Predicting Patient Adherence: Why and How

To contain costs and improve healthcare outcomes, players across the value chain must apply advanced analytics to measure and understand patients’ failure to follow treatment therapies, and to then determine effective remedial action.

Executive Summary

The new healthcare regime — both in the U.S. and across the world — can be boiled down to reducing costs and enhancing the quality of patient care. Improving patient adherence to a treatment regimen can be a crucial factor. And as with many other areas of modern healthcare and life sciences, the role of data analytics is of paramount importance.

The World Health Organization (WHO) defines patient adherence as “the extent to which a person’s behavior – taking medication, following a diet and/or executing lifestyle changes – corresponds with agreed recommendations from a healthcare provider.”

Adherence is a combination of compliance (correct use of medication as prescribed) and persistence (continued effort in taking medication). Adherence is what is expected of the patient.

There are multiple estimates of non-adherence and its associated impact on cost reduction, all of which are quite alarming. As per the Annals of Internal Medicine, non-adherence impacts the U.S. healthcare system between $100 billion and $289 billion annually, 20% to 30% of which equates to medication prescriptions that are never filled and 50% for medications that are not taken as prescribed to treat chronic diseases. In Europe, the situation is no better as non-adherence is said to cause 200,000 deaths per annum and cost the economy €125 billion each year. And if the increase in age of the global population is factored in, the cost will likely spike manyfold in coming years. So it is in the interest of payers, drug manufacturers and policy makers to contain this cost by applying advanced analytics.

On average, it costs six times more to attract new patients than it does to retain existing ones. Increasing patient adherence can boost profitability in the following ways:

- **Payers:** Reduction in healthcare expenses.
- **Patients:** Better health.
- **Pharma:** Enhanced patient loyalty and retention.

This white paper lays out a framework for enabling patient adherence management and some general prescriptions on how to convert lofty concepts to meaningful action.
Analytics Framework for Adherence Management

Players across the healthcare value chain need to understand the patient journey. Patient adherence is a complex issue, and requires a thorough understanding of the root causes of discontinuing treatment. Measuring and tracking adherence may help to illuminate specific strategies, but such tactics needs to be integrated with prediction and action for the organization to succeed.

Measure and Track

This phase primarily consists of:

- Developing a patient adherence index.
- Tracking the adherence progress across different therapeutic areas, by geography, patients and physician segments.
- Assessing the ROI of various marketing channels (through advanced analytics techniques such as multivariate regression and test and control analysis).

The most critical of all these, however, is developing an adherence index. Multiple measures exist for this:

- **Direct or clinical methods such as the level of medicine or biological marker in the blood, etc.** However, on a regular basis, measuring and keeping track of non-adherence by direct methods is not very practical since patients require diagnostic procedures to obtain these measures.

- **Indirect methods, based on prescription refills or pill counts, are much more popular.** Depending on data availability, these two measures can be interchangeably used. For example, if the pharmacy refill data is available, pill count is probably the best measure; however, if the analysis is based on patient claims or longitudinal patient data, frequency of claims or refills is probably the most dependable metric.

Two common measurements that can define an adherence index are: (1) Medication possession ratio (MPR) — i.e., the number of days of medicine supplied within a time interval/total number of days in the period; and (2) period of days covered (PDC) — i.e., the number of days of medication covered over a time period. For a single drug medication, these measurements are actually the same, but for a multidrug therapy they might differ considerably.

In the case of multidrug therapy, MPR would be calculated as (total days of supply) x (number of days in the interval). For PDC, it is the proportion of days when all the medications were available.

Let’s consider a hypothetical example of a three-drug medication and 10-day interval time period to understand the difference between MPR and PDC. The first drug was available for all 10 days, drug two for the last seven days, and drug three only for the last three days.

- MPR = 67% \( \frac{(10+7+3)}{3}/10 = 6.6 \) while PDC (a more accurate measure) = 33% \( \frac{10}{3} = 3.3 \).

Apart from the objective measures as described above there are quite a few self-reported, and hence subjective, measures that are based on questions answered by patients. These include...
the Morisky scale, medication adherence report scale (MARS), beliefs about medication questionnaire (BaMQ), etc.

**Prediction**

The measure and track stage is a completely retrospective analysis. It’s a good first step for any company starting patient adherence analysis, but is not enough. That is simply because once a patient becomes non-adherent, bringing him or her into the adherence zone is much more costly. Hence, predicting the probable non-adherence and taking proactive actions is required to stay ahead of the curve. Given huge healthcare data sets, and ever-escalating computing speeds, this is actually not such a big deal. However, analysis should follow a systematic approach and companies are likely to encounter several challenges along the way:

- **Define “bad” adherence:** The sole objective of the predict phase is to discover the factor/s influencing adherence and understanding why the patient is entering the non-adherence zone. But what level of adherence is non-adherence or bad adherence? Many times this is guided by past experience; however, a data-driven approach can be more illuminating. An analysis of the association between non-adherence and the treatment outcome – whether an adherence rate below a certain level has significant impact on treatment success rate – is helpful here. For example, in the case of diabetes, a benchmark can be decided by the MPR level below which we see a dramatic rise in the blood sugar level.

