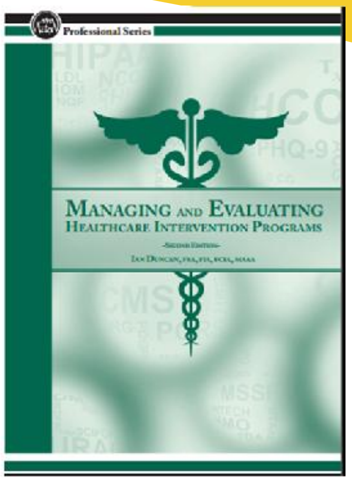
Using Actuarial Methods to Address Chronic Disease

Ian Duncan FSA FIA FCIA FCA MAAA
University of California, Santa Barbara

Introductions

Ian Duncan, FSA, FIA, FCIA, FCA, MAAA

- Founder and former president of health analytics company, Solucia Consulting (now SCIO Health Analytics).
- Former head of Clinical Research, Walgreen Co.
- Professor of Actuarial Statistics, University of California Santa Barbara since 2011.
- Author of several books and many peer-reviewed studies on healthcare management and predictive modeling.
- Former board member, Society of Actuaries and chair, SOA's Predictive Modeling workgroup.



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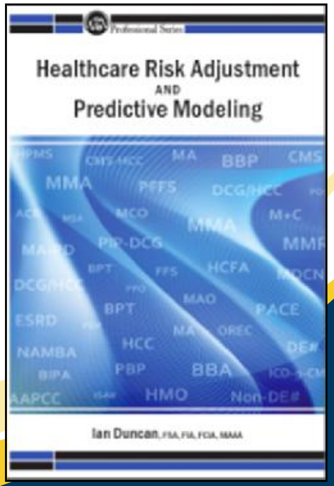
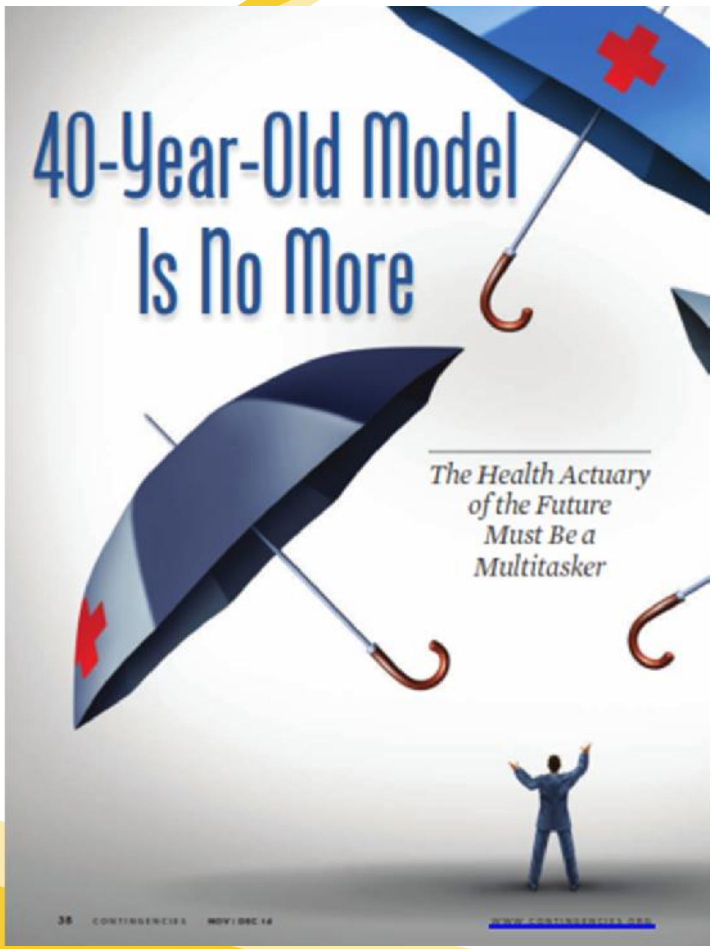


Agenda

1. Introductions
2. Background: Chronic Disease and Disease State Transitions.
3. A predictive modeling example: end of life.
4. Opportunity Analysis.
5. Discussion.

