQL

**RWD Reasoning**
Assumes a perfect SQL assistant is available
Measures only how hard it is to identify the correct real-world data concept or event relationship

**Low SQL / High RWD Example**
A simple query that depends on distinguishing admitting diagnosis from principal diagnosis.

**High SQL / Medium RWD Example**
An obvious clinical concept that requires multi-step earliest-event logic across datasets.

### SQL Question Difficulty

**Level 1**
Simple single-table selection, DISTINCT, or COUNT with at most one obvious filter on a clearly indicated field.

**Examples**
Count distinct inpatients; select all outpatients in 2006; select patients with a diagnosis from one table.

**Level 2**
One substantive SQL operation beyond Level 1, such as a join, union, simple group by, or straightforward calculation.

**Examples**
Join claims to beneficiary table; group by patient; calculate treatment duration within one query.

**Level 3**
Combination of Level-2 elements, or multi-step logic such as subqueries, temp tables, earliest/latest comparisons, or complex branching.

**Examples**
Compare earliest diagnosis versus earliest drug exposure; identify patients who died during hospitalization after prior exposure.

### RWD Reasoning

**Low**
Can be answered from prompt wording plus schema / data-dictionary lookup. No substantive claims interpretation is needed.

**Examples**
Count inpatients; select all outpatients; select distinct patients.

**Medium**
Requires one nontrivial domain interpretation, such as selecting among plausible fields or understanding what a coded field operationally represents.

**Examples**
Race code meaning; claim admission date vs claim start date; covered days; BENE_DEATH_DT = 0 means alive.

**High**
Requires multiple domain concepts or interpretation of real-world temporal relationships between events, independent of the SQL used to implement them.

**Examples**
Diagnosis A before diagnosis B; age at diagnosis; admitting vs principal diagnosis; hospitalized because of a disease.

### SQL Evaluation Standard

**Evaluation principle**
A response can be marked Correct if it reflects a reasonable interpretation of the prompt and does not materially change the intended result set, even when it differs from the benchmark SQL. Benchmark SQL is a reference point, not the only acceptable answer.

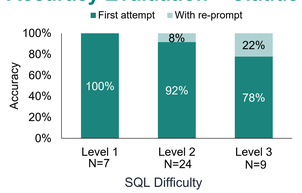
**Mark as Correct when**

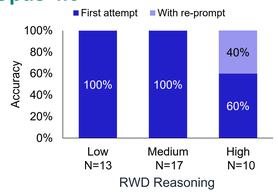
- The SQL gives a defensible interpretation of the prompt
- The chosen tables and fields are appropriate for that interpretation
- Differences from the benchmark are minor or not materially cohort-changing

**Mark as Wrong when**

- The SQL answers a different substantive question
- Required tables, event sources, or logic are missing
- Encoded values or temporal logic are misinterpreted
- Date logic materially changes who enters the cohort

### Accuracy Evaluation – Claude Opus 4.6



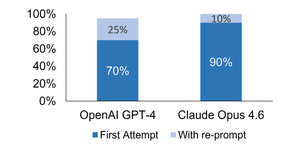




First-pass performance was higher for simpler questions, though a single re-prompt was able to resolve all errors, achieving 100% accuracy for every category.

**Common errors**

- Ambiguous date boundaries
- Event-sequencing errors
- Incomplete diagnosis-field coverage
- Invalid encoded-value or date handling

### Improvement in LLMs




- Newer LLM performs better on both SQL coding and RWD Reasoning metrics, answering 90% of questions on the first attempt and 100% when allowed a re-prompt, as compared to 70% and 95% for GPT-4.
- Data Scientist /informaticist review is important due to inherent ambiguity in natural language questions

**Implications**

- Higher first-pass accuracy can reduce analyst iteration burden.
- Metadata retrieval and Golden Examples help translate model gains into workflow gains.
- Decision-grade use still depends on transparent evaluation and human oversight.

## Discussions and Conclusions

- An LLM-driven, RAG-enhanced text-to-SQL assistant can reliably generate executable SQL for many RWD tasks and support iterative query refinement.
- The value of such a system depends not only on model capability, but also on maintained metadata assets, validated examples, transparent evaluation, and expert review.
- The most difficult problems often involve preserving scientific intent in temporal logic, diagnosis definitions, and cohort construction.
- Future work should expand benchmarking, quantify time-to-correct-query, and evaluate controlled efficiency and usability outcomes.

**Poster takeaway**
A use-specific benchmark and robust evaluation framework is very helpful for optimizing AI tools

**Keywords:** artificial intelligence; large language models; Text-to-SQL; real-world data; and retrieval-augmented generation.

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