- **Predictive modeling:** Once bad adherence is defined, the next order of business is to predict whether a patient breaches the benchmark. Typically, a statistical model with a binary dependent variable is developed, using any of three techniques: logistic regression, decision-tree analysis or a neural network model. There are a plethora of statistical measure to judge the model qualities: C-statistics, coefficient P-values, Hosmer and Lemshow test, goodness of fit test, to name a few. However, the final decision in predictive modeling is based on whether the result remains “valid outside the modeling data set.” Generally, the data set is divided into two components – development and validation (a 50:50 or 60:40 split). While the model is estimated on the development sample, validation data is checked to see whether the model equation works equally efficiently. Metrics for efficiency include KS statistic, ROC, etc.

However, the challenges typically entail finding the proper set of explanatory variables rather than the techniques used to model them. Primarily, there are five types of variables:

- **Demographic variables:** Age, sex, race, marital status, number of people in household, etc.
  > Source: Patient enrollment file with healthcare payers, patient registry, longitudinal patient data and medical claims data.

- **Treatment variables:** Number of medications used, duration of treatment, cost of medication or treatment, frequency of dosing, complexity of treatment regimen, etc.
  > Source: Medical claims data, EHR/EMR data, longitudinal patient data, patient registry, etc.

- **Disease factors:** State of disease, diagnostic tests, time, etc.
  > Source: EHR/EMR, patient registries and medical claims.

- **Patient factors:** Knowledge about disease, poor communication by healthcare provider, patient’s own belief in the effectiveness of his therapy regimen, etc.
  > Source: There is no syndicated data source to capture patient-related factors. Data is primarily collected through questionnaires presented to patients.

- **Health insurance variables:** Formulary status of the drug being used, co-pay amount, etc.
  > Source: Medical claims data, IMS PlanTrak, Source®Payer, etc.

Clearly, data for this analysis can come from disparate sources. Hence, the challenge is to integrate and collate relevant information from all inputs and, in the absence of a primary joining key, the best technique to utilize is name matching or text matching.

**Action**

The actions based on the “prediction” stage are primarily to design adherence strategies that
include changing dosage and delivery, education and communication, such as behavioral coaching/patient education, program reminders and financial assistance (i.e., co-pay discounts, etc.). However, these activities need to be assisted by additional analysis and modeling exercises.

- **Patient segmentation based on adherence score and rationale:** Targeting strategy needs to vary according to patient behavior. For example, if the reason for non-adherence is frequency of dosages or the method of delivery, stakeholders need to adopt different strategies. In the former case, it might be moving toward longer-lasting medications and hence less frequency, while in the latter case it may be moving from injectible to oral medication.

- **Segmentation of healthcare professionals (HCPs) based on their patient profile:** As the first patient touch point, HCPs play a critical role in adherence. An SDI (formerly Verispan) study suggests that physicians’ choice of language can influence adherence. For instance, patients who were coached by a physician to take their medication regularly had a 21% greater Rx utilization. They need to be informed and coached as well. They can be segmented based on their prescribed population profile (classified as referenced above).

- **Marketing budget optimization:** A multi-channel optimization analysis is needed to decide where investment should be made to reinforce adherence. (This is largely influenced by the ROI analysis undertaken as part of the “measure and track” stage.)

**Looking Forward**

Improvement in adherence quality is necessary for the well-being of patients and the healthcare industry as a whole. Analytics can help rank the patient and physician population, and act as an aid for designing education and other targeting strategies. However, analytics based on “garbage in, garbage out” principles will not fly, given the current immature state of healthcare data, a situation exacerbated by these factors:

- A good number of healthcare and pharma companies do not have a properly functioning data warehouse.
- Many players across the value chain cannot match systems of records with internally supplied data.
- Quality of third-party-supplied data is generally poor.

Given these challenges, the approach that healthcare and life sciences companies should take is to not force complex analytics when and where it is not possible. Successful implementation of analytics therefore becomes a function of data quality and analytical maturity (i.e., management push to use a data-driven approach to inform key decisions). While government initiatives such as “meaningful use” by CMS in the U.S. will create incentives for better data quality, pharma companies and healthcare players should sincerely rethink data strategy – from collection and storage through retrieval – as well as the ROI of such strategies.

Hence, both basic data analysis solutions and complex predictive analytics solutions can be used to solve patient non-adherence challenges. The precise approach will depend on the severity of the problems faced and the ease and pace of the implementation strategy considered by the organization.

**Footnotes**

2. European Federation of Pharmaceutical Industry and Associations.
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