### c. The "Nuts & Bolts" of the acgPM Model

#### i. Specifying the Predictor Variables

The acgPM modeling strategy makes use of the comprehensive array of morbidity metrics that are available within ACGs. The model incorporates the morbidity-based ACGs, selected disease-specific EDCs, and a newly developed diagnostic indicator of the likelihood that someone will be hospitalized in an ensuing year. We have also added an indicator of the level of prior pharmacy use.

First, a brief word on the issue of prior-use measures. Prior use is a fallible indicator of future use because it includes many acute conditions that get resolved. The acgPM focuses on individuals with a high morbidity burden and with high-impact chronic conditions that are likely to continue to require significant health care resources. Prior-use measures are also not appropriate as "risk factors" for "risk-adjusted" rate setting or profiling as they potentially could provide incentives to overuse resources. That is, providers can readily increase the risk rating of their patient (and potentially reimbursement) simply by ordering more services. Including prior use is appropriate for high-risk case identification since the goal is to identify and potentially intervene among high-cost users. Several alternative prior-use measures were assessed for inclusion in the acgPM model, but levels of previous pharmacy expense proved to be the most powerful resource predictor with the clearest clinical implications and with a minimal addition to the burden of data collection.

The acgPM "risk factor" variables used in the model are as follows:

- age (seven age groups from infants to 64 years of age),
- sex,
- ACGs (three broad morbidity groupings from low to high in addition to selected individual ACGs),
- a "hospital dominant" marker (reflecting diagnoses where hospital care was "dominant," though care could be provided in a variety of settings),
- identification of pregnancy, where no delivery has yet occurred,
- pharmacy expense levels, and
- EDCs (a limited set that represent high impact and chronic conditions).

Specific EDC disease markers were incorporated into the model if they represented

- common high-cost chronic conditions that were frequent targets for disease management programs,
- uncommon, but high impact on both cost and health, conditions,

- conditions for which the evidence linking health care to outcomes is strong,
- complications that potentially signify instability in a chronic illness. (e.g., retinopathy), or
- conditions that are a major biologic influence on health status (e.g., transplant status, malignancy).

The focus of the current acgPM software release is on the non-elderly (i.e., under 65 years of age) population.

The specific ACGs and EDCs that were used in building acgPM are documented in **Appendix 1.**

### ii. Defining the Model Outputs

As noted earlier, the acgPM model offers two types of outputs: a probability score of being a member of the high-risk[1] group next year and a predicted resource index reflecting expected cumulative resource use. The two indicators are intended for different purposes (case selection for the former and cost estimation for the latter) and benefit from somewhat different statistical methodologies. Probability scores range between zero and one. For example, conceptually, an individual with a probability score of .4 has a 40 in 100 chance of being in the high-risk cohort next year. The predicted resource index ranges from zero to roughly 40 with a population mean of 1.0. The index can be readily converted to a predicted dollar amount. These two outputs are repeated for both total costs and for pharmacy costs only.

The Johns Hopkins ACG development team chose to use logistic regression (logit) to develop the probability score for a patient becoming a member of the high-risk group next year. This is an important departure from the prevailing strategies for high-risk case identification that usually employ ordinary least squares (OLS) regression based on linear modeling strategies. Logit models are best for predicting events (yes/no occurrences)—in this case, being a high user of resources

In terms of estimating resource use using multivariate methods, regression is the most effective strategy for estimating dollars. Therefore we used an OLS model for the resource-use prediction component of our model. The acgPM's predicted resource index is presented as a

[2] Based upon repeated testing of alternative thresholds, for model development we have defined "high risk" to represent individuals whose predicted costs for the following year are expected to fall within the top 5% of a plan's members. This choice of high risk definition does not preclude users from adopting other definitions, e.g., the top 1%, ½ or 1% or even top 10% of plan members.

relative value that can be adjusted to reflect local mean costs. This adjusted scale can be readily converted into dollar amounts comparable to future cost estimates by a simple algebraic process. The process for deriving dollar values is discussed later in this chapter.

### d. A Framework for Discussing the Performance of Predictive Models

There are many different ways to apply the acgPM model, and each organization will have unique data and contextual issues. Furthermore, there are few standard approaches in the literature for evaluating the "accuracy" of any predictive model for resource use. Thus assessing and reporting the performance of predictive models is not straightforward. We are providing users with several alternative ways to assess performance because ACG users tend to be discerning with regard to appropriate methods and statistical techniques.

What follows is a summary of an evaluation that assessed the performance of our models in helping to identify persons who are members of high-risk/high-cost cohorts in the subsequent year. We tested the models using actual data from a very large data set, consisting of over two million lives enrolled in several health plans. We adopted a split half approach, using a random selection of half the observations to build the models and the other half of the observations to validate the model. The performance figures reported in the following section are based on the validation half of the data. Unless otherwise specified, we apply the version of our model that includes pharmacy cost as one of the risk factor inputs.

