Advancing Real-World Evidence with Xplain Data Causal AI

Xplain Data
Discover Causality

# UNLOCKING ACTIONABLE INSIGHTS FROM REAL-WORLD PATIENT DATA

## Standard Adjustment vs. Causal Discovery – What's the Difference?

**Conventional methods/Standard Adjustment** for estimating intervention effects (e.g., propensity scores, regression, stratification) depend on strong **assumptions**:

- Require **predefined hypotheses** about interventions (you cannot simply ask "which factors matter?").
- **Confounders** must be explicitly specified for adjustment, introducing further assumptions.

**Assembling corresponding variables in a flat table causes a loss of rich information from the original, complex patient data.**

**Causal Discovery – A Different Approach**:

- **Requires no assumptions.**
- **Works directly with complex real-world data** (e.g., EMRs with dozens of interrelated tables), preserving the full richness of information.
- Enables **open-ended exploration:** "Show me all causal pathways leading to the outcome of interest."

**Represents an unbiased search for causal factors and confounders within the full complexity of real-world data.**

## Xplain Data ObjectAnalytics – Enabling Deep Causal Search

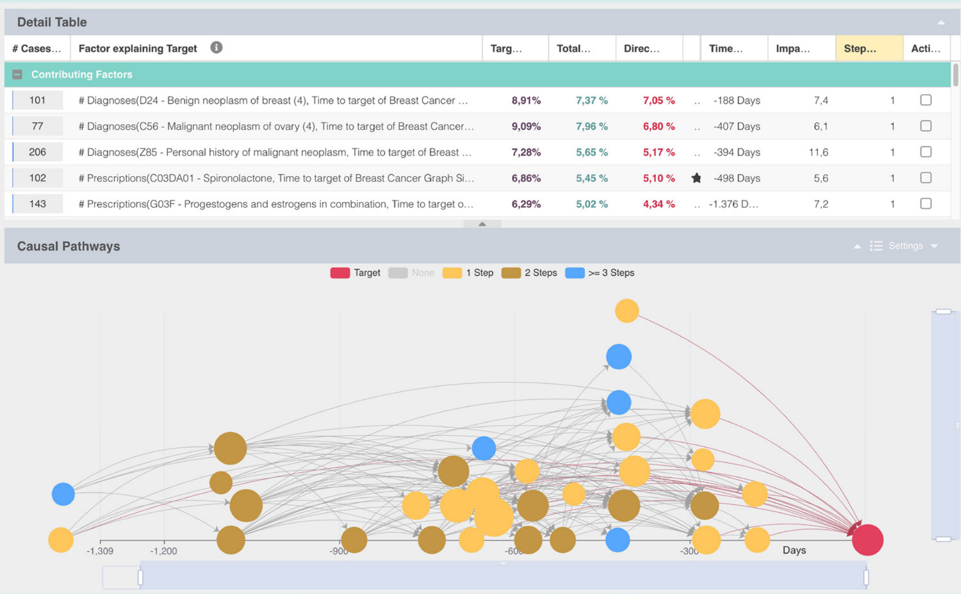


Figure 1.
Example Results: Causal network for target "Breast Cancer". Explore nodes that influence the outcome, directly or indirectly.

**Comprehensive patient information is necessary for identifying all factors and confounders. This information can span dozens of interrelated tables.**

**Challenge:** Causal algorithms must operate in this complex environment.

**Solution: ObjectAnalytics** – transforms fragmented RWD into holistic patient objects:

- **Patented, object-centered model** integrates fragmented, longitudinal data from multiple tables and sources (RWD) into a unified 360° patient view.
- All patient-related information is **linked in an object tree**: patient as root, with diagnoses, treatments, prescriptions, etc. as sub-objects.
- **Overcomes the flat-table limitations** of relational databases.
- Provides the **foundation for Causal Discovery** algorithms to conduct deep, automated confounder search **without prior assumptions.**

