

# Data-driven Prescribing for Anxiety & Depression

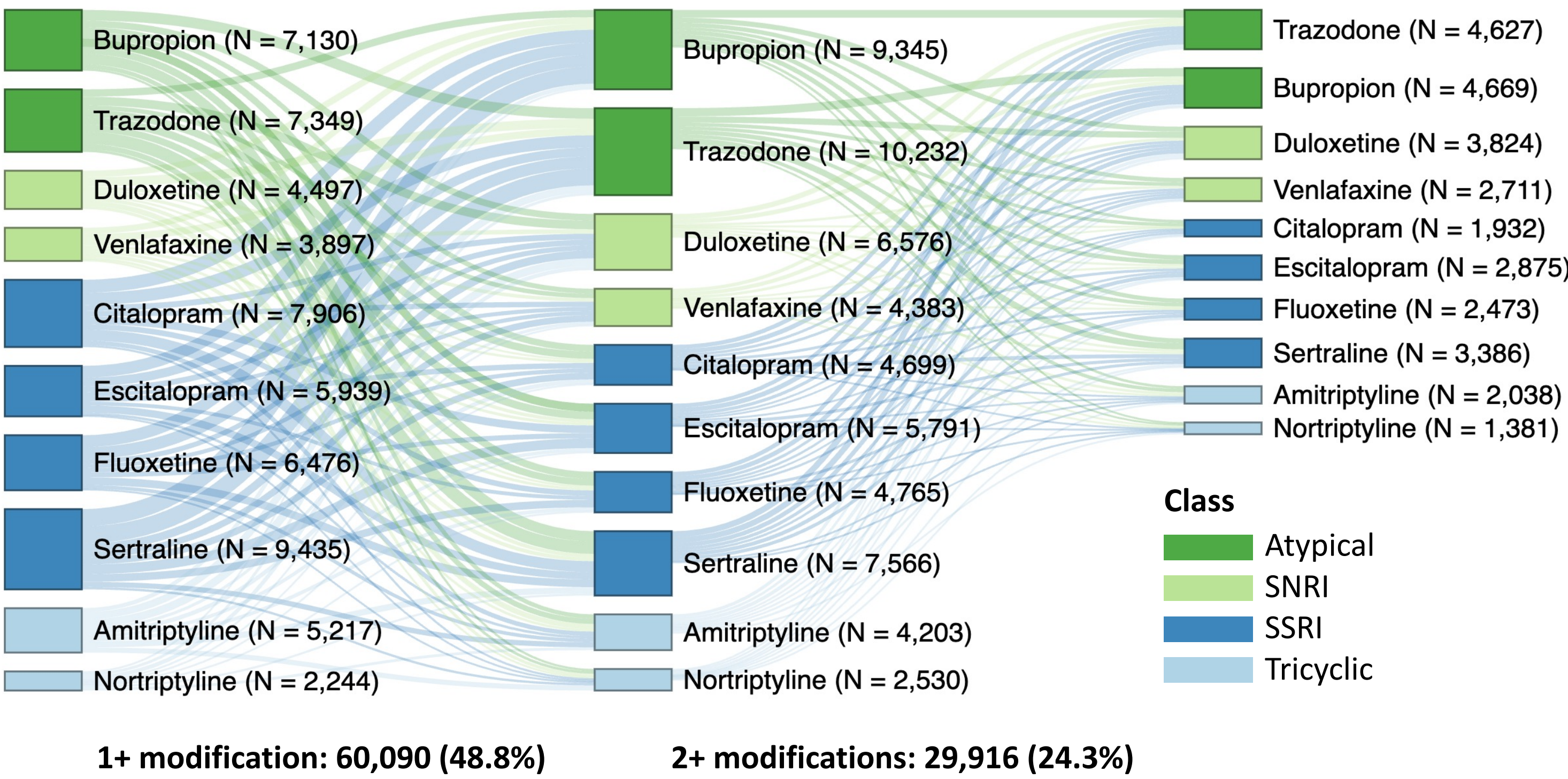
## Better, faster care with generative AI & interpretable ML

### Extract, Predict, Support: Improving Medication Choice and Outcomes from Clinical Data to Decision Support

**The Need:** Alongside psychotherapy, medication is widely used to treat Anxiety and Depression, with hundreds of millions of prescriptions written each year. However, **no individual medication is universally effective, and limited information is available to guide treatment choice.** This is a significant issue: upwards of 45% of patients switch medications due to ineffectiveness or adverse side effects, including weight changes, sexual dysfunction, fatigue, headaches, and suicidal ideation.

