## White Paper

**Predictive Models for Hospitals**

*Promoting and encouraging strategies for prevention and quality, safety and care coordination*

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How hospitals can benefit from healthcare transformation

Healthcare is undergoing a radical transformation. Reimbursements are moving from volume to value. Single hospitals are being absorbed into larger systems. Physicians are opting for employment over private practice. And consumers, who had few healthcare choices in the past, are now making informed decisions and driving their own care.

How can hospitals benefit from these fundamental changes? Healthcare predictive models are the answer. When designed and implemented using best practices, they can empower hospitals to intelligently acquire new patients, manage populations by providing the right care at the right time, and gain alignment and loyalty from affiliated physicians.

Predictive models enable hospitals to plan for the future to maximize market share, improve patient care, and manage costs.

Understanding predictive models

What value do healthcare-specific predictive analytical models provide? They inform hospitals exactly who their patients are and who may need their services soon. Standard analytics can tell hospitals what happened in the past. Monitoring can tell them what is happening now. But predictive analytics can provide a glimpse into what may happen in the future — so hospitals can plan for it.

PREDICTIVE MODELS ARE:

- Statistical formulas designed to capture trends and relationships between variables. Predictive models are based on detailed, collected data. They are validated and revised as additional data become available.
- Mathematical methods to best analyze a particular problem. Sophisticated development methods produce a simple outcome that is easy to understand.
- Tools used to predict future behavior. In healthcare, predictive models forecast the likelihood of a future health event for individuals. Hospitals can then project future population health needs for strategic planning and communication.

EXAMPLES OF PREDICTIVE MODEL APPLICATIONS:

Predictive models solve problems in a wide variety of contexts. Credit card companies can flag suspicious buying behavior to detect fraud. Consumer websites like Netflix and Amazon can make highly relevant, personalized recommendations. Predictive models revolutionized direct marketing by allowing managers to focus on the individuals most likely to make a purchase.
In healthcare, predictive modeling adds value by identifying individuals most likely to have medical needs. Neural networks are the most useful predictive modeling method for healthcare. Neural networks identify risk by capturing the uniquely complex interaction between healthcare utilization, demographics, medical codes, and visit history.

**HOW DO NEURAL NETWORKS WORK?**

A neural network is a mathematical model that converts input values to an output score through a process called artificial learning. Four key attributes make neural networks effective at understanding health utilization:

1. **Scalable**: neural networks quickly score large data sets, allowing a score refresh with each database update.

2. **Ignore noise**: neural networks automatically identify important variables and ignore others. For example, if RV ownership does not impact diabetes risk, the neural network ignores an ‘RV Owner’ input variable to avoid over-fitting.
3. Identify nonlinearities: many healthcare relationships are complex. For example, aging from 20 to 30 years old has only a small impact on the risk of heart disease relative to aging from 70 to 80 years old.

4. Find interactions: the effect of some variables can be enhanced or mitigated by other variables. For example, heart disease risk increases with age more quickly for males than for females.

Building a smart model

All patients are unique and smart predictive models can help identify specific health risks and needs. A hospital database might contain a patient — we’ll call him John Smith — who is a sedentary, 55-year-old man. John might be considered a typical cardiac patient, given his age and aversion to exercise. His younger wife, Susan (also in the database), is 40 and an avid runner. She doesn’t appear to be an obvious candidate for cardiology services.

Surprisingly, Susan is more likely to need cardiology services than her husband. This insight is possible because her predicted risk scores for heart-related diseases are much higher than John’s. The data reveal that Susan has a family history of heart disease and was recently diagnosed with hypertension.

Patients are not typical and do not always fit a stereotype. Smart predictive modeling enables hospitals to find individuals who need health services. It finds at-risk audiences, so physicians can provide appropriate patient diagnosis and care.

LEGACY MODEL: CLUSTER CODES

In the past, predictive modeling in healthcare was difficult due to a lack of comprehensive and historical patient data. Prior to using predictive models, marketers, statisticians, and clinicians used cluster codes to find prospects.

Cluster codes place households into cohorts that share a set of socioeconomic characteristics. A cluster will typically span a range of ages and incomes, and possibly ethnicity, urbanization, and patterns of consumption. Cluster assignment is based on geo-coded address, with this organizing principle: someone who lives in the same neighborhood as households with known characteristics probably shares those characteristics. Cluster codes use very small geographic divisions such as Census blocks and six-digit postal code extensions. Clusters are given creative names such as “Milk and Cookies” or “Shotguns and Pickups” to evoke images of their lifestyles and associated economic behaviors.

