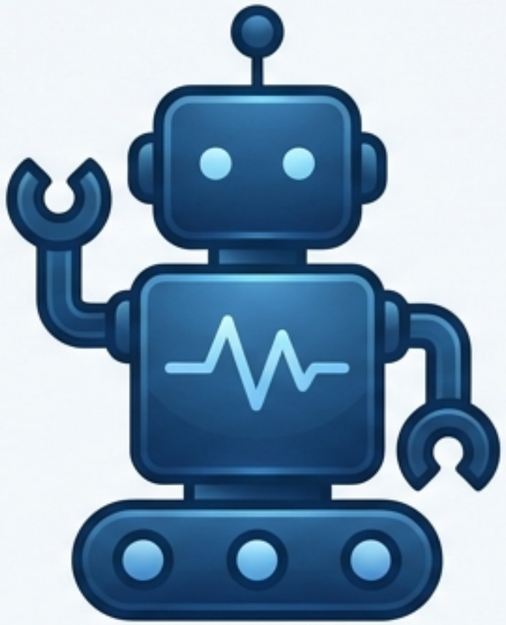


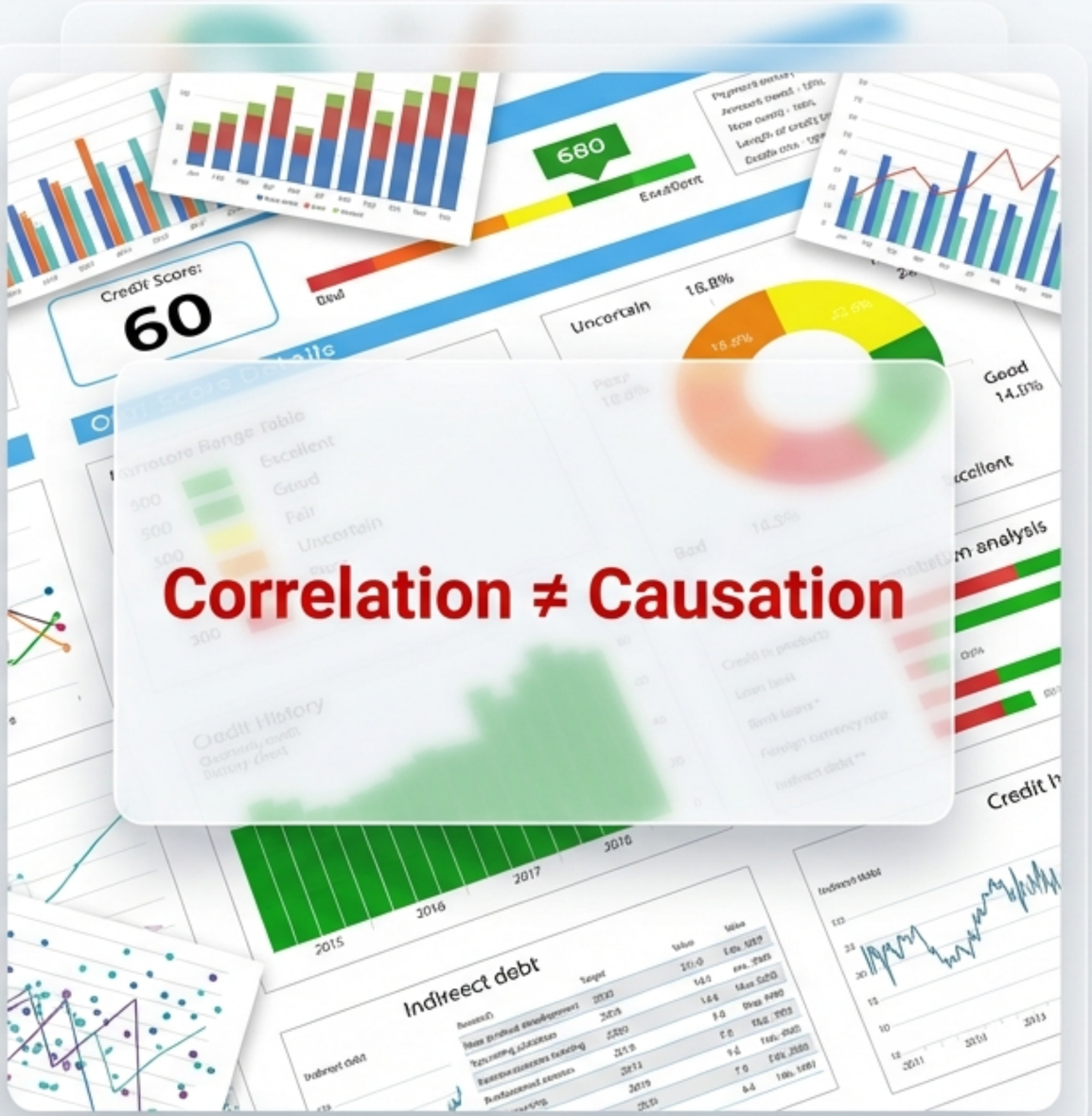
Causal Agent: Automating the Search for True Impact

