Healthcare

Driving dollars through data: an innovative way to improve self-debt collections

Collecting from self-pay accounts is an increasing challenge for healthcare providers. Approximately 40 percent of all hospitals experience bad debt and/or uncompensated care[1]. Furthermore, self-pay after insurance collection rates dropped over 20 percentage points between 2020 and 2021, going from 76 percent to 55 percent[2]. These trends are likely to persist as high deductibles mean individual patients are responsible for greater shares of their healthcare bills.

Few healthcare providers are well equipped to manage outstanding debt, especially given shortages of revenue professionals[3]. It's time-consuming to chase collections and difficult to decide when to consider writing off an amount as bad debt. Poor decisions can lead to patient friction and hurt satisfaction scores. Yet aging receivables also represent revenue that providers need to improve cash flows and overall patient care.

Segmenting accounts receivables can enable healthcare providers to collect more revenue owed to them while making the best use of their resources. In short, using artificial intelligence and machine learning (AIML) algorithms, outstanding accounts can be segmented and prioritized so that maximum effort could be put toward the accounts most likely to deliver maximum return. Prioritizing patient and payer accounts by propensity to pay can lead to a 10 to 15 percent increase in collections.

Intelligently determining propensity to pay

A critical factor in the success of account segmentation is a tailored approach to scoring accounts that moves away from "one-size-fits-all" methodology. Every patient has unique experiences, health conditions, socioeconomic class and other variables that can positively or negatively impact their ability—and willingness—to pay.

Building a data model for intelligent segmentation is a detailed process that includes analyzing the variables that affect propensity to pay. Creating these models requires expertise in healthcare's unique revenue cycle factors as well as application of AIML algorithms to ensure the model accurately assigns payment probability. An AIML model is built and tested with different types of information, including the following:

- Patient demographics, geographic locations, historical payment behavior and various diagnosis and procedure codes.
- Zip codes, hospital facility type, bill amount and the 3-digit credit score.
- The outstanding amount involved in each of the accounts.

Note that a repeatable and reproducible process is best accomplished with an AIML model. Business rules created on spreadsheets cannot take into consideration multivariate analysis or understand the complex relationships among the variables that drive results. An AIML model can derive repeatable results from any random sample of the relevant data. In contrast, spreadsheets require manual execution, which introduces the opportunity for operator bias, such as applying a "gut feeling" to an account vs. using an objective analysis of how the data variables interact.

After the model is finalized, it is used to score and segment accounts, ranking their propensity to pay as high, medium and low. Healthcare providers can then prioritize and tailor their collection activities based on these scores. For example, instead of working through all the outstanding accounts, a provider can put the greatest effort against accounts ranked as having the highest propensity to pay.

If necessary, the accounts in the high category can be further stratified so providers with limited resources can be confident they are pursuing those with the highest probability of payment. For example, analyses indicate patients with chronic conditions who are older, married and from dual-income households are the most likely to pay. Those paying for a minor, such as a parent or a guardian in their mid-thirties or forties, also tend to have a higher probability of paying. Unmarried younger people without a chronic illness are least likely to pay.

While this means that fewer patients may be contacted, those that are reached represent higher value targets with a high propensity to pay so the effort expended holds the potential for better returns for the provider. Further, models built with AIML algorithms are easier to refresh from time to time with latest payment behaviors, leading to more accurate scoring with time.

Avoiding common account segmentation mistakes

Healthcare organizations and vendors that try to segment accounts without comprehensive data analyses often make choices that can lead to unsatisfactory results. Here's what to avoid:

- **Relying on a single credit score and zip code.** These two variables provide important data points. However, these alone are not sufficient indicators of a patient's ability or willingness to pay. Yet we see collection companies using these variables exclusively to segment accounts. This approach does not capture other key variables that influence propensity to pay, from a patient's age to their geographic location. Propensity to pay scores based on a single factor will most likely be unreliable.
- **Using a one-size-fits-all model.** Some collection vendors apply a single prioritization model to all provider accounts receivables inventories across the U.S. This is an ineffective approach because it doesn't encompass the variables of a provider's specific patient population. Disease and demographic profiles vary widely across geographies, including within a single large metropolitan area. For example, an important variable is the number of alternative provider options available to patients. A patient in a large city has many providers from which to choose, so these patients are less likely to pay as they can just go to another provider the next time they need care. Conversely, patients in a rural town may only have one nearby provider. That makes them more likely to pay so they can continue receiving care from that provider. Applying just one model to all outstanding accounts won't capture these nuances.
- **Ignoring interactions between variables.** As previously mentioned, variables in patient accounts often interact with each other in a way in which manual processes and reviews cannot account. Expanding on the example above, a patient in a metropolitan area

typically has a number of providers from which to choose, lowering propensity to pay. However, if the patient is happy with the healthcare services they received, and the patient currently has a high credit score, then patient satisfaction and the risk of credit score impact could strengthen the likelihood of payment. Evaluation of how one variable may offset two or three others can return completely different outcomes than initial assumptions.

- **Prioritizing high dollar value accounts vs. higher propensity to pay.** It can be a waste of time and money to chase high dollar accounts that have low propensity to pay scores. The effort expended may result in disproportionately low collections. In contrast, putting resources against accounts with higher propensity of payment could net higher returns.

Getting started with intelligent segmentation

Making the effort to segment accounts pays off. For example, a large network based in Tennessee saw a 25 percent increase in collections in comparison to the same period a year prior after intelligently segmenting accounts.

Account segmentation: A real-world report

Situation

A provider was accumulating about $4.5 million monthly in bad debt from unpaid patient accounts. The health system initially used a third-party vendor to attempt collections. That vendor made random calls across the entire base of patients with delinquent accounts. Despite making almost 750,000 calls over approximately nine months, the vendor's collection rate was just 6 percent.

Solution

The provider implemented intelligent account segmentation and prioritized collection efforts based on data analyses yielding patients' propensity to pay scores.

Outcomes

The collection rate increased by 25 percent, with collections in the first month alone being 23 percent greater than before segmentation. The number of calls required to collect decreased to 1.6 from 2.76. Time to collect the first 50 percent of money owed dropped to 2.5 months from 4 months.

It can make sense for a healthcare provider that has operational issues like staffing shortages and budgetary constraints to use an experienced third-party service provider to develop and manage an intelligent segmentation program. Healthcare providers should evaluate service providers with healthcare-specific revenue cycle management (RCM) experience and segmentation models. While every provider will have a unique mix of payer and patient accounts for an AIML model to learn, an experienced vendor likely will have existing models that are well-trained on healthcare receivables idiosyncrasies. These models can reduce deployment timelines and work efforts for providers.

The Healthcare Financial Management Association recommends bad debt should be less than 3% of total expected collections[4]. Intelligent account segmentation enables healthcare providers to make smarter use of their time and resources to achieve such benchmarks. Providers can improve personnel productivity and job satisfaction by prioritizing account follow-up that will result in recouping revenues. Increased productivity can allow providers to also shift personnel to more complex tasks, such as providing pre-registration patient financial counseling. With successful self-pay segmentation, providers can achieve healthier and faster cash flows and a stronger balance sheet.

For more information about account segmentation, visit our website at cognizantrcm.com.

References

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