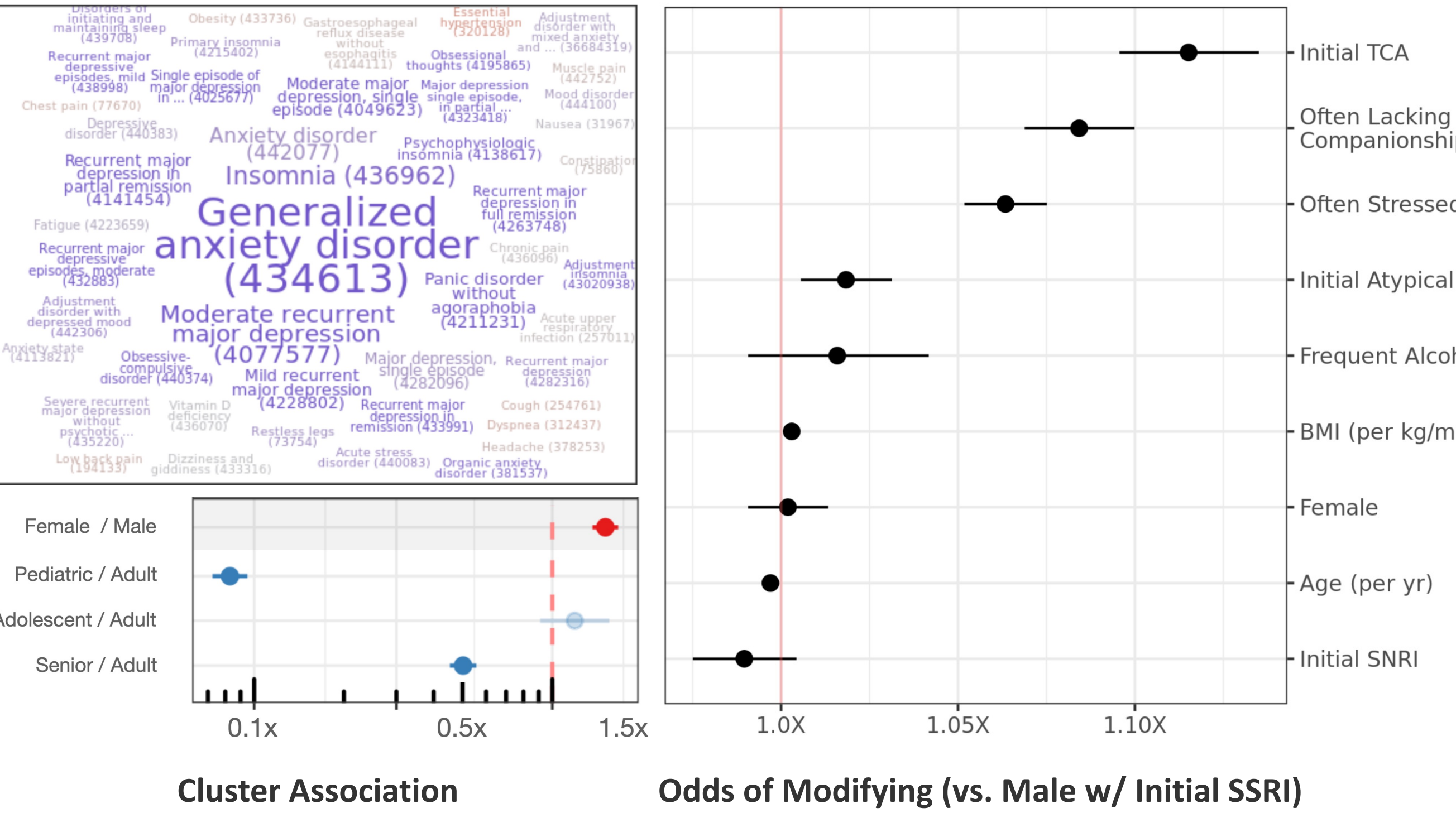
**The goal:** We aim to help patients find the right medication faster and with less trial-and-error. Using large-scale Electronic Health Record (EHR) data, we are developing privacy-preserving, explainable machine learning (ML) models to predict medication effectiveness for individual patients. To assist prescribers in interpreting and using this information, we are integrating these models alongside established care guidelines in generative-AI interfaces, providing on-demand decision support respecting clinician expertise and supporting patient engagement for improved, personalized care.