Health Actuary of the Future



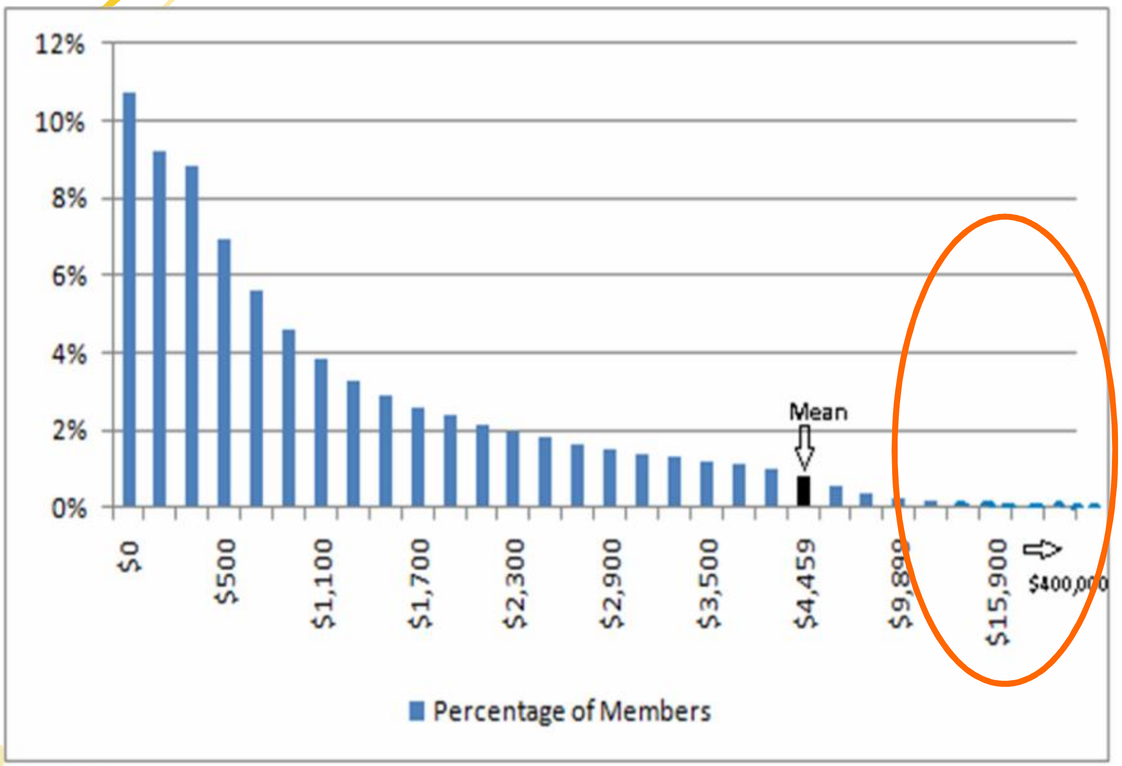
Health actuaries, whose role has traditionally been financial (pricing; reserving), will require a considerable amount of new learning, because they are increasingly working in a broader world populated with other health care disciplines such as physicians, health economists, and epidemiologists. Perhaps more so than other actuarial disciplines, health actuaries work in a multidisciplinary environment as a member of the team rather than as its captain.

the health actuary of the future at a minimum will need to be part clinician, part behavioral psychologist, part health economist, and part epidemiologist. Not to mention biostatistician, although that is a topic for a different book. In part, this transformation is being driven by ACA changes in health insurance.

A common mis-conception about health spend

Gawande’s solution: care intervention programs that focus on the 5% that account for 60% of health spending.

Typical Health Cost Distribution



Not easy to find these patients – and focusing on high-cost, high-utilizing patients is not enough.

* Distribution of allowed charges within the SCIO Health Analytics database (multi-million member national database).