Cluster codes perform well for general, nonmedical household data based on ZIP codes, buying patterns, and generic information. But they don’t enable hospitals to understand a population’s health situation or identify individuals who may soon need certain services.
CONSUMER MODEL

A consumer model is designed to run in an environment in which access to health records is not available. It uses market demographics to predict future health needs for both patients and non-patients.

Every patient in a hospital database should receive a set of scores from multiple (100 or more) patient models. In addition, patients and prospective patients should also receive a set of scores from multiple consumer models, which can be re-calculated monthly for each individual. Including a geo-coded component provides U.S. Census information about the neighborhood where the individual lives.

Hospitals can create consumer and patient models for nearly all service lines and some sub-service line specialties. Some models can also target utilization by encounter type: inpatient, outpatient or emergency services.

Consumer models are trained using only the demographic data for patients who have used medical services for the procedures or diagnoses targeted by the model. When a consumer model assigns a risk score to individuals, it is based on how closely their demographics resemble the patient the model was trained to recognize.
In the examples below, hospitals learn the exact demographics and health risks in a specific geographic area.

The scores are based on output of what the models identify about each person in the database.

EXAMPLE 1

DEMOGRAPHICS
- Male
- Age 45
- Married
- Children present
- Median household income
- ZIP code

CONSUMER SCORES
- Medical cardiology inpatient score: 731
- Diabetes outpatient score: 773
- Noncompliant emergency: 718

EXAMPLE 2

DEMOGRAPHICS
- Female
- Age 60
- Divorced
- No children present
- High household income
- ZIP code

CONSUMER SCORES
- Medical cardiology inpatient score: 537
- Diabetes outpatient score: 443
- Noncompliant emergency: 179

EXAMPLE 3

DEMOGRAPHICS
- Female
- Age 30
- Single
- Children present
- Low household income
- ZIP code

CONSUMER SCORES
- Medical cardiology inpatient score: 324
- Diabetes outpatient score: 394
- Noncompliant emergency: 745

Consumer models are more targeted and economical than cluster coding or random selection.

The solution for each of these individuals is more targeted and economical than cluster coding or random selection. Consumer models serve as predictors for the kinds and quantities of disorders and diseases in a market, helping hospitals to optimize strategic plans by identifying who needs what health service.

PATIENT MODEL

With the widespread adoption of Electronic Health Records (EHRs), hospitals can now obtain an accurate picture of their patient population and make decisions based on real data, not assumptions. A patient model assigns medical utilization risk, taking into account an individual’s medical history. It examines recency, frequency, type, and service line of a patient’s medical visits.

Ideally, the model should use hundreds of demographic data points and all available medical records to predict patients’ future health needs. It should consider the
The same demographic variables used in the consumer model, as well as codes for chronic conditions, personal and family history, evaluation and management, and medical imaging.

The patient model should be trained using the coded medical histories of patients who have utilized medical services for targeted procedures or diagnoses. It can then assign risk scores to ensuing patients based on how closely their medical history resembles the patients it has been trained to recognize.

In the examples below, hospitals can predict what health condition(s) a current or past patient has, and assign them a risk score to give a sense of urgency. The scores are based on the output of what the models identify about each person in the database.

In the examples below, hospitals can predict what health condition(s) a current or past patient has, and assigns that patient a risk score to give a sense of urgency.

**EXAMPLE 1**
Patient has normal cholesterol, diagnosed with patellofemoral pain syndrome (runner’s knee)

**DEMOGRAPHICS**
- Male
- Age 45
- Married
- Children present
- Median household income
- ZIP code

**PATIENT SCORES**
- Medical cardiology inpatient score: 628
- Diabetes outpatient score: 674
- Noncompliant emergency: 568

**EXAMPLE 2**
Patient has personal history of tobacco use, diagnosed with benign essential hypertension (elevated blood pressure)

**DEMOGRAPHICS**
- Female
- Age 60
- Divorced
- No children present
- High household income
- ZIP code

**PATIENT SCORES**
- Medical cardiology inpatient score: 813
- Diabetes outpatient score: 782
- Noncompliant emergency: 709

**EXAMPLE 3**
Patient has family history of heart disease, diagnosed with impaired fasting glycemia (prediabetes)

**DEMOGRAPHICS**
- Female
- Age 30
- Single
- Children present
- Low household income
- ZIP code

**PATIENT SCORES**
- Medical cardiology inpatient score: 660
- Diabetes outpatient score: 627
- Noncompliant emergency: 787
A patient model scores patients higher or lower depending on events in their medical history. Medical codes that appear more frequently prior to the target utilization raise the score, while medical codes appearing less frequently lower the score. The model should also be sensitive to code combinations seen more frequently prior to a visit.

