In an increasingly difficult business environment, pharmaceutical manufacturers must do everything possible to understand the factors that affect promotion effectiveness. Rigorous analysis of Anonymized Patient Level Data (APLD) provides novel insight into these factors. Based on findings from a recent ZS Associates study, sales promotion efforts for as many as one-half of all targeted physicians could change significantly once these new data are factored into a company’s promotion strategy. The results have implications for pharma and biotech companies that rely on sales force effort — regardless of their size or market.

Thinking Beyond the “Average Patient”

How Anonymized Patient-Level Data Analysis Could Help Companies Redirect Half of Their Physician-Targeting Efforts

Pratap Khedkar & Jude Konzelmann
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The Advent of APLD

Drug makers charting a course toward continued organic growth face daunting obstacles: Blockbuster drug patent expirations, MCO pressures to contain costs and the reality that many diseases already have effective drug therapies.

In the face of these challenges, full understanding of the precise factors that increase or decrease promotion effectiveness is more important than ever. Fortunately, a new and more sophisticated approach to analyzing Anonymized Patient Level Data (APLD) has the potential to improve dramatically the overall promotion effectiveness for nearly every pharma and biotech company on the market. Indeed, the insight that APLD provides may affect the efforts allocated to as many as half of all doctors on a target list.

APLD has been collected largely from transactions between pharmacies and the managed care organizations that serve and track millions of patients. These data follow anonymized patients over time with information about physician prescriptions, drug therapies and treatment patterns.

Before the advent of APLD, companies relied on physician-level data. These data count the total number of prescriptions a doctor writes for each product in a particular market, but they provide little information about the patient-related factors behind a physician’s choice to prescribe a particular remedy.

While pharma companies have often designed promotional messages for specific patient types, reach and frequency decisions were based on an “average” patient; that is, one for whom all prescriptions were written in a similar context.

With APLD, however, companies can segment patients into discrete categories beyond the average and determine the number of prescriptions each doctor writes by category. Equally important, APLD can give companies the physician-decision information and insight necessary to make dramatic improvements both in their targeting efforts and in the amount and type of information they offer doctors.
Armed with this data, a pharmaceutical or biotech company can significantly sharpen its efforts based on clear answers to several previously impossible-to-answer questions concerning the impact of sales force activity on a doctor’s choices. For example:

- Is Dr. Smith more likely to start new high-cholesterol patients on our drug, Brand A, if we sample him frequently?
- Why did Dr. Johns prescribe Brand A for one patient and Brand B for another, even though both patients have the same illness?
- Can our sales representatives help reduce the number of patients Dr. Yu switches from our Brand A to competitor Brand Y?
- If we stopped calling on our loyalist Dr. Juarez, who has many patients continuing on Brand A, would we lose some of his patients to a competing brand? And, if so, how quickly?

**Leveraging the Power of APLD**

The key to leveraging the power of APLD is the accurate interpretation of the factors behind a physician’s decision to prescribe certain drugs — and the proper application of that interpretation to sales force promotion strategies.

We recently examined physician decisions related to drug therapy for a class of mental illness — though our conclusions could apply to most drugs that treat either chronic or acute conditions and to most medical devices. We were able to use APLD to separate the traditional “average” patient-decision into three distinct patient categories, or physician-decision types:

- **New Patient Decisions** — Decisions made for patients who start treatment in a therapy area for the first time. These are relatively “clean-slate” decisions.
- **Continuing Patient Decisions** — Decisions made for those patients who continue with one drug and simply refill the same prescription — even if they change doctors. Practically speaking, these types
of decisions may not be decisions at all, since the current drug therapy is performing as expected.

- **Switch Patient Decisions** — Decisions made for patients who, for any reason, must switch from one drug to a competing drug in the same therapy area (While the change can be for any reason, it’s usually because the current drug underperforms in some way.)

Such fine-tuning makes it possible to study the promotional impact on each patient-decision type as patients flow through the steps in their treatment. As Figure 1 illustrates, patients on a drug can result from three very different kinds of decisions by the prescriber.