### Over 45% of patients switch or augment to find effective treatment.



Across 123,010 patients with an initial diagnosis of anxiety and/or depression treated with medication, **48% switch to (or later augment with) another medication, 24% more than once.** Top ten medications and up to two modifications shown; see QR code for methods, limitations, and data sources.

### Large-scale EHR data uncovers patterns and predicts outcomes.



**Unsupervised clustering reveals patterns in comorbidities and patient features (left);** female patients are strongly associated with this cluster, one of many across 8M+ patients. **Switching/augmenting can be predicted (right);** stress, companionship, and medication class influence baseline modification rates.

## Generative AI Can Help!

### Generative AI turns *explainable* ML into *interpretable* ML.

**Clinical Decision Support**

Patient MRN: MRN 123456

Age: 52 BMI: 29.4

Sex: Female

Initial Medication Class: SNRI

Custom Instructions: Exclude activating antidepressants for patients reporting insomnia.

Comorbidities / Risk Factors: ☒ Alcohol ☒ Insomnia ☐ Adhd ☒ Stress ☒ Fatigue

**Run Prediction**

**Prediction**

43% probability of success

Top contributing factors: Initial SNRI vs SSRI: +0.55 Alcohol: -0.35 Stress: -0.30 Insomnia: -0.22 Age (52): +0.18 Fatigue: -0.12

**Interpretation:** The model predicts this patient is **more likely to find success with an SNRI** compared to an SSRI. Older age also increases success probability, while **stress, alcohol use, insomnia, fatigue, and ADHD** modestly decrease it.

**Recommendation:** Given **insomnia** and a **higher BMI**, consider an SNRI that avoids stimulating or weight-increasing effects (e.g., **duloxetine**). Supporting stress and sleep management may further improve success.

**Follow-up question**

Type a question...

How is this information generated? What contraindicates duloxetine?

What other medications are predicted effective and why?

Clinicians make rapid decisions in information-rich environments. Explainable machine learning promises an era of personalized medicine, but these complex methods require time and specialized knowledge to use effectively. **Generative AI-enhanced interfaces can serve as interpreters for effective decision making backed by models, data, and guidelines;** co-designed interfaces **facilitate shared decision making and patient engagement.** Example interface and mock data shown.

### Important ‘dark data’ is buried in sensitive clinical notes.

**Results**

The patient reports ongoing restlessness and difficulty controlling anxious thoughts, especially at night. She describes persistent muscle tension, fatigue, and sleep disturbance characterized by difficulty staying asleep and early-morning awakenings with anxiety. She notes partial improvement since starting escitalopram 10mg daily, with decreased daily anxiety intensity but continued sleep issues. Reports mild side effects of fatigue and loss of appetite, which have persisted for several weeks. Denies suicidal ideation or intent. Reports ongoing psychotherapy (CBT) every two weeks.