Key Concept: Member Transition

	Baseline Year	Subsequent Year		
Baseline Year Cost Group	Baseline Percentage Membership	LOW <$2,000	MODERATE $2,000-$24,999	HIGH $25,000+
LOW <$2,000	69.5%	57.4%		
			11.7%	
				0.4%
MODERATE $2,000-$24,999	28.7%	9.9%		
			17.7%	
				1.1%
HIGH $25,000+	1.8%	0.2%		
			0.9%	
				0.6%
TOTAL	100.0%	67.6%	30.3%	2.2%

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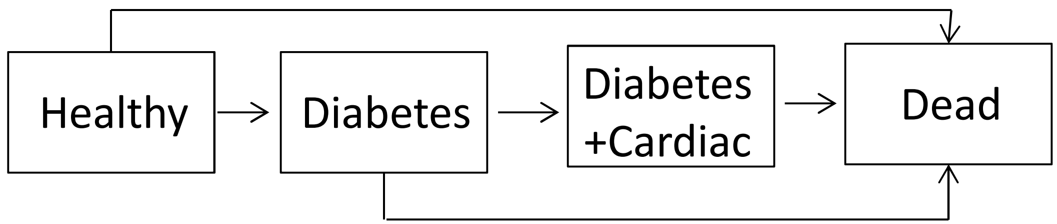
Current research focused on risk transitions

- As studies show, traditional approaches to predicting *future* high utilizers are not too accurate.
- My own research is focused on the application of actuarial models to risk transition in chronic populations, using an NHS (UK) dataset (800,000 lives; 25 years longitudinally, including clinical and behavioral data).
- Actuaries have traditionally built models to predict mortality (Life Tables). These allow us to price products rationally, knowing how deaths will occur in a large population.
- The idea is to build similar morbidity models. Knowing how diseases progress (statistically) we can better target interventions and evaluate whether our interventions worked.
- An example of a (simple) transition model for diabetes follows.

Research focused on risk transitions

- The concept: Markov Models (transition models)
- Capture the multi-state transition probabilities inherent in medical states (and cost).
- Simple Markov Concept:



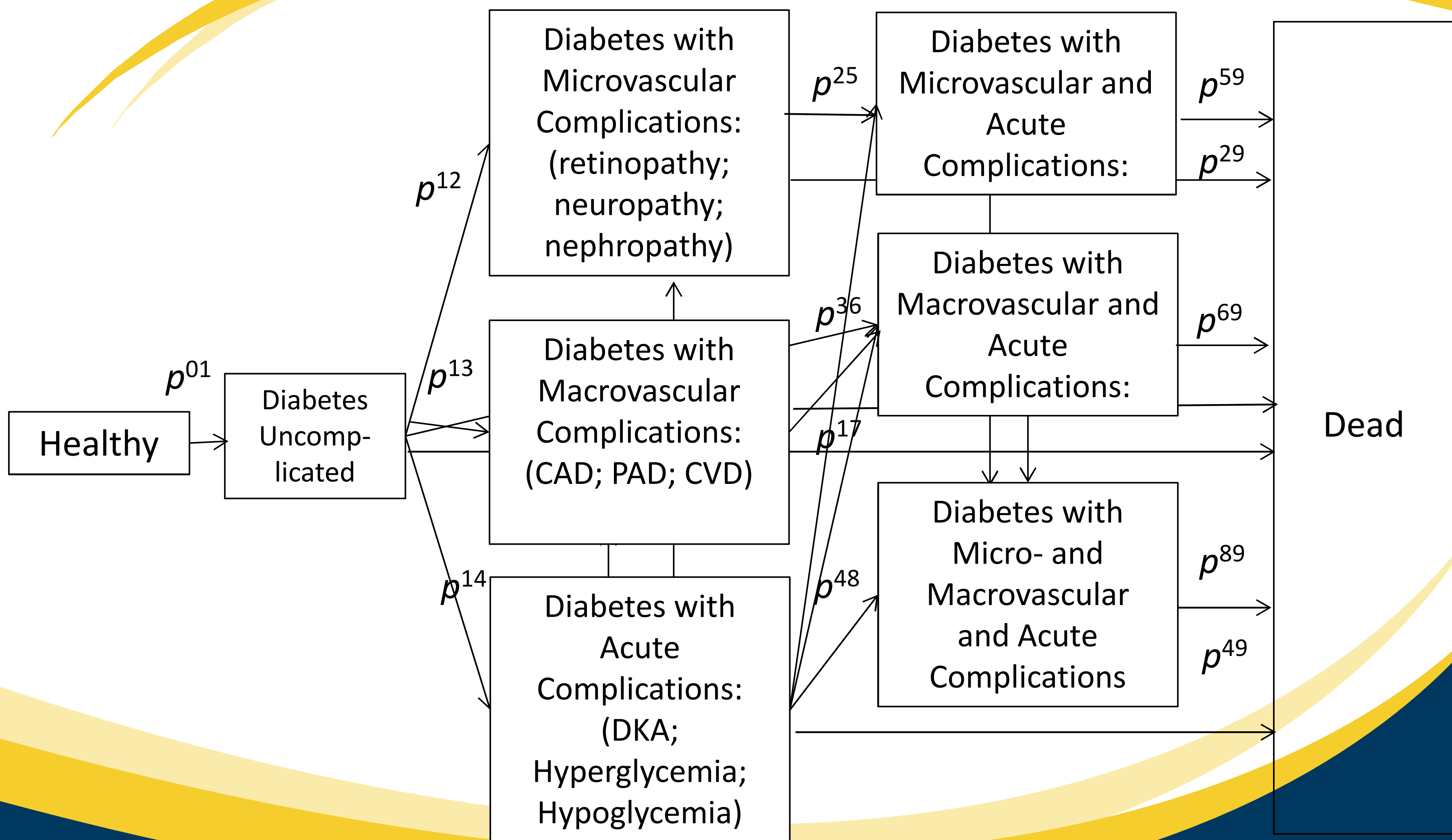
- Transitions between states have associated probabilities.   Transition is a function of (multiple) risk factors + time.

<u>Problem</u>: medical states are time-independent.

Need for time-dependent (semi-Markov) models.

Current thinking is to develop a 2-stage model with time-in-state estimated by Weibull distribution and transitions (dependent on estimated time-in-state) by exponential (e.g. log-normal).

Diabetes Example



Human vs. Machine

- This study assessed the predictions made by:
    - Physicians
    - Case managers
    - Nurses

- *"...none of the AUC values were statistically different from chance"*

Allaudeen N, Schnipper JL, Orav EJ, Wachter RM, Vidyarthi AR. Inability of providers to predict unplanned readmissions. J Gen Intern Med. 2011;26(7):771-6

Inability of Providers to Predict Unplanned Readmissions

Nazima Allaudeen, MD[1,2], Jeffrey L. Schnipper, MD, MPH[3], E. John Orav, PhD[4], Robert M. Wachter, MD[2], and Arpana R. Vidyarthi, MD[2]

[1]Department of Medicine, VA Palo Alto Heathcare System, Palo Alto, CA, USA; [2]Division of Hospital Medicine, Department of Medicine, University of California, San Francisco, CA, USA; [3]BWH Academic Hospitalist Service and Division of General Medicine, Brigham and Women's Hospital, Harvard Medical School, Boston, MA, USA; [4]Department of Biostatistics, Harvard School of Public Health, Boston, MA, USA.

BACKGROUND: Readmissions cause significant distress to patients and considerable financial costs. Identifying hospitalized patients at high risk for readmission is an important strategy in reducing readmissions. We aimed to evaluate how well physicians, case managers, and nurses can predict whether their older patients will be readmitted and to compare their predictions to a standardized risk tool (Probability of Repeat Admission, or P_{ra}).