Drilling deeper into APLD, we were able to relate the percentages of patient-decisions made by each doctor for New Patients, Continuing Patients and Switch Patients to the number of details and samples directed to a specific doctor. From this, we could determine more precisely the impact of sales promotion on the doctor’s decision to a) prescribe a drug in the first place; or b) prescribe one drug over another.

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**Figure 1.** Figure 1 shows how APLD segments the “average” patient into three groups: New Patient, Continuing Patient and Switch Patient.
The two charts below demonstrate the differences between the broad conclusions that would be drawn from viewing the “average” patients of physician-level data and the more specific insights that were gleaned from viewing the three more precise types of patients that can be identified in APLD.

**Figure 2.** Figure 2 demonstrates how sales force promotion will have a far greater impact on a physician’s New Patient-decisions and Switch Patient-decisions than it will on those decisions related to Continuing Patients.
The top bar in Figure 2 uses only physician-level data and average patients. Looking at this unrefined data alone, one might conclude that of every 100 patient decisions, 17 were the result of detailing, eight were the result of sampling and 75 were the result of a third category we call “carry-over,” (i.e., physician-decisions based on either the doctor’s loyalty to the brand or the patient’s adherence to it).

By contrast, the lower three bars of APLD clearly separate patients by our three distinct decision-types: New, Continuing and Switch. If you match the different decision-types against the doctor-details and analyze this further, you can measure the impact that sales promotion has on physician decisions. We now see that:

- New Patient Decisions: Of every 100 physician-decisions related to this drug, 27 could be attributed to detailing, 22 to sampling, 13 to other factors and 38 to physician loyalty/carryover.
- Switch Patient Decisions: Of every 100 physician-decisions on this drug, 23 decisions could be attributed to detailing, 15 to sampling, 32 to other factors and 30 to carryover.
- Continuing Patient Decisions: Of every 100 physician-decisions related to this drug, 11 decisions could be attributed to detailing, 10 to other factors and 80 to carryover. In this case, we also noticed that revenue from one of every 100 decisions was lost from over-sampling.

Understanding this subtle distinction between physician loyalties and patient continuity can be tremendously valuable — particularly if you’re targeting physicians with an “end-of-life” brand and want to weigh the physician’s need for information against the risk of scaling back promotion.

If we compare the physician-level data in the top bar of Figure 2 with the APLD data in the lower bars, we see some other important differences between the two data sets. According to the less precise physician-level data depicted in the top bar, slightly more than 20 percent of all patient-decisions in this case can be tied to pharma promotions. But the APLD data show something much more specific: The impact of promotion on New Patient-decisions (49 percent) is nearly five times...
greater than it is on Continuing Patient-decisions (11 percent). Further, the impact of promotion on Switch Patient-decisions (38 percent) is nearly four times greater than it is on Continuing Patient-decisions.

Reviewing the data at this level of detail can help representatives better understand individual physician information needs and improve the sales rep-physician dynamic. While each physician has his own unique mix of patients and patient-decision types, even if they all write the same number of prescriptions, it’s clear that physicians treating mostly New Patients merit more detailing and sampling and those who serve mostly Continuing Patients should receive less.

We also can predict that if a pharmaceutical company dropped promotion to those doctors handling mostly New Patients, it could conceivably lose 49 percent of its potential sales through that physician. Conversely, if that company dropped its detailing and sampling for doctors that primarily serve Continuing Patients, it would likely lose only 11 percent of its potential sales from these doctors — but perhaps earn a bit more appreciation from the time-pressed physicians.

The findings suggest that as many as half the physicians could receive fewer details and samplings — and 15 percent of them, theoretically, could be dropped from the targeting plan without consequence to profitability. Rather than dropping these doctors completely, however, we recommend scaling back the targeting investment in physicians serving a high number of Continuing Patients. Repeat customers are highly profitable for a drug-maker, so sales representatives should detail defensively and provide only enough promotion to protect the incumbent position from competitors.