Moving beyond simple correlation to measure causal effect using a Multi-Agent LLM Framework.

AI-POWERED AUTOMATION FOR CAUSAL INFERENCE

The Limits of Traditional A/B Testing

- **The Challenge:** In complex real-world environments, A/B testing is often skewed by confounding variables like seasonality, demographics, and prior behavior.
- **The Risk:** Relying on simple correlation can lead to misleading conclusions about what actually drove an outcome.
- **The Need:** Business leaders need to know *why* something happened, not just *that* it happened. We need to isolate the 'Treatment Effect' from the noise.

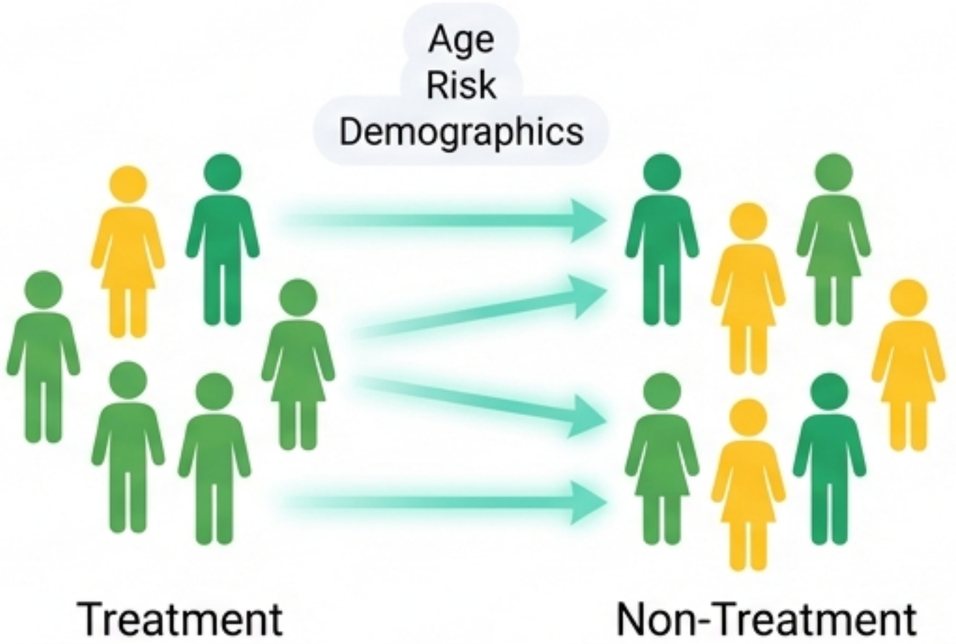


Mimicking the Gold Standard of Randomization

The Ideal: Randomized Control Trials (RCTs)

Randomization creates groups balanced on baseline characteristics, satisfying the unconfoundedness assumption.

The Reality: Propensity Score Matching (PSM)



We match treated participants with non-participants who share identical characteristics to create a synthetic control group.

The Causal Agent Framework

Scope

An agentic framework designed to evaluate clinical programs, compliance interventions, and marketing campaigns.

Scalability & Metrics

Robust calculation of Average Treatment Effect (ATE), Heterogeneous Treatment Effect (HTE), and Individual Treatment Effect (ITE).