## Examples of Causal Discovery in Healthcare

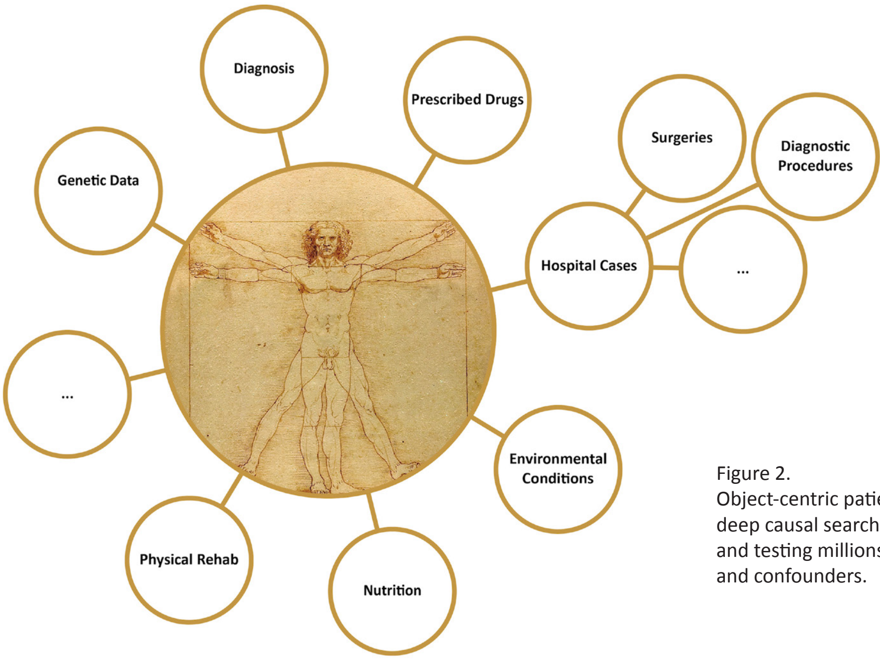


Figure 2.
Object-centric patient view: foundation for deep causal search by rapidly generating and testing millions of hypotheses for factors and confounders.

### Market Access: Causal Drivers in the Therapy Journey

- **Therapy starts & restarts:** Analyze the causal drivers behind ***why*** patients choose Product X over competing products.
- **Switch Wins | Losses:** Comprehend market dynamics and reasons for switching.

### Real-World Evidence: Causal Pathways in the Diseases Journey

- **Analyze typical disease pathways:** prior conditions, progression, escalation.
- **Understand causal factors:** triggers of disease onset or relapse.
- **Perceive entire causal pathways:** direct & indirect drivers across multiple hubs.
- **Perform deep confounder search:** robust drug-effect evaluation in RWD studies.

### Treatment Effectiveness & Optimization:

- **Predict response vs. non-response** based on patient characteristics.
- Determine causal factors of **dose optimization** and **titration success.**
- Analyze causal interactions and synergies in **combination therapies**.

### Other applications:

Healthcare resource utilization, safety and pharma-covigilance, precision medicine, and biomarker discovery, among others.

## RELEVANCE FOR LIFE SCIENCE ORGANIZATIONS AND RESEARCHERS

- **Faster evidence generation:** uncover causal drivers without months of manual hypothesis testing.
- **More robust RWE studies:** unbiased adjustment for confounders improves credibility with regulators and payers.
- **Deeper market insights:** identify true drivers of therapy choice, switching, and adherence.
- **Improved treatment optimization:** personalize dosage, predict response, and optimize drug combinations.
- **Competitive advantage:** leverage the full richness of RWD while competitors rely on limited regression-based methods.
- **Scalability:** a framework that can handle millions of patient records and hundreds of variables simultaneously.

## About Xplain Data

Xplain Data is a pioneer in Causal AI, helping health-care and life sciences uncover true cause-and-effect in complex data. Based on our patented ObjectAnalytics® platform, we deliver a 360° view of healthcare data to reveal causal pathways without prior assumptions. Trusted by 50+ global pharma companies and Germany's largest health insurers, we generate causal real-world evidence that drives better decisions and outcomes.

***Contact us to discuss, how Xplain Data's Causal AI solution can unlock the full potential of your healthcare data!***

**More Info:**


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