One way to assess predictive models is to ascertain how well they classify cases as actually being a member of a high-risk group in a future period. This yes/no accuracy assessment is similar in many ways to the statistical/epidemiologic approaches that are used to assess the accuracy of diagnostic screening tests or exams. However, this quantitative approach does not tell the full story regarding model performance. Other important questions are, What are the prediction characteristics of the model? and Can it aid in the identification of cases where intervention is possible and where care can be improved? There is no explicit "test" to determine this result, but our performance assessment attempts to consider this capability as well.

Epidemiologists often use sensitivity and specificity to assess the validity of screening tests. These performance indicators are defined as follows:

- Sensitivity is the percentage of true high-risk cases that are successfully identified:

Sensitivity = true positives/(true positives + false negatives).

- Specificity is the percentage of true low-risk cases that are successfully identified:

  Specificity = true negatives/(true negatives + false positives).

Specificity is not especially useful in assessing this or any other predictive model since the focus is on only a very small subset of high-risk persons and a large number of true negatives. Positive predictive value (PPV) represents a potentially more useful alternative to sensitivity.

- PPV is defined as the probability that someone predicted by the model to have high expected Year 2 resource use does, in fact, have high Year 2 resource use. Mathematically, this is expressed as:

  PPV = true positives/(true positives + false positives).

A PPV score gives information about the likelihood that a person who tests "positive" (in this case is predicted to be high-risk) actually will be a high-resource user in Year 2.

Finally, another widely used measure of the ability of such models to correctly classify patients is the c-statistic. The c-statistic provides an overall measure of model performance and represents the probability that an observation is correctly classified as a true positive or true negative along a continuum of "test thresholds" (in this case probability score thresholds). The closer the c-statistic is to 1.0, the better the model. For a summary of these and other performance indicators that are often applied to diagnostic tests and predictive models, see Appendix 2.

### e. Performance of the acgPM Model

We sought to assess our model's performance by asking several key questions:

- How well does acgPM improve upon prior cost alone in identifying high-risk cases?
- Do the cases identified by the model represent a group meriting intervention?
- How well does acgPM do in estimating future costs of care?
- What added predictive value is gained by including the optional pharmacy cost predictor?

### i. How Well Does the acgPM Improve on Prior Cost Alone in Identifying High-risk Cases?

The statistical properties of the acgPM total cost model are compared to prior cost only predictions in Table 2. The performance of the acgPM is shown with respect to a series of probability "thresholds" based on the prediction scores output by the model for all members of a large health plan "test" population.

Table 2 shows the acgPM's accuracy at six different probability score cut-offs within the large health plan test population of about 410,000 persons (under the age of 65 years). By setting the risk threshold low, e.g., .4 or higher, a higher percentage of cases is included (in the example, about 1.33% of the population). Set the risk threshold higher and select a lower percentage of cases (only 0.10% at a minimum threshold of .9 or higher). Thus certainty, expressed as the PPV, comes at a price. By setting a high threshold, you come close to certainty that every case you select will become high cost in Year 2. Set a lower threshold and there is less certainty but a higher likelihood that you're picking up all the potentially high-cost cases. Even with probability floors as low as .4, the likelihood is still better than chance (via PPV) that an acgPM-predicted high-risk patient will actually turn out to be a high consumer of resources.

For comparison purposes, in Table 2 we also show performance statistics associated with using prior cost as the only predictor in an identically sized group. That is, we identified the highest cost individuals from Year 1 on the basis of actual experience. This "prior cost" cohort was selected to be exactly the same size as the number of individuals identified using the various acgPM probability thresholds (see the proportion of population in column 2 of Table 2.

Table 2 indicates that the acgPM consistently outperforms prior cost in predicting actual Year 2 cost. Sensitivity for both the acgPM and the prior cost groups is low given that these represent very small highly targeted groups and thus do not capture many cases. However, as the PPVs suggest, most of the identified cases turn out to be truly high cost in the following year.

**Table 2. Model Performance (Total Cost) at Different acgPM Probability Scores vs. Same-sized Prior Cost Cohort**

| Probability Score Threshold | Percentage of Population | acgPM | | Prior Cost* | |
|---|---|---|---|---|---|
| | | Sensitivity | PPV | Sensitivity | PPV |
| .4 | 1.33% | 0.16 | 0.59 | 0.12 | 0.46 |
| .5 | 0.89% | 0.12 | 0.66 | 0.09 | 0.50 |
| .6 | 0.63% | 0.09 | 0.72 | 0.07 | 0.54 |
| .7 | 0.42% | 0.06 | 0.76 | 0.05 | 0.57 |
| .8 | 0.25% | 0.04 | 0.80 | 0.03 | 0.62 |
| .9 | 0.10% | 0.02 | 0.84 | 0.01 | 0.69 |