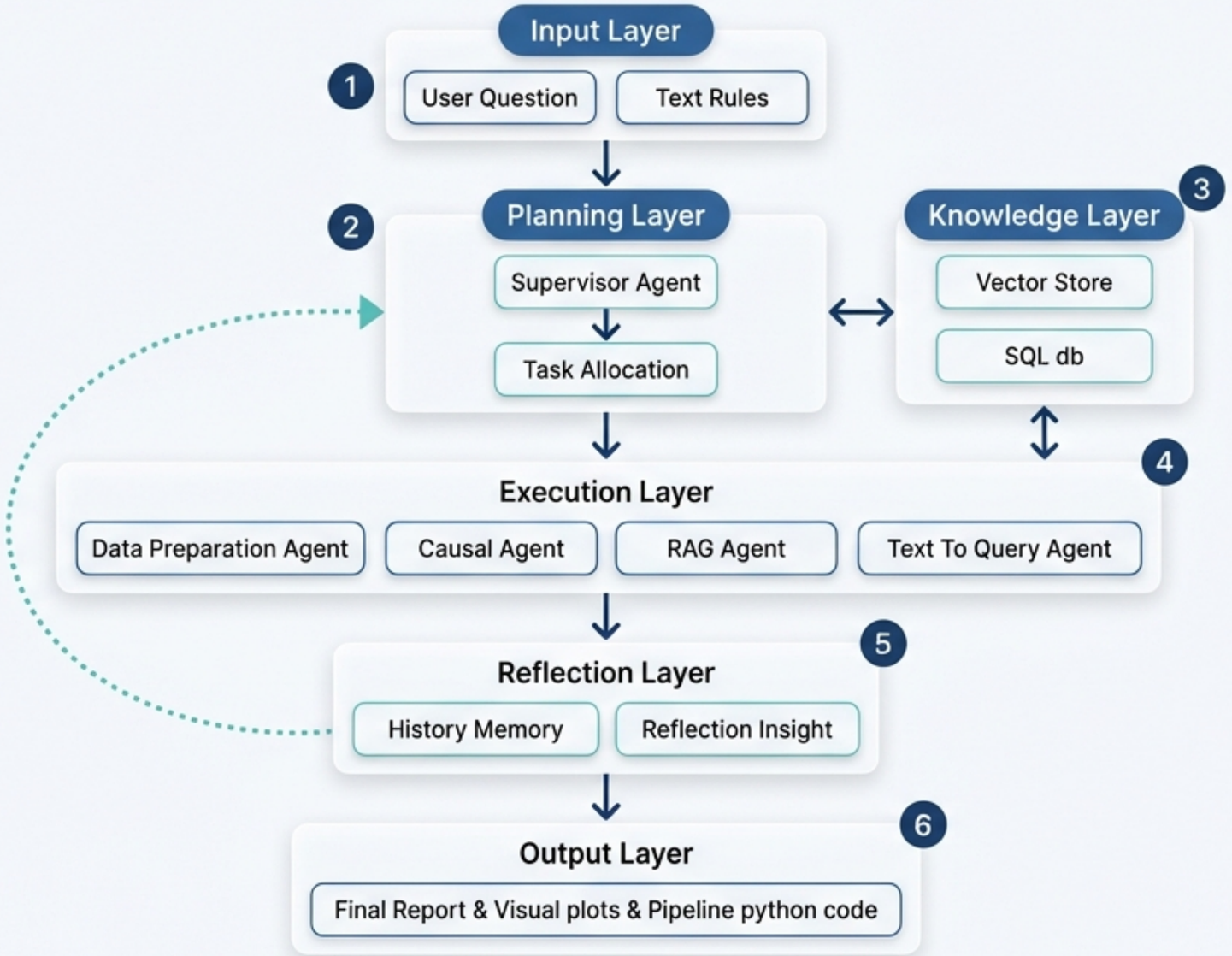
Output includes visual plots and exportable Python code for reproducibility.

Easy to Use

Natural language interaction bridges the gap between technical data scientists and business analysts.