**Focus and Fine-Tune**

New APLD insights are especially crucial considering the state of the industry. There are fewer new drugs on the market than a decade ago, and there are fewer new patients. Therefore, patient level data that help sales teams better target their resources will help them succeed in a more challenging market.
Knowing which types of physician-decisions are more influenced by promotion enables companies to fine-tune targeting strategies for greater results. Without increasing promotion resources, you can make your sales force more productive by doing more with what you have. To wit:

- Sales management and operations can either fine-tune its sales force size or focus its sales forces more precisely. In the case where details and samples for almost half the targeted physicians should have been altered or modified, the absolute number of sales calls should have remained the same. It’s just that doctors with a higher percentage of New Patients and Switch Patients should have received more attention than they did, and doctors with a higher proportion of Continuing Patients should have received less.

- Marketing management can give new relevance to the messages behind a drug if it understands the physician’s patient mix. Doctors with more New Patient decisions, for example, are more interested in the drug’s benefits as a good first-line therapy. Those with a higher percentage of Switch Patients will respond better to data regarding a drug’s relevant advantages as an alternative therapy.

Brand management can make marketing investment decisions for products anywhere in the life cycle — from launch to “end-of-life” — based on the likely promotional impact on the different patient-types in their therapy area. Managers can launch drugs or medical devices more effectively, knowing the past performance of other products in the target therapy. They also can quantify how, why and when sales force investment should begin to decline as the brand matures. Because promotion changes the mix of patients on that brand (i.e., the brand gets less of its sales from New Patients over time), that patient mix, in turn, impacts the effectiveness of the promotion. This dynamic interplay changes the optimal resource allocation every year.

In addition to helping sales teams better understand doctor prescription decisions, rigorous APLD analysis has practical implications for teams looking to reformulate sales strategy. As Figure 3 illustrates, sales teams can use a four-stage process to integrate APLD data and make better use of their resources:
The Challenge of Raw Data

While the conclusions we can draw from rigorously analyzed APLD are clear, analyzing the voluminous and cumbersome raw data is inherently complicated. Patient-level data come from many sources rather than a census; and each source has its own strengths and limitations. State laws governing prescription refills linked to doctor visits can complicate new prescription- and patient-related brand choices made by a doctor. The three types of patient decisions — New, Continuing and Switch — are linked over time for an individual patient, so they cannot be studied in isolation. Complicating matters further, data vendors have different approaches to classifying patients.

Conclusion

Faced with the challenges of the 21st century, today’s pharmaceutical and biotech companies need the best possible market intelligence they can command. Properly interpreted and applied, Anonymized Patient Level Data fills the need for sharper customer focus. The dramatically improved insights provided by patient-level data can help ensure better use of promotion dollars, more successful product launches, more productive sales manager-sales rep and sales rep-doctor interactions, and a more clearly charted course toward improved sales rep-physician relations and profitable growth.

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<thead>
<tr>
<th>Product Launch Stage</th>
<th>Growth Stage</th>
<th>Post-Competitive Launch Stage</th>
<th>End Stage</th>
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<tr>
<td>First 6-12 Months</td>
<td>Years 2-5</td>
<td>Years 5+</td>
<td>Last 12-18 Months</td>
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<tr>
<td>Focus targeting efforts on doctors with a high percentage of New and Switch patients.</td>
<td>Measure promotional response by each patient category (New/Continuing/Switch). Then adjust accordingly, focusing on targeting strategies and the messages reps are carrying.</td>
<td>Identify doctors that are switching to your competition, and focus sales resources on those physicians.</td>
<td>Identify and scale back targeting efforts on doctors that have a high Continuing Patient base and therefore a sustainable level of carry-over.</td>
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Figure 3. Figure 3 summarizes several implications of research findings over a brand’s lifecycle.
About ZS Associates

ZS Associates is a global management consulting firm specializing in sales and marketing consulting, capability building, and outsourcing.

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