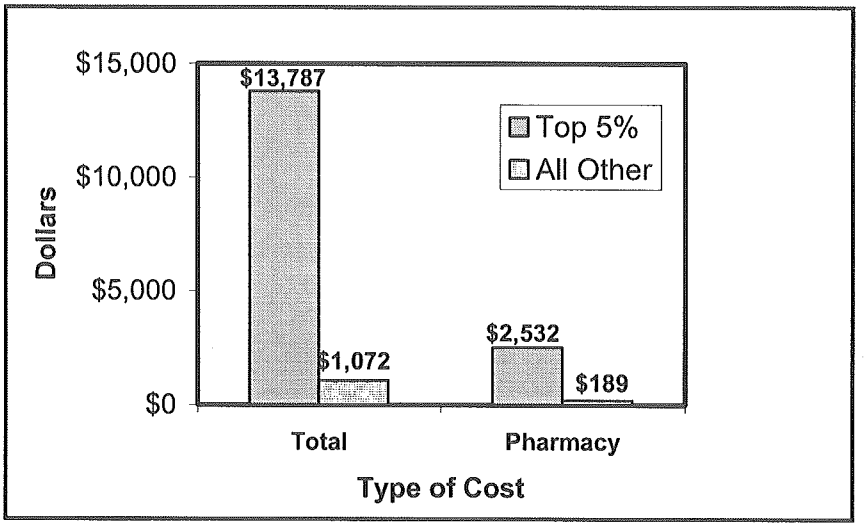
Based on a validation sample of approximately 410,000 covered lives.

* Prior cost cohorts were chosen to the same size as acgPM high-cost cohorts, i.e., if selecting cases with an acgPM probability score of .7 or higher yielded 100 predicted high-risk patients, the prior cost comparison would be the 100 cases at the highest Year 1 cost.

### ii. Do the Cases Identified by the Model Represent a Group Meriting Intervention?

There is a clear distinction in terms of mean cost between cases identified by the acgPM as potentially high-risk and those not so identified. As shown in Figure 3, predicted high-risk cases proved to be nearly 13 times as expensive in actual Year 2 dollars as those not so identified. Individuals identified as being high-risk for pharmacy service use were almost 14 times as expensive as those not so identified. The model, thus, is identifying cases that are quite distinct in terms of very high resource use.

**Figure 3. Mean Costs of High-risk Versus All Other Cases by Cost Category**




***With an acgPM probability score of 0.4 or higher.**

The model also preferentially captures cases with chronic conditions for which case management services are often available. As shown in Table 3, the acgPM-identified "at-risk" group includes a higher percentage of these potentially case manageable chronic conditions than does prior cost.

**Table 3. Percentage of Selected Chronic Conditions in "High-risk" Cohorts Identified by acgPM and Prior Cost Approaches.**

| Condition | Percentage of High-risk Cohort | |
|---|---|---|
| | acgPM | Prior Cost |
| Hypertension | 37.91 | 26.96 |
| Low Back Pain | 27.42 | 17.19 |
| Diabetes | 24.00 | 13.39 |
| Ischemic Heart Disease | 17.83 | 22.72 |
| Arthritis | 17.26 | 13.33 |
| Lipoid Metabolism | 21.49 | 13.30 |
| Congestive Heart Failure | 8.45 | 7.42 |
| Asthma | 14.03 | 6.87 |
| COPD | 10.01 | 7.05 |
| Depression | 11.00 | 4.85 |
| Chronic Renal Failure | 5.66 | 5.40 |

### iii. How Well Does acgPM Do in Estimating Future Costs of Care?

The acgPM offers a predictive resource index that is a relative value for resource use related to both total and pharmacy costs in Year 2. This relative value can be used for many applications including the estimation of future expenditures for specific subgroups of patients who are targeted for case management. The probability model results and the linear modeling results can work in tandem. The acgPM's probability score output is recommended for selecting patients, while the predictive resource index is recommended for calculating expected costs (or potential cost savings) for population subgroups.

The R-squared statistic is commonly used to assess the performance of OLS-based linear models. The R-squared expresses the percentage of variation in the outcome variable that is explained by the model. We believe this is an appropriate evaluative benchmark for cost predictors calculated on a linear basis (in our case the relative weight for resource use) but not for yes/no logistic predictions (such as our risk probability score). When assessing our predicted resource index model, the performance characteristics of the acgPM are comparable to prior cost: the acgPM explains 14% of the variation in total charges compared to 12% for prior cost.

### iv. What Is the Performance "Bonus" if Pharmacy Cost Data Are Available as a Risk Factor?

When they are available, we encourage the use of pharmacy cost data as a source of risk-factor information[2]. The acgPM performance statistics presented in the preceding text are based on models that include pharmacy cost as an input variable. We compare the performance of the acgPM probability score based on models with and without pharmacy cost data in Table 4. While there is added information if pharmacy costs are available, if they are not available, the performance penalty is not high, especially in predicting total costs.