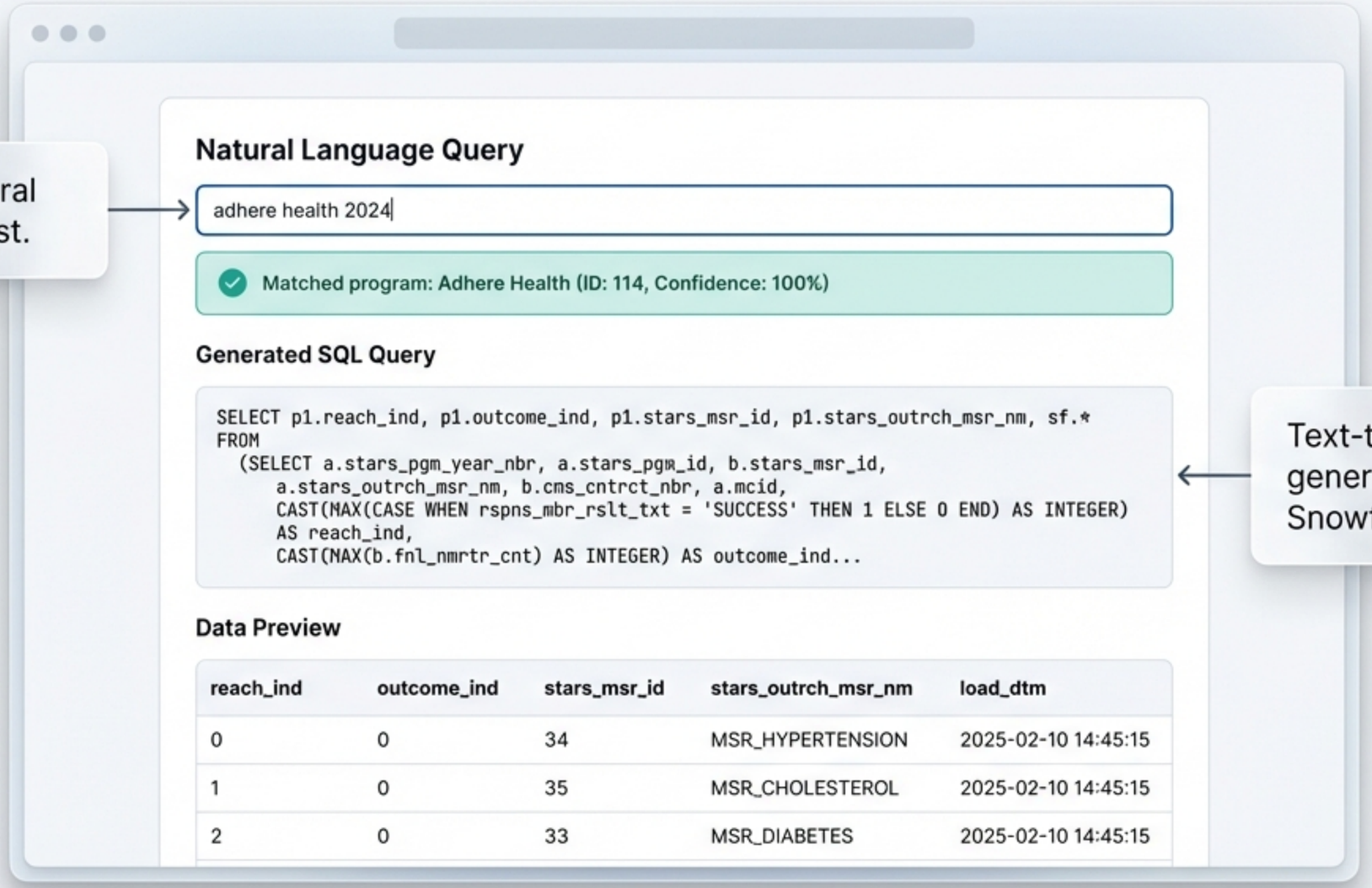
LLM & Agent + CausalPipe = Causal Agent Framework

