

## 1. Overall Context and Objective

The meeting focused on **defining a high-impact, AI-driven analytics project** for a pharmaceutical client operating in the **obesity / GLP-1 market**. The intent was **not** to build a traditional operational solution (e.g., a gateway or standard dashboard), but instead to design a **strategic, forward-looking analytics and AI capability** that can:

- Predict **which physicians (HCPs / FCPs)** will adopt **new obesity therapies**, especially **oral GLP-1s**
- Continuously learn and improve as **new products enter the market**
- Directly support **commercial targeting and go-to-market decisions**

This is positioned as a **strategy + AI project**, not just a reporting or technical exercise.

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## 2. Key Business Problem Being Solved

The client is entering a **rapidly evolving obesity market** characterized by:

- Multiple **injectable GLP-1 products already in market**
- The **recent launch of oral GLP-1s**
- **Upcoming launches** from competitors
- Market distortions due to **drug shortages, payer changes, and telehealth expansion**

The central commercial question is:

**“Before launch, can we predict which physicians will be the earliest adopters of a new oral obesity drug—and how confident can we be in that prediction?”**

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## 3. Strategic Framing of the Project

The discussion converged on a **simulation-style project**, where the analytics team effectively **“pretends to be the manufacturer”** at different points in time.

**The core framing:**

- Build models **before oral prescription data exists**
- Make **forward-looking predictions**
- Validate predictions once real data arrives
- Learn, recalibrate, and improve accuracy

This creates a **repeatable AI capability**, not a one-time analysis.

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## 4. Data Landscape and Constraints

### Available / Planned Data Sources

#### 1. LAAD (claims-based data)

- Available immediately
- Strong for prescription behavior and volumes
- Limited clinical detail (diagnoses gaps)

#### 2. Exponent (HCP-level enrichment)

- Expected in ~3–4 weeks
- Adds deeper physician attributes and behaviors
- Critical for refined targeting and validation

#### 3. Optum / EHR-linked data (via C4)

- Rich in patient clinical context
- Useful for **patient-type modeling and validation**
- No direct MPI-level HCP linkage (cannot directly target physicians)

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## 5. Major Analytical Workstreams Discussed

### 5.1 HCP Segmentation (Foundational Layer)

**Goal:** Create AI-driven segments of ~400,000 physicians based on behavior, not just demographics.

Key ideas:

- Use **unsupervised clustering / advanced analytics**
- Segment physicians by:
  - Adoption timing
  - Prescribing preferences (oral vs injectable)
  - Therapy loyalty vs switching behavior
- Design segmentation to be:

- **Refreshable**
- **Future-proof**, as new drugs enter the market

Important caveat:

- Segmentation **must explicitly account for external market factors**, including:
  - Drug shortages
  - Payer coverage changes
  - Market awareness waves

Without this, adoption signals could be misleading.

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## 5.2 Early Adopter Prediction (Core AI Use Case)

**This became the centerpiece of the project.**

### Concept:

Use **historical injectable prescribing behavior** to predict **future oral adoption**, even before oral data is available.

### Example framing:

- “If we were launching an oral obesity drug in January, based only on data up to November:
  - Who should we target?
  - Why?”

### Key predictive signals discussed:

- Preference for oral vs injectable therapies in other disease areas
- Speed of adoption of prior new therapies
- Willingness to experiment with new treatments
- Patient mix (chronic weight, T2D, comorbidities)
- Exposure to consumer-driven demand

The team explicitly acknowledged:

- **Predictions will initially be wrong**
- That is expected and acceptable
- The value is in **learning velocity and improvement over time**

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### 5.3 Patient Type Modeling (Enabler, Not the End Goal)

The group discussed the importance of understanding:

- Different **patient phenotypes** (e.g., obesity + CV risk, obesity + T2D)
- How different drugs will likely serve different patient niches

Challenges identified:

- Obesity diagnosis is **poorly coded in claims**
- Medical benefit data has **diagnostic gaps**

Proposed solution:

- Use **AI / probabilistic models** to infer missing diagnoses
- Leverage **Optum EHR data** for:
  - Discovery
  - Validation
  - Patient clustering

This work improves **downstream HCP segmentation and prediction quality**.

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### 6. Validation and Success Criteria

A key question raised was:

“How do we know if the segmentation and prediction are actually good?”

**Agreed success framework:**

#### 1. Pre-launch prediction

- Predict oral adopters using only historical data

#### 2. Post-launch validation

- Once oral prescription data arrives:
  - Measure how many actual adopters were correctly predicted

#### 3. Accuracy benchmarks

- ~60% accuracy early = success
- Model improvement over time is expected:

- 70% → 80% with new data and retraining

#### 4. Business relevance

- Ability to generate a **defensible target list**
- Clear rationale for why each physician is included

This reframes success from “perfect accuracy” to **commercial usefulness and learning speed**.

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#### 7. Market Dynamics Explicitly Incorporated

The team emphasized that **this market is not static**, and models must account for:

- Drug shortages forcing substitution behavior
- Loyalty vs experimentation dynamics
- Telehealth providers adopting faster (especially cash-pay)
- Differences between reimbursed vs cash markets
- Continuous pipeline of:
  - New orals
  - New injectables
  - New indications

This reinforces the need for **adaptive, AI-driven models**, not rule-based logic.

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#### 8. Final Agreed Project Vision

**The project, in one sentence:**

**Build an AI system that predicts which physicians will adopt new obesity therapies before launch, validates itself post-launch, and continuously improves as the market evolves.**

**Why this matters:**

- Direct commercial impact
- Highly differentiating capability
- Reusable across future launches
- Strong alignment with advanced analytics and AI strategy

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## 9. Next Steps Agreed

1. Develop a **clear project roadmap**
2. Secure access to:
  - LAAD
  - Optum (where feasible)
  - Exponent (once available)
3. Set up **regular hypothesis-driven working sessions**
4. Align with internal analytics and data access teams
5. Begin modeling immediately, even with imperfect data

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## 10. Final Tone of the Meeting

- The project is **challenging but exciting**
- It is **strategic, not just technical**
- It pushes beyond what has been done previously
- Strong enthusiasm and alignment across stakeholders

This was positioned as a **flagship AI-ready initiative** rather than a routine analytics engagement.