[3] The acgPM model includes a simple five category variable based on previous pharmacy cost history. Each person is placed into one of five groupings, from very low to very high.

**Table 4. Performance Characteristics of acgPM with and without Inclusion of Prior Pharmacy Cost as a Risk Factor**

| Model | Sensitivity | PPV | C-Statistic |
|---|---|---|---|
| | | | |
| acgPM Total Cost | 3 | 66 | 0.79 |
| acgPM Total Cost with Pharmacy | 9 | 72 | 0.81 |
| acgPM Pharmacy Cost | 6 | 60 | 0.87 |
| acgPM Pharmacy Cost with Pharmacy | 32 | 71 | 0.93 |

Model performance data are based on an acgPM probability score threshold of 0.6, representing approximately half of 1% of the population for total cost and the top 2% of the population for pharmacy costs.

The inclusion of prior pharmacy costs as a predictor variable for the predicted resource index has little impact on the model's R-squared associated with total cost (.14 up from .11). However, the addition of the pharmacy categorical cost information does have a significant impact on the R-squared associated with prediction of next year's pharmacy use (.34 up from .17).

Understandably, it does appear that prior pharmacy cost is an important factor in predicting future pharmacy costs. Users who wish to focus on pharmacy cost would be advised to incorporate prior cost data if they are available.

### f. Reports

The software currently puts two reports into the ACG output stream: and (1) High Risk Individuals and Expected Resource Use by Disease Category and (2) Frequency and Percent Distribution of Probability Scores. Each report is discussed below.

#### i. High Risk Individuals and Expected Resource Use by Disease Category

This report (see Figure 4) shows how your population is distributed by EDC category and how they are predicted to consume resources among some of the "riskier" probability levels. The columns represent a range of probability scores from a minimum value to the highest reported value. The 11 EDCs represent chronic conditions that are often the subject of case and disease management initiatives. For an example of how to use this report see the following section (Application Issues).

## Figure 4. acgPM Report One.

Table 5A. The Number of Cases and Associated Predicted acgPM Relative Resource Use by Alternative acgPM Risk Probability Thresholds for Selected Chronic Conditions

| | | Number of Cases | | | Mean Predicted Relative Resource Use | | | |
|---|---|---|---|---|---|---|---|---|
| | | Probability Score Category | | | Probability Score Category | | | |
| Condition | Total | >=0.4 | >=0.6 | >=0.8 | <0.4 | >=0.4 | >=0.6 | >=0.8 |
| Arthritis | 33151 | 1745 | 570 | 189 | 2.3468 | 11.4409 | 17.5739 | 24.7928 |
| Asthma | 51260 | 1697 | 550 | 171 | 1.5370 | 9.9019 | 15.3937 | 22.0877 |
| Diabetes | 33207 | 3425 | 1442 | 552 | 3.2615 | 13.0168 | 18.2980 | 25.7959 |
| Hypertension | 87165 | 4308 | 1685 | 660 | 2.2534 | 13.0622 | 19.3029 | 26.3734 |
| Ischemetic Heart Disease | 18412 | 2479 | 966 | 372 | 3.9585 | 12.7378 | 18.3667 | 25.2287 |
| Congestive Heart Failure | 3473 | 1194 | 642 | 304 | 7.0640 | 16.7073 | 21.4372 | 27.5916 |
| Hyperlipidemia | 50168 | 1914 | 621 | 215 | 2.1891 | 11.4765 | 17.3417 | 23.9408 |
| Low Back Pain | 111080 | 4219 | 1049 | 319 | 1.8185 | 9.0035 | 15.4531 | 22.4705 |
| Depression | 18405 | 1286 | 367 | 112 | 2.3574 | 9.3546 | 14.4691 | 22.2320 |
| Chronic Renal Failure | 821 | 296 | 234 | 159 | 7.6968 | 25.7199 | 28.5952 | 32.0830 |
| COPD | 10920 | 1282 | 573 | 221 | 2.8903 | 13.1668 | 18.4649 | 24.9244 |

### ii. Frequency and Percent Distribution of Probability Scores

This report (see Figure 5) is intended to provide you with a sense of how your population is distributed according to probability score. The information is intended to help you establish the size of potential cohorts for case/disease management. This distribution will, of course, change within specific EDCs.