Under the Hood: The Multi-Agent Architecture



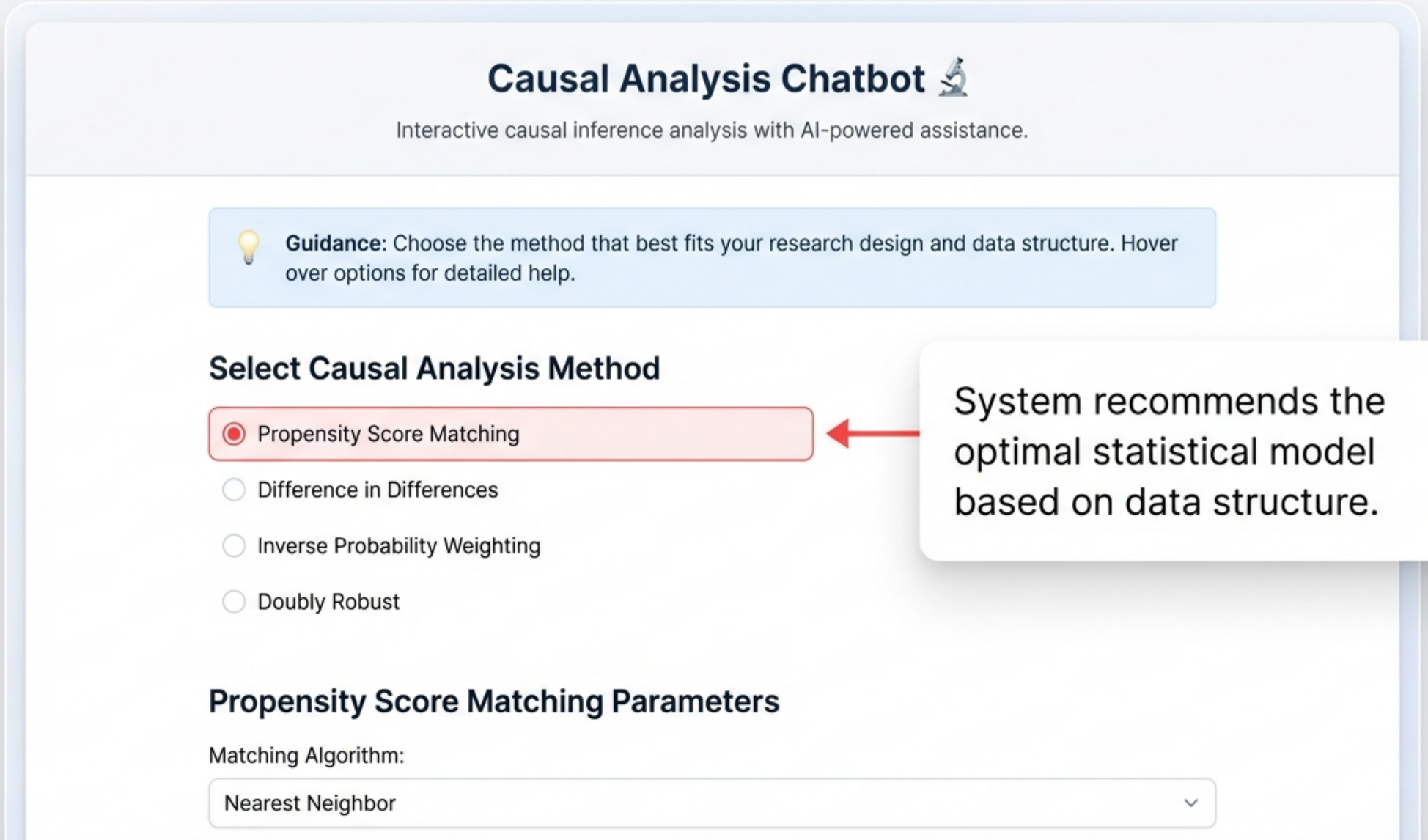
Step 1: Natural Language Data Ingestion

User types natural language request.