**INTERPRETING CONSUMER AND PATIENT MODEL SCORES**

Consumer models and patient models should be created using several years of pooled de-identified data, preferably from multiple healthcare organizations that present a cross-section of the national population.

An individual’s medical history then allows consumer and patient model scores to be generated at a specified point in time. Hospitals can measure model performance by examining the individual’s medical history following the score.

**SCORE**

Each individual should receive a score of 0 to 999 for each consumer model and patient model. These scores represent risk in an actuarial sense, meaning a relative abstract likelihood of the targeted event occurring within the next 12 months. A score of 800 indicates greater risk than 400, but not necessarily twice the risk; it simply serves as a metric that sorts individuals according to risk.

It is important to note that relative risk is not the same thing as probability. Actual probability of the event occurring for a particular score depends on the utilization rate with which the event occurs in the population, and on the predictive power of the model. The term “risk” can also apply to positive events (for example, obstetrics patients and foundation donors).
LIFT

Lift (and cumulative lift) is a useful metric to convey the predictive power of a model [Figure 1]. It is the factor multiplied by the population utilization rate to produce the rate of utilization for a given score.

Cumulative lift is assessed over a sorted or classified interval of population. A model with a cumulative lift of 5 at 900 means that individuals with a score of 900 or higher have the targeted medical event five times as often as the general population. Describing predictive power in terms of lift as a multiplying factor removes variation in population utilization rate for differing medical events.

Lift extends directly to campaign planning. If 10 percent of the population falls in the 900+ score range, then for the cost of messaging 10 percent of the population, a campaign will reach 5 x 10 percent = 50 percent of the individuals who may have the targeted medical event in the next year. This estimate is possible without knowing the exact service utilization rate. A known utilization rate permits estimates of specific numbers of individuals and medical encounters.

Picking people randomly (no models) has a lift of 1x.

Models with a lift of 5x are five times better at getting to the right person than picking at random.
UTILIZATION CURVE

A utilization curve (also known as a cumulative response curve) extends the concept of lift. It shows the cumulative percent of the total population using services for the targeted medical event (vertical) for the cumulative percent of population as ranked by score (horizontal). Lift is the slope of the curve on the graph in Figure 2. A diagonal line has a lift of 1, and is equivalent to using no model, or to randomly selecting individuals using no criteria. On the left there is high lift where the curve rises sharply. Where the curve rounds out, there is low lift. Where the curve is flat near the top of the chart, there is a lift value less than 1. Messaging individuals in the flat range of the utilization curve is counterproductive, because utilization is concentrated in the high-scoring population. Reading a utilization curve gives a quick sense of the ROI that a model provides.

Quickly see who is at risk for a medical event.
The future of healthcare is hardly certain. CMS programs for value-based purchasing and meaningful use of information technology, combined with other Affordable Care Act provisions and a shifting quality focus, make for a confusing path forward.

Predictive models can help hospitals set and meet goals in the face of uncertainty. They indicate priorities in consumer, patient, and physician engagement to increase satisfaction and improve health outcomes. Knowing individual medical risks empowers economical, data-driven strategies to address them through preventive care and timely interventions.

**Benefit the community: proactively manage population health and optimize health outcomes.**

Predictive models identify and stratify individuals within populations, enabling actions that can save lives. Whether someone is at high risk or is already diagnosed with one or more diseases, hospitals can target an intervention and guide that person to the most suitable physician. They can also plan for utilization and staffing in risk areas by identifying physicians for increased alignment or loyalty. By focusing on those who need it most, hospitals can deliver higher-quality care and ultimately improve outcomes.