**Cognitive and behavioral therapy (4043071/Procedure)**

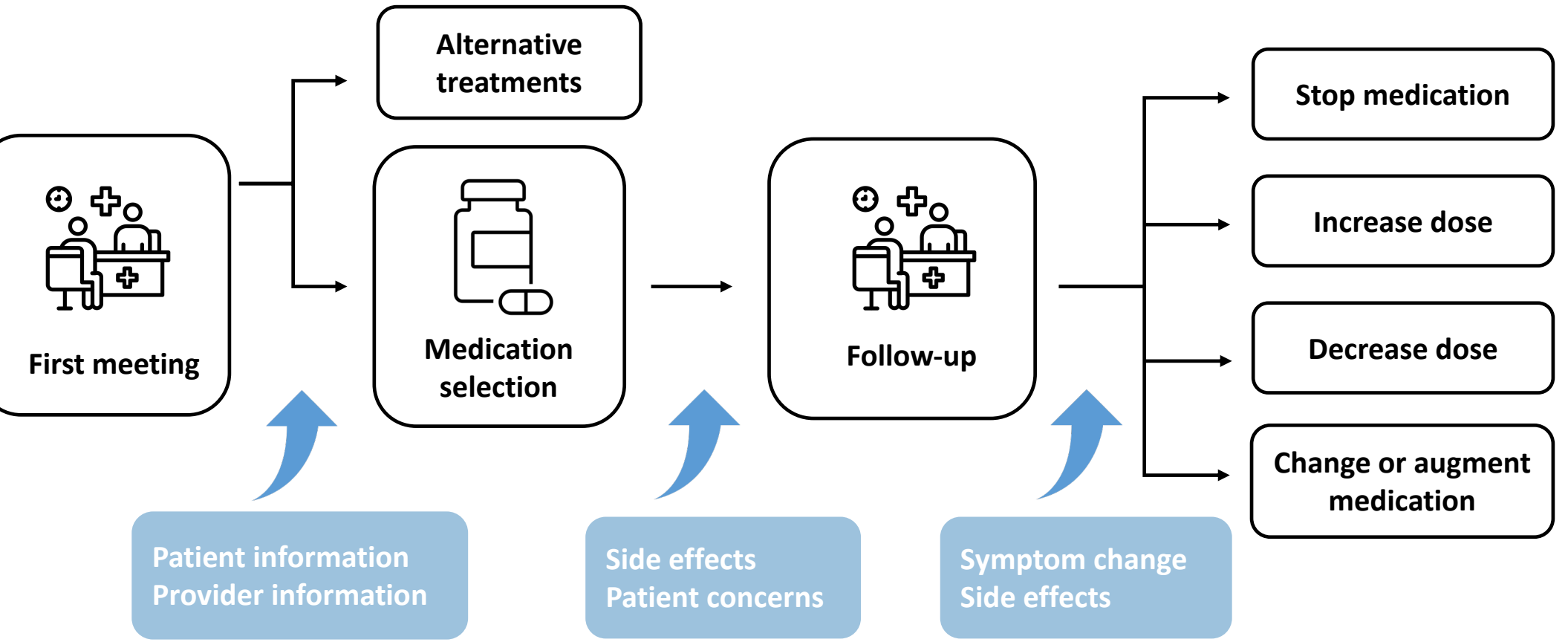
mention_str	concept_name	domain_id	vocabulary_id	concept_code	standard	negated
early-morning awakenings	Terminal insomnia	Condition	SNOMED	67062000	<input checked="" type="checkbox"/>	<input type="checkbox"/>
suicidal ideation or intent	Suicidal thoughts	Condition	SNOMED	6471006	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
side effects of fatigue	Fatigue due to treatment	Observation	SNOMED	704369007	<input checked="" type="checkbox"/>	<input type="checkbox"/>

Structured EHR data enables predictive modeling, but misses information found only in privacy-sensitive free-text notes. We are developing LLM-based pipelines to ‘code’ outcomes and risk factors, **quantifying how patients experience these conditions and treatments, improving models, and enhancing privacy in research.** Our agent-based pipeline navigates medical vocabularies inspired by human annotation processes, including re-phrasing and hierarchical medical concept searching. Mock note data shown.

## Patient Voices, Clinician Expertise

In addition to core team members’ significant experiences and patient advocacy, we are incorporating both lived experience and clinician knowledge via a **Community Advisory Board (CAB)**. Early ‘journey mapping’ exercises with both groups reveal a diversity of considerations for decision-making, and we will incorporate CAB input at multiple stages, including **modeling choices and validation, interface design and testing, and publication and dissemination.** The CAB will supplement a **Steering Committee providing ethical oversight**, considering issues in data safety, bias, stigmatization, and benefit distribution.

### Journey mapping reveals decision points and influences.



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