## Figure 5. acgPM Report Two.

Table 5B. Frequency and Percent Distribution of Probability Scores

| Probability Score | Number | Percent | Cumulative Percent |
|---|---|---|---|
| 0.90 or higher | 621 | 0.03 | 0.03 |
| 0.80-0.89 | 828 | 0.04 | 0.07 |
| 0.70-0.79 | 1172 | 0.05 | 0.12 |
| 0.60-0.69 | 1834 | 0.09 | 0.21 |
| 0.50-0.59 | 4446 | 0.21 | 0.42 |
| 0.40-0.49 | 19111 | 0.89 | 1.31 |
| 0.30-0.39 | 9838 | 0.46 | 1.77 |
| 0.20-0.29 | 26299 | 1.23 | 3.00 |
| 0.10-0.19 | 138757 | 6.48 | 9.47 |
| <0.10 | 1938946 | 90.53 | 100.00 |
| Total | 2141852 | 100.00 | |

## g. Application Issues

### i. Using the acgPM Case Management Report

As described in the section on model performance, the acgPM identifies a group of patients distinct from those who would have been selected by prior cost alone. Further, this group of patients appears to have a higher percentage of those who are typically case managed. To illustrate how the model might be used to better target individualized case management

interventions, we provide a sample output report (Table 5) as produced by the acgPM software (if users request this with a control card). For a series of probability thresholds, the table shows how individuals in a large health plan are distributed within selected chronic disease groups and how their acgPM predicted resource use varies for each risk-level cohort. The diseases represent a sampling of some of the conditions for which "disease management" or "case management" services are often available within an integrated delivery organization.

These chronically ill patients are all projected to use resources well above the plan's average (of 1.00). In a comparison of the three potential "case management" cohorts defined on the basis of the three alternative acgPM probability score thresholds (i.e., .4 or higher, .6 or higher, .8 or higher), the projected intensity of resource use generally doubles from the lowest to highest risk group within each disease. Moreover, when resource use in the top acgPM risk category (with a score of .8 or higher) is compared with the cohort of persons with the disease, but who were not identified as being in one of the top tier risk groups (i.e., those with probability score of less than .4), the predicted expenditure variation is dramatic—at times almost ten-fold.

Persons with chronic renal failure experience very high predicted resource use within all of the probability score cohorts. To a lesser degree, the same is true for congestive heart failure. For conditions such as these, projected resource use appears to be high regardless of the probability level. Aside from employing individualized case management, it may be especially appropriate to employ disease management programs that address the cohort of patients with these diseases. It is evident that persons within each disease group will require a different approach to care management, but the various predictive measures produced by the acgPM system will provide valuable additional information to allow clinical professionals to better design and implement these interventions.

All of the remaining diseases that are depicted in Table 5 appear to be appropriate candidates for case management. To have the greatest impact, it would be useful to focus on those individuals at higher predictive risk levels who are currently experiencing relatively low resource use. Our experience suggests that at least 10% of patients will fall into this group.

Finally, it is important to consider the comorbidity profiles of these high-risk groups. It is likely that high risk cases are affected by multiple diseases and that the condition reported in

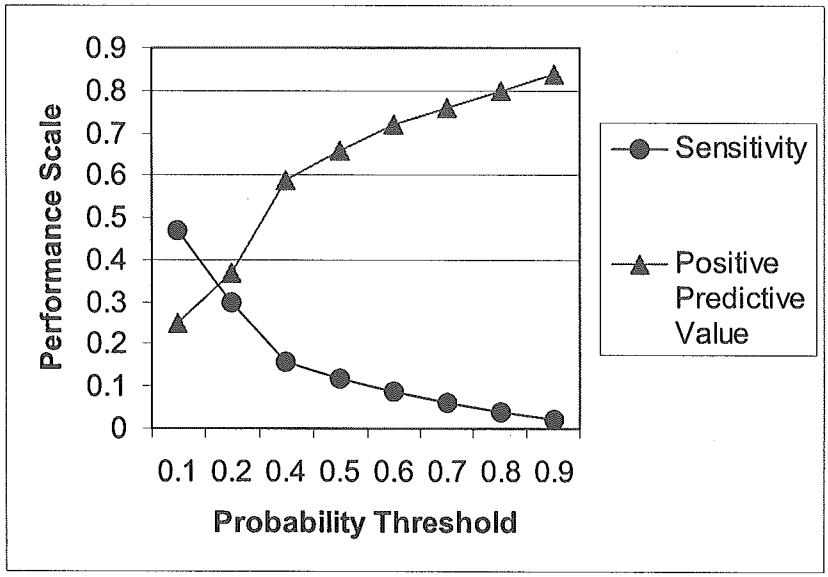
Table 5 may not be the primary cost driver. Thus patterns of comorbidities should also be assessed in the course of planning case management initiatives.