**Innovative hospitals engage at-risk patients while reducing costs.**

While hospitals can easily identify high-risk patients from their medical records, predictive models empower them to find moderate-risk individuals — both patients and prospects — before they become high risk. These people benefit most from proactive communications that provide education and encourage a doctor’s visit. Strategic use of consumer and patient models for this purpose combines the predictive model with filter criteria to select patients and prospects with high scores who have not already had a major procedure or diagnosis. When hospitals identify and engage these individuals, they lower their direct costs of care by preventing major medical events.

**Growing market share still matters.**

Growing market share is important to the financial health of many hospitals. Consumer models can map utilization versus risk throughout a service area. Hospitals can then message prospects in areas where consumer model scores indicate higher potential demand for healthcare services.

Used strategically, predictive models can help hospitals offer preventive care, proactively engage patients, and take positive steps toward population health, increased care quality, and proven ROI.
OPTIMIZING MODEL STRENGTH

- **Comprehensive**
  All available data should be collected to create the most accurate and complete view of the market and patient population.

- **Clean**
  Legacy healthcare IT has created a “best-of-breed” approach, meaning there are few places in which integrated data exists. Often data accuracy is less than optimal.

- **Actionable**
  Data without insight is just noise. Disparate information sources (information silos) must be compiled into a centralized database, and scrubbed prior to analysis, to avoid duplication and other inconsistencies. This is a highly organized process that transforms information once designed for specific purposes into a flexible scientific data powerhouse. *Example:* To gain actionable insights, hospitals can use a full demographic data set lined up next to a list of medical histories.

- **Accurate**
  To ensure the database has the best possible information for modeling and reporting, data from a wide variety of sources should be incorporated and linked.

- **Robust:**
  The database must be tailored to represent an individual healthcare market based on specific data sources. Healthcare-specific models should contain hundreds of data sources and represent as much of a given population as possible. Market data points need to be matched to hospital records.

Predictive models should be benchmarked against other healthcare organizations’ medical data when possible. Hospitals can continually improve the quality and accuracy of their models by comparing predicted outcomes to actual outcomes.

Better-informed models mean better predictions and better outcomes for hospitals.

To get to actionable intelligence about patients, include the right data and use the most informed models that predict the most accurate outcomes.
CONCLUSION

Armed with powerful consumer and patient data models, hospitals can reach the right audience with the right message via the right channel at the right time.

Predictive models are advanced mathematical techniques that can be used to more accurately identify individuals in the marketplace based on their health status. They are superior to cluster codes in selecting appropriate patients and consumers for education, disease management, and intervention programs. Predictive modeling is more efficient in reaching the right individuals with the right message, so hospitals can ensure they deliver the right care.

Using predictive model best practices improves targeted population health by helping consumers and patients make healthier choices.
Case Study: A test of Healthgrades predictive models

How effective are Healthgrades consumer and patient models? We performed a comparison test against two other methods commonly used: cluster codes and expert queries.

CONSUMER MODEL VS. CLUSTER CODES

Though cluster codes are designed for the general purposes of marketing and not specifically for healthcare utilization, certain clusters may use certain medical services at higher rates than other clusters. To apply cluster codes to healthcare customers, Healthgrades first cluster-coded patients and prospects in the service area. Then, we performed a detailed analysis of utilization by service line to establish the variation in utilization rates. At this point, lift could be determined for each service and cluster combination. The clusters were ranked from high to low and selected for messaging according to their lift or utilization rate.

While some clusters showed increased lift for certain medical events, clusters typically comprised a small percentage of the population because the population is typically divided into 60 or more clusters. Several clusters needed to be combined to create a campaign that reached a significant fraction of the utilization of the targeted service.

Healthgrades performed a test of cluster codes vs. consumer and patient models for the purpose of messaging patients and prospects for selected service lines (medical cardiology, diabetes, joint replacement, obstetrics and emergency room non-compliance). Scores for the consumer model and patient model were generated for 1.4 million patients and 4 million prospects in the combined service area of a large multi-hospital network using the date Jan 1, 2012. Patient medical history prior to 2012 and utilization in 2012 was available for the test, as was demographic information for all patients and prospects in the service area. Addresses were geo-coded and clusters were applied. Because cluster codes apply to a household, when a model selected a household for messaging, credit was given if anyone in the household utilized the targeted service.