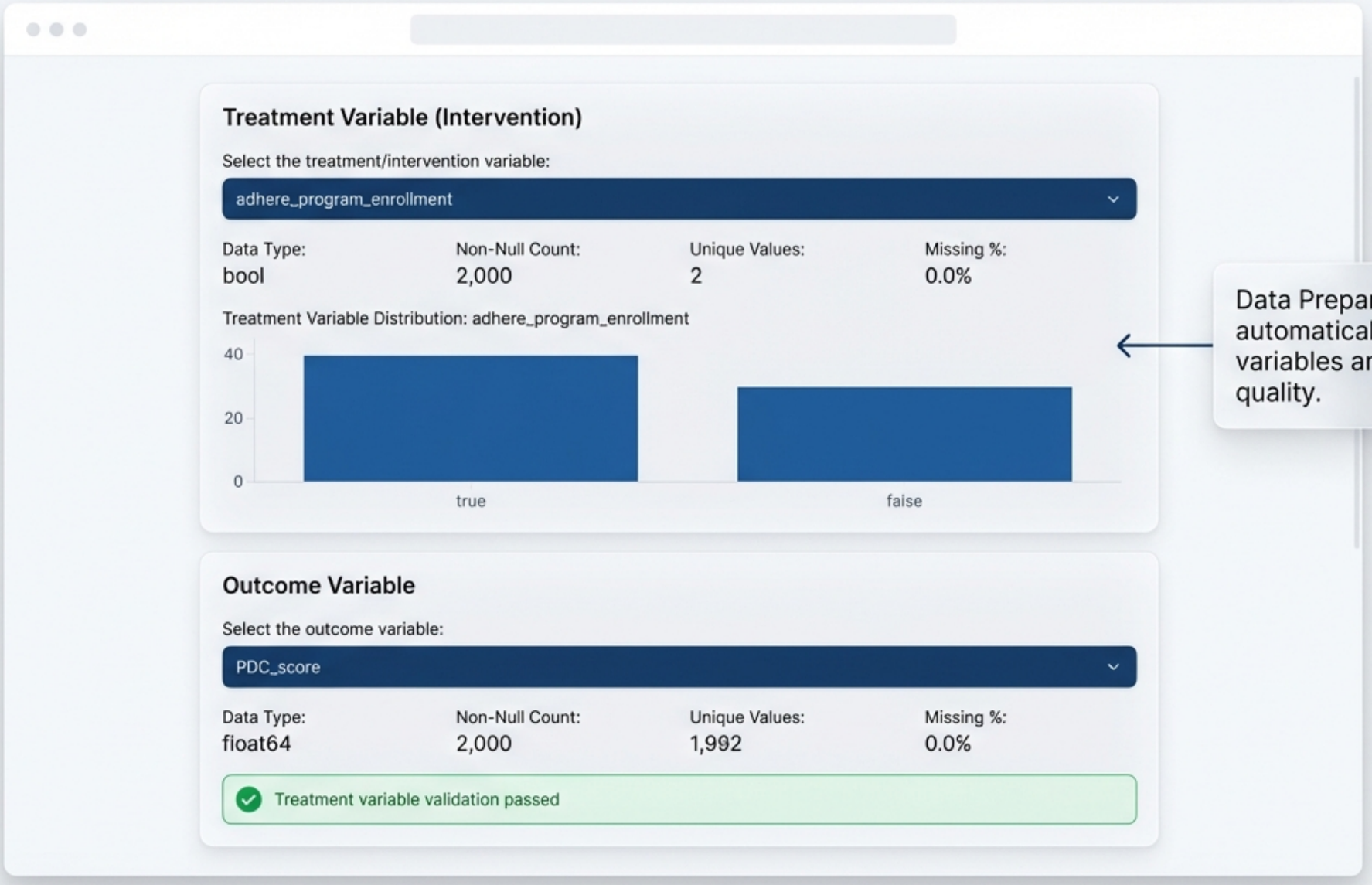


Text-to-Query Agent generates and validates Snowflake SQL.

Step 2: Intelligent Method Selection



Step 3: Automated Data Preparation



Data Preparation Agent automatically identifies variables and checks quality.

Step 4: Execution & Natural Language Interpretation

Analysis Assistant

Ask questions about your data, methodology, or results. I can help interpret findings and suggest follow-up analyses.

Is my treatment effect statistically significant?

09:55:19

Yes, your treatment effect is statistically significant.

Here's why:

- **P-value: 0.0000** (well below the conventional threshold of 0.05), indicating strong evidence against the null hypothesis of no effect.
- **95% Confidence Interval: [0.1101, 0.1329]** does not include zero, which means the effect is statistically significant at the 5% level.
- **Average Treatment Effect (ATE):** 0.1215, with a tight confidence interval, further supporting the result.