METHODS: Patients aged ≥65 discharged from the general medical service at University of California, San Francisco Medical Center, a 550-bed tertiary care academic medical center, were eligible for enrollment over a 5-week period. At the time of discharge, the inpatient team members caring for each patient estimated the chance of unscheduled readmission within 30 days and predicted the reason for potential readmission. We also calculated the P_{ra} for each patient. We identified readmissions through electronic medical record (EMR) review and phone calls with patients/caregivers. Discrimination was determined by creating ROC curves for each provider group and the P_{ra}.

RESULTS: One hundred sixty-four patients were eligible for enrollment. Of these patients, five died during the 30-day period post-discharge. Of the remaining 159 patients, 52 patients (32.7%) were readmitted. Mean readmission predictions for the physician providers were closest to the actual readmission rate, while case managers, nurses, and the P_{ra} all overestimated readmissions. The ability to discriminate between readmissions and non-readmissions was poor for all provider groups and the P_{ra} (AUC from 0.50 for case managers to 0.59 for interns, 0.56 for P_{ra}). None of the provider groups predicted the reason for readmission with accuracy.

CONCLUSIONS: This study found (1) overall readmission rates were higher than previously reported, possibly because we employed a more thorough follow-up methodology, and (2) neither providers nor a published algorithm were able to accurately predict which patients were at highest risk of readmission. Amid increasing pressure to reduce readmission rates, hospitals do not have accurate predictive tools to guide their efforts.

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KEY WORDS: readmission; unplanned; prediction.
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BACKGROUND

Against the background of rising concerns about both the cost and quality of American medical care, hospital readmissions have come under increasing scrutiny from both outside and within the government.[1–3] Hospital readmissions may be a marker for poor quality care, are dissatisfying for patients and families, and increase health care costs. Medicare estimates that $15 billion is spent on the 17.6% of patients who are readmitted within 30 days[4].

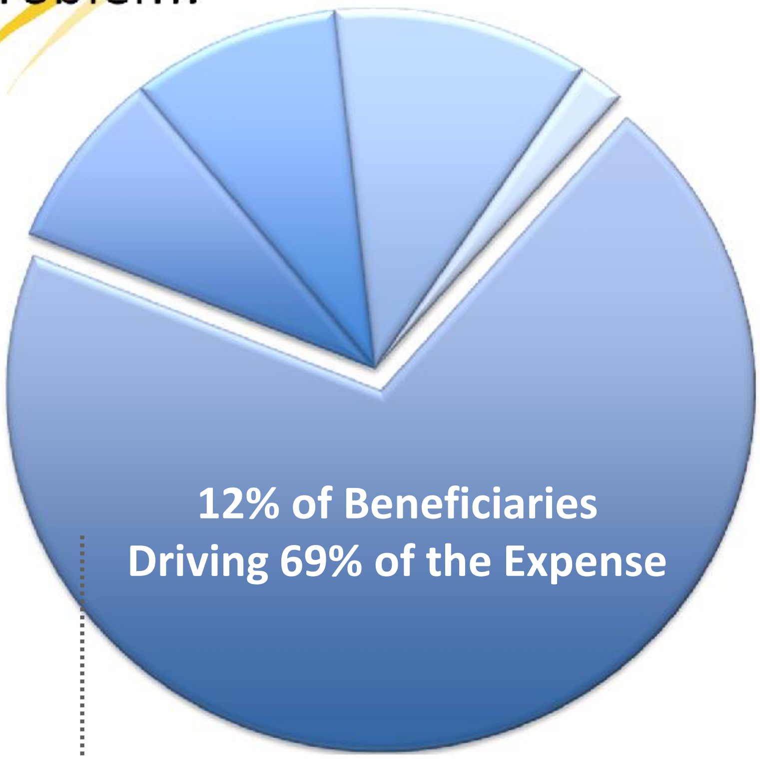
Although it would be ideal to develop interventions that improve the hospital-to-home transition for all patients, given limited resources, some have argued for targeting intense efforts—such as comprehensive discharge planning, post-discharge phone calls or home visits, and early clinic visits—towards high risk patients. However, such strategies require that we have accurate methods to identify patients at highest risk.