**Table 5. The Number of Cases and Associated Predicted acgPM Relative Resource Use by Alternative acgPM Risk Probability Thresholds for Selected Chronic Conditions**

| | | Number of Cases | | | Mean Predicted Relative Resource Use | | | |
|---|---|---|---|---|---|---|---|---|
| | | Probability Score Category | | | Probability Score Category | | | |
| **Disease Category** | **Total** | **≥0.4** | **≥0.6** | **≥0.8** | **<0.4** | **≥0.4** | **≥0.6** | **≥0.8** |
| Arthritis | 17,679 | 940 | 463 | 172 | 2.18 | 9.22 | 11.69 | 15.71 |
| Asthma | 27,863 | 764 | 386 | 136 | 1.43 | 9.02 | 11.25 | 14.85 |
| Diabetes | 16,991 | 1,307 | 716 | 345 | 2.67 | 11.03 | 13.87 | 17.36 |
| Hypertension | 50,122 | 2,064 | 1,011 | 457 | 2.06 | 10.34 | 13.57 | 17.57 |
| Ischemic Heart Disease | 9,330 | 971 | 514 | 242 | 3.27 | 10.70 | 13.64 | 17.33 |
| Congestive Heart Failure | 1,634 | 460 | 292 | 184 | 5.17 | 13.94 | 16.90 | 19.61 |
| Hyperlipidemia | 31,240 | 1,170 | 529 | 186 | 1.97 | 9.15 | 11.59 | 15.46 |
| Low Back Pain | 61,980 | 1,493 | 723 | 279 | 1.76 | 8.64 | 10.89 | 14.27 |
| Depression | 10,190 | 599 | 298 | 113 | 2.09 | 8.82 | 11.03 | 14.30 |
| Chronic Renal Failure | 742 | 308 | 253 | 183 | 13.11 | 22.33 | 23.60 | 25.21 |
| COPD | 6,204 | 545 | 301 | 147 | 2.58 | 10.84 | 13.38 | 16.68 |

There are trade-offs involved in setting probability threshold levels for case identification. The higher the minimum probability, the greater the projected resource use, but also the smaller the target group. As noted earlier, higher probabilities also improve the likelihood that cases identified do indeed turn out to be high resource users. The performance implications at a range of thresholds based on the acgPM probability score among a large test population are depicted graphically in Figure 6.

**Figure 6. Trends in Model Performance, by Probability Threshold**




The user's choice of a case identification probability threshold relates to the desired application, availability of resources for case management, and prevailing local practices. Depending on the intervention an organization might prefer to maximize sensitivity, while at other times, maximization of predictive value might be the goal. For example, when implementing a customized web-based informational campaign within a health plan, the goal may be to contact the highest 5% or 10% of the persons "at-risk." This goal could represent all those persons with a probability score of .1 or higher. Based on the sensitivity of the model at these probability levels, it may be possible to capture over 50% of those persons who will be members of the highest resource use cohort next year. However, the PPVs for this group will be in the .25 range, and thus most of these individuals will not actually be members of the highest resource use group next year. But given the non-intensive nature of the intervention, that is of small concern. Moreover, even the individuals targeted for this program who do not end up in the highest resource group in the subsequent period (the false positives) will still have risk and associated resource use that is far higher than the underlying population.

Many types of individualized case management can be quite resource-intensive in their own right, and so there should be a high likelihood that persons targeted for case management are, in fact, truly high risk. Thus for these types of programs, very high PPVs are desirable. Still, many patients who might be appropriate candidates for case management will be excluded from

selection, given the corresponding low sensitivities. It should be noted that even when cases are included that have probabilities as low as .4, the overall odds of these individuals being very high resource users next year are still much higher than random. In this case about 60% will be high risk next year compared to 5% of the population overall if selected at random.

For individualized case management programs, having access to current and predicted resource use data for candidate individuals can be of real utility in setting priorities for inclusion. When there are more persons who would likely benefit than current program resources allow, these data could be used to help make an argument for expanding such resources on the basis of the potential return on investment (ROI). Using the approach described below (see the section entitled Adjusting Relative Weights to Compute Predicted Costs), you can assign a projected cost to each individual within your targeted high-risk group. Ordering this population by the difference between current and projected cost will quickly highlight those individuals for whom case management has the greatest potential.

# APPENDICES

## Appendix 1. ACGs and EDCs Included in the acgPM

**ACGs**

| |
|---|
| 4220: 4-5 Other ADG Combinations, Age 1-17, 1+ Major ADGs |
| 4330: 4-5 Other ADG Combinations, Age 18-44, 2+ Major ADGs |
| 4420: 4-5 Other ADG Combinations, Age >44, 1 Major ADGs |
| 4430: 4-5 Other ADG Combinations, Age >44, 2+ Major ADGs |
| 4510: 6-9 Other ADG Combinations, Age 1-5, No Major ADGs |
| 4520: 6-9 Other ADG Combinations, Age 1-5, 1+ Major ADGs |
| 4610: 6-9 Other ADG Combinations, Age 6-17, No Major ADGs |
| 4620: 6-9 Other ADG Combinations, Age 6-17, 1+ Major ADGs |
| 4730: 6-9 Other ADG Combinations, Male, Age 18-34, 2+ Major ADGs |
| 4830: 6-9 Other ADG Combinations, Female, Age 18-34, 2+ Major ADGs |
| 4910: 6-9 Other ADG Combinations, Age >34, 0-1 Major ADGs |
| 4920: 6-9 Other ADG Combinations, Age >34, 2 Major ADGs |
| 4930: 6-9 Other ADG Combinations, Age >34, 3 Major ADGs |
| 4940: 6-9 Other ADG Combinations, Age >34, 4+ Major ADGs |
| 5010: 10+ Other ADG Combinations, Age 1-17 No Major ADGs |
| 5020: 10+ Other ADG Combinations, Age 1-17, 1 Major ADGs |
| 5030: 10+ Other ADG Combinations, Age 1-17, 2+ Major ADGs |
| 5040: 10+ Other ADG Combinations, Age 18+, 0-1 Major ADGs |
| 5050: 10+ Other ADG Combinations, Age 18+, 2 Major ADGs |
| 5060: 10+ Other ADG Combinations, Age 18+, 3 Major ADGs |
| 5070: 10+ Other ADG Combinations, Age 18+, 4+ Major ADGs |
| 5320: Infants: 0-5 ADGs, 1+ Major ADGs |
| 5330: Infants: 6+ ADGs, No Major |
| 5340: Infants: 6+ ADGs, 1+ Major ADG |
| Pregnancy w/out Delivery |