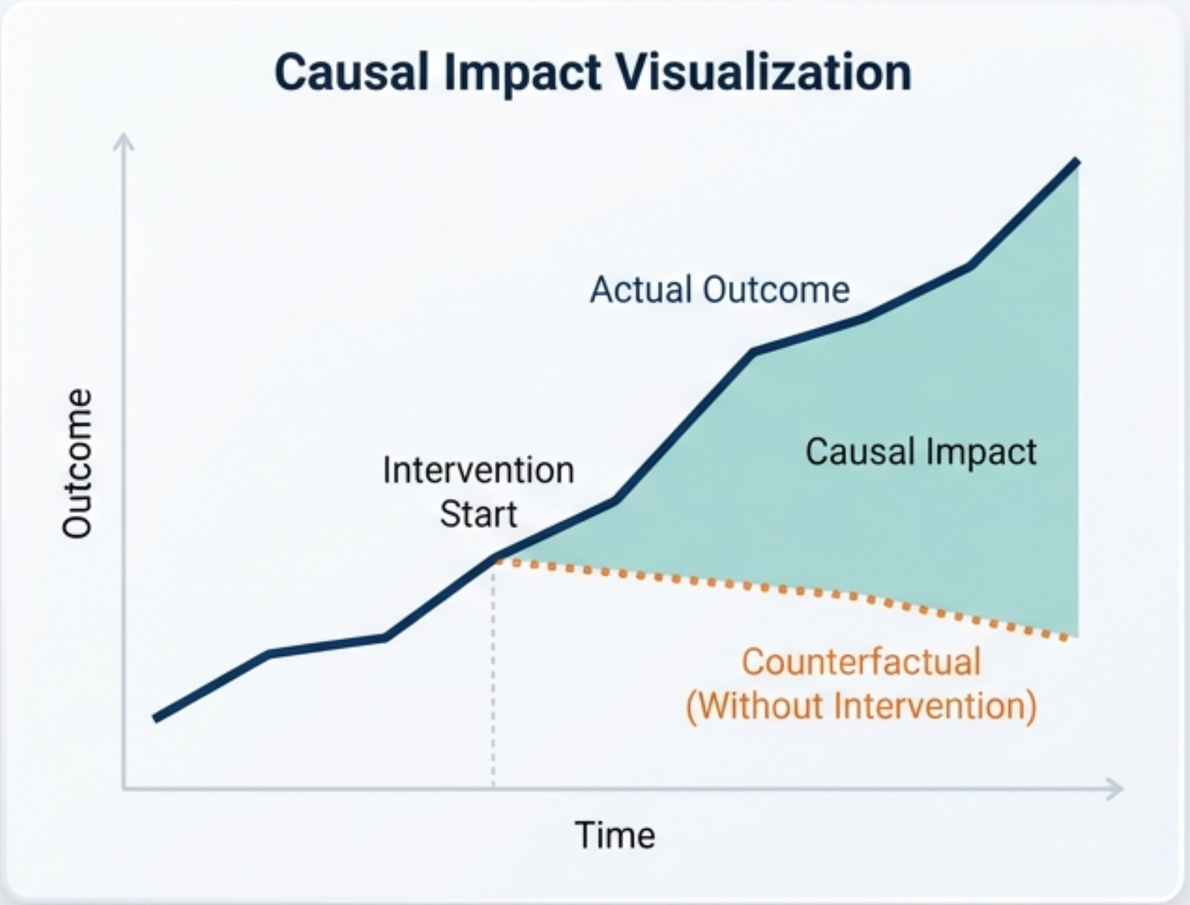
Conclusion:

The effect of `adherence_program_enrollment` on `PDC_score` is statistically significant in your analysis.

09:55:21
Answered by: AI_InterpretationAgent

Beyond Observation: Counterfactual Analysis

Answering the “What If?” questions that drive strategy.



Counterfactual analysis estimates campaign impact by predicting outcomes *without* intervention exposure.

Strategic Value:

- **Optimize Decisions**: Allocate resources based on proven causality.
- **Stop** funding programs that correlate with success but don’t cause it.

Real-World Applications

Clinical & Compliance

Evaluating patient adherence programs and intervention efficacy.

Ensuring health outcomes are driven by care, not just patient demographics.

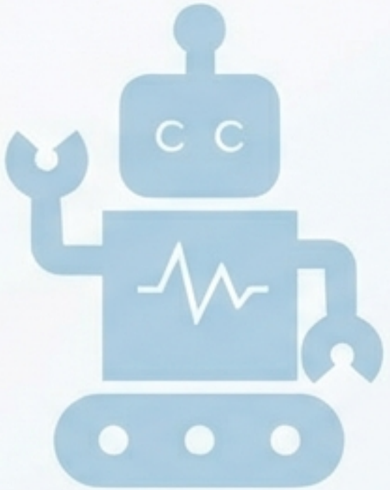
Marketing Optimization

Measuring the true lift of outreach campaigns.

Filter out customers who would have purchased anyway to calculate true ROI.

Operational Strategy

Analyzing the impact of training programs on employee performance and optimizing resource allocation across departments.



Democratizing Causal Inference

Empowering analysts, program owners, and data scientists to move from ‘I think’ to ‘I know’.

AI-Powered Automation for Causal Inference