The value of the consumer and patient models is in finding the moderate-risk patients and prospects who have not yet become high-risk patients.
Based on the actual behavior of the people in the study, lift and utilization curves were generated to show the comparative performance of the models. In all comparisons, the consumer and patient models exceeded the performance of the cluster codes. Since cluster codes do not have access to a patient’s medical history when a cluster is assigned, the discussion of cluster-code performance in this section pertains only to consumer models.

For medical cardiology, the top-eight performing clusters comprising about 2 percent of the population of the service area were “Rural Bypasses,” “Social Security Net,” “Modest Income Homes,” “Urban Rows,” “City Dimensions,” “City Commons,” “Simple Living” and “Pacific Heights.” The lift of these combined basic cluster codes was 4.1. Their combined utilization accounts for about 8 percent of total medical cardiology services. By comparison, using the more specific consumer models, the top 2 percent of the population has a medical cardiology lift of 5.5, accounting for 12 percent of the total medical cardiology utilization [Figure 3].

Consumer and patient models do not make accurate patient diagnoses.

As we stated earlier, risk is not the same concept as probability. While the patient may get a high-risk score, the probability of the event occurring may still be low. If only 0.1 percent of the patient population undergoes a certain procedure in one year, then a model that assigns a high-risk score with a lift of 20 will correctly predict the event only 2 percent (0.1 percent x 20) of the time. The value of the consumer and patient model is that you can communicate with future patients far more efficiently and with far less analysis than other methods.

Figure 3

Medical Cardiology Utilization Curve

![Medical Cardiology Utilization Curve](image-url)

*Tapistry is the grouping of the cluster codes included in the case study.
Going deeper into the population, the cluster approach takes the top 22 clusters combined to find 38 percent of the utilization in 17 percent of the population with a cumulative lift of 2.3. At the same list size, the consumer model achieves a lift of 3.6 and accounts for 61 percent of the medical cardiology utilization [Figure 4]. All services examined experienced similar performances. The cluster codes begin to lag behind the consumer model in the most at-risk segments. The performance gap steadily widens as the reach exceeds 20 percent of the population.

The best-performing cluster and service-line combination was a lift of 10.6 for “Dorms to Diplomas” for emergency room non-compliance. Unfortunately, only 0.6 percent of the population in the service area was coded with this cluster. A cluster named “Prosperous Empty Nesters” also had a lift of 0.9 for obstetrics. This signifies that they utilized obstetrics services at a slightly lower rate than average for the service area. The lift indicated that they should not be targeted in an obstetrics campaign, but we know there are women giving birth within this higher-income cluster, and these prospects will be overlooked in a cluster-based obstetrics campaign. A consumer model indicated the specific households where age and presence of children combine with other variables to suggest a higher likelihood of utilization.
There are two principal flaws in using cluster codes for healthcare marketing. The first flaw is that the clusters are not designed based on the characteristics of patients utilizing medical services. Consumer and patient models are essentially clusters based specifically on utilization. It is far more effective to choose a consumer model-based group of households defined by the service line “Medical Cardiology” than it is to piece together several clusters defined by the patterns of consumption by retirees.

The second flaw is the fact that membership in a cluster is exclusive. If your household is labeled “Milk and Cookies,” you cannot also be labeled “Heartland Communities” or “High-Rise Renters.” Therefore, some clusters will be selected at the cost of excluding others. In addition, many excluded clusters contain individuals with a targeted risk, but they are the minority population within a cluster dominated by people with lower risk. Assigning someone a high risk for diabetes prevents assigning that same person a high risk for heart disease. With consumer and patient models, every person receives scores for every model. The highest-risk condition does not conceal other conditions with elevated risk. It is often very useful to investigate populations at risk for multiple related conditions.

Use predictive models to identify whom to include in a communication campaign.

<table>
<thead>
<tr>
<th>Healthgrades Predictive Models</th>
<th>Cluster Codes</th>
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<tr>
<td>Based on healthcare variables and predictive algorithm</td>
<td>Based on non-healthcare variables and clustering algorithm</td>
</tr>
<tr>
<td>Segments market based on differences</td>
<td>Segments market based on similarities</td>
</tr>
<tr>
<td>Predicts individual service use</td>
<td>Predicts group/family behavior</td>
</tr>
<tr>
<td>Based on millions of encounters</td>
<td>Based on 10 variables</td>
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<tr>
<td>Scores based on ICD-9, MS-DRG, CPT categories</td>
<td>Scores based on single market model — around 30 segments</td>
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<tr>
<td>Provides 300+ scores when consumer and patient models are combined</td>
<td>One score per family</td>
</tr>
<tr>
<td>Dynamic, updated and integrated with EHR data in CRM database</td>
<td>Static, stale data that is not integrated with EHR data</td>
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CONSUMER AND PATIENT MODELS VS. EXPERT QUERIES

An expert query is another tool available to healthcare marketers who have access to patient medical records. For certain service lines, good lift can be obtained by only using a few criteria. As a basic example of an expert query Healthgrades created a list for obstetrics utilization based on a target female between ages 24 to 39. This set of individuals comprised approximately 12 percent of the service area population, and accounted for 81 percent of all obstetrics services utilized, for a lift of 6.3. At 12 percent of the population messaged, an expert query found 27 percent of the utilization, with a lift of 2.2. The consumer model found 98 percent of the utilization, with a lift of 7.5. Finding 81 percent of obstetric utilization with the consumer model only required 2.3 percent of the population to be messaged, achieving a lift of 33 [Figure 5].

Finding 81 percent of obstetric utilization with the consumer model only required 2.3 percent of the population to be messaged, achieving a lift of 33.

Expert queries can be combined with other models, such as clusters and consumer models. An expert query can be used as an exclusion criterion to filter selected individuals and households from the campaign. An expert query can also be used as an inclusion criterion to ensure that selected individuals and households are included in the campaign, regardless of inclusion by the model.

In our obstetrics example, when we used the expert query (female aged 24 to 39) as an exclusion criterion, it filtered the prospects to 12 percent of the service area in which 81 percent of the utilization occurs. When cluster codes were applied to the filtered population, there was a small gain due to the few clusters performing better than 6.3 lift, but this occurred only for a fraction of a percent of the population. The
filtered cluster found 70 percent of the obstetrics utilization in 8.6 percent of the population, an 8.1 lift. The consumer model did not get a significant boost from the expert criteria. The exclusion criteria constrained the consumer model to selecting no more than 81 percent of the utilization because, while small, the remaining obstetric utilization occurred for women outside the 24-to-39 age range. The consumer model found most of this utilization by considering other demographic variables.

Using the expert query as an inclusion list added no performance to the obstetrics consumer model because the consumer model was already trained to select nearly every one of the prospects that are selected by the filter. The combination of the inclusion list and cluster codes performed no better than the filter alone because the filter selected nearly every one of the prospects coded by the high-utilization clusters.

Our obstetrics example was limited to prospects, and it used criteria that did not require medical expertise to design. When campaigns are limited to the patient population, marketers can select the campaign target based on diagnosis and prior visits. These criteria will require medical expertise and knowledge of medical coding. As an exclusion filter becomes more detailed, it restricts the list to a smaller number of patients. An expert query can be elaborately designed to conditionally include patients based on a tree of decisions. Designing a set of advanced expert criteria is limited only by the data available and the resources with which to analyze it.

Healthgrades has found that advanced expert queries can perform at a level comparable to a patient model for specific conditions and procedures within a service line. It is, however, very difficult for a human to write a comprehensive set of criteria to achieve patient model lift for a more generally defined service line combining a variety of related procedures and conditions. Our experience working with consumer and patient models has shown that a simple set of expert criteria can augment the performance of a predictive model when applied either as an exclusion filter or inclusion list pertaining to specific diagnoses and procedures.

Using an expert query to match the predictive power of Healthgrades consumer and patient models requires considerable resources, and means essentially developing hospital-specific models. However, expert queries do consistently outperform cluster codes, especially when patient data is available.

Our experience working with consumer and patient models shows that a simple set of expert criteria can augment the performance of a predictive model when applied as an exclusion filter or inclusion list.
About Healthgrades

We’re not simply experts in patient and physician engagement. We actually invented Health Relationship Management nearly 25 years ago. Let us show you engagement solutions that combine evidence-based, multichannel communications with a business intelligence platform to build relationships, influence behaviors and improve healthcare utilization — all with a measurable contribution margin for your hospital.

To learn about communications solutions that improve health and financial outcomes, and to discover an entire suite of solutions that are already empowering more than 1,000 hospitals across America, call 855.665.9276 or visit healthgrades.com/hospitals.