**EDCs**

| |
|---|
| ADM04: Complications of Mechanical Devices |
| ALL04: Asthma, w/o status asthmaticus |
| ALL05: Asthma, WITH status asthmaticus |
| ALL06: Disorders of the Immune System |
| CAR03: Ischemic heart disease (excluding acute myocardial infarction) |
| CAR04: Congenital heart disease |
| CAR05: Congestive heart failure |
| CAR06: Cardiac valve disorders |
| CAR07: Cardiomyopathy |
| CAR09: Cardiac arrhythmia |
| CAR14: Hypertension, w/o major complications |
| CAR15: Hypertension, WITH major complications |
| END02: Osteoporosis |
| END09: Type 1 Diabetes with major complicating condition |

| |
|---|
| END08: Type 1 Diabetes w/o major complicating condition |
| END07: Type 2 Diabetes with major complicating condition |
| END06: Type 2 Diabetes w/o major complicating condition |
| EYE13: Diabetic Retinopathy |
| GAS02: Inflammatory bowel disease |
| GAS05: Chronic liver diseases |
| GAS06: Peptic ulcer disease |
| GAS12: Chronic pancreatitis |
| GSI08: Edema |
| GSU11: Peripheral vascular disease |
| GSU13: Aortic aneurysm |
| GSU14: Gastrointestinal Obstruction/Perforation |
| GTC01: Chromosomal anomalies |
| GUR04: Prostatic hypertrophy |
| HEM01: Hemolytic anemia |
| HEM05: Aplastic anemia |
| HEM06: Deep vein thrombosis |
| HEM07: Hemophilia, coagulation Disorder |
| INF04: HIV, AIDS |
| MAL02: Low impact malignant neoplasms |
| MAL03: High impact malignant neoplasms |
| MAL04: Malignant neoplasms, breast |
| MAL06: Malignant neoplasms, ovary |
| MAL07: Malignant neoplasms, esophagus |
| MAL08: Malignant neoplasms, kidney |
| MAL09: Malignant neoplasms, liver and biliary tract |
| MAL10: Malignant neoplasms, lung |
| MAL11: Malignant neoplasms, lymphomas |
| MAL12: Malignant neoplasms, colorectal |
| MAL13: Malignant neoplasms, pancreas |
| MAL14: Malignant neoplasms, prostate |
| MAL15: Malignant neoplasms, stomach |
| MAL16: Acute Leukemias |
| MAL18: Malignant neoplasms, bladder |
| MUS10: Fracture of neck of femur (hip) |
| MUS14: Low back pain |
| NUR05: Cerebrovascular disease |
| NUR07: Seizure disorders |
| NUR08: Multiple sclerosis |
| NUR09: Muscular dystrophy |
| NUR12: Quadriplegia and Paraplegia |
| NUR15: Head Injury |
| NUR16: Spinal Cord Injury/Disorders |
| NUR17: Paralytic Syndromes, Other |
| NUR18: Cerebral Palsy |
| NUR19: Developmental disorders |
| NUT02: Nutritional deficiencies |

| |
|---|
| PSY01: Anxiety, neuroses |
| PSY03: Tobacco abuse |
| PSY05: Attention deficit disorder |
| PSY07: Schizophrenia and affective psychosis |
| PSY08: Personality disorders |
| PSY09: Depression |
| REC01: Cleft lip and palate |
| REC03: Chronic ulcer of the skin |
| REN01: Chronic renal failure |
| RES03: Cystic fibrosis |
| RES04: COPD |
| RES09: Tracheostomy |

ACGs Included in the Three Resource Utilization Bands (RUBs)

| | |
|---|---|
| **ACG RUB Level 1 (Included in Intercept)** | Reference Group<br>ACG 0100 0200 0300 1100 1200 1600 5100 5110 5200 9900 |
| **ACG RUB Level 2** | ACG 0400 0500 0600 0900 1000 1300 1800 1900 2000 2100 2200 2300 2400 2500 2800 2900 3000 3100 3400 3900 4000 1711 1721 1731 1741 |
| **ACG RUB Level 3** | ACG 0700 0800 1400 1500 2600 2700 3200 3300 3500 3600 3700 3800 4100 4210 4310 4320 4410 4710 4720 4810 4820 5310 1751 1761 1771 |

**Appendix 2. Summary of Performance Measures for Diagnostic Testing***

| | | "True" Condition | |
|---|---|---|---|
| | | + | − |
| "Screening Test" | + | TP (True Positive) | FP (False Positive) |
| | − | FN (False Negative) | TN (True Negative) |
| Predictive Value + | = | TP/ TP + FP | |
| Predictive Value − | = | TN/ FN + TN | |
| Sensitivity | = | TP/ TP + FN | |
| Specificity | = | TN/ FP + TN | |
| Receiver Operating Characteristic (ROC) (C Statistic = area under curve) | = | Function of Sensitivity vs. 1- Specificity at different screening thresholds | |

* In the context of predictive modeling, a "+" for the "true" condition reflects a person being a member of the high-risk cohort (i.e., represents with the top 5% of costs in Year 2). The "+" for the "screening test" in this case would represent an individual with an acgPM probability score that is about the threshold considered actionable (e.g., a score that would place a person in the top half of 1% of the population.

# Section 3

## Improvements to the Johns Hopkins Expanded Diagnosis Clusters

This section discusses Release 6.0 improvements to the Johns Hopkins expanded diagnosis clusters (EDCs) methodology, including:

- refinements of the EDC taxonomy, and
- enhanced reporting features.

New users of the software are encouraged to review Chapter 13, " 'Dino-Clusters': The Johns Hopkins Expanded Diagnosis Clusters (EDCs)" of the *Version 5.0 Documentation and Application Manual* for complete details of the EDC taxonomy, a discussion of the EDC output file, and technical specifications for customizing EDC reports.

### a. Overview

Expanded diagnosis clusters (EDCs) were added to the ACG System in 2001 to provide the ability to partition populations into diagnosis-specific subgroups for a more complete understanding of case mix. Our intent was to condense the unwieldy list of ICD-9 codes into a much smaller number of clinically homogeneous clusters. As was the case for the original "diagnosis clusters," our system places an emphasis on commonly occurring conditions treated primarily in ambulatory settings. The EDC system has undergone considerable refinement and now also includes less commonly occurring conditions, many of which may be treated in the hospital. In some instances, the original EDCs have been further subdivided to better reflect the effect of complicated illness, examples of which are presented on Table 1.

**Table 7. Subdivision of EDCs for Additional Clinical Specificity**

| VERSION 5 EDC | REVISED VERSION 6 EDCs |
|---|---|
| ALL02 Asthma | ALL04 Asthma, w/o status asthmaticus<br>ALL05 Asthma WITH status asthmaticus |
| CAR02 Hypertension | CAR14 Hypertension, w/o major complications<br>CAR15 Hypertension, WITH major complications |
| END01 Diabetes Mellitus | END06 Type 2 diabetes w/o major complicating conditions<br>END07 Type 2 diabetes WITH major complicating conditions<br>END08 Type 1 diabetes w/o major complicating conditions<br>END09 Type 1 diabetes WITH major complicating conditions |

As these examples illustrate, in some instances the main refinement was to split the original category into complicated and uncomplicated subgroups. As a case in point, the asthma

EDC has been divided on the basis of the presence of status asthmaticus (i.e., an acute exacerbation of asthma). In the cardiology cluster, hypertension has been divided on the basis of the presence of a complicating condition. In other instances, the disease itself was further delineated, such as within the endocrine cluster where diabetes mellitus has been split into four categories—first by categorizing patients according to type 1 versus type 2 diabetes, and second according to the presence of a major, complicating comorbidity. (See Table A.1 in the Appendix to this chapter for a complete listing of these complicating conditions.)

In addition to splitting existing EDCs, new categories have been added to the current software release. Table 2 provides a summary of new EDCs. In most instances, the additions within a given major EDC have been modest. For example, in the Administrative cluster, categories for transplant status and complications of mechanical devices were added. In the Cardiology cluster, a new category for acute myocardial infarction (CAR11) and Cardiac arrest/shock (CAR12) have been added. The malignancy and neurologic MEDC categories have been substantially expanded.

All in all, 40 new EDC categories have been added and affect 16 of the 27 major EDC (MEDC) clusters, and several existing EDCs have been subdivided to provide additional clinical specificity. There are now a total of 236 EDC categories in ACG Release 6.0. For a sense of how these EDCs are distributed in the "real world," their frequency of occurrence in a large under-65 population (2 million covered lives) is provided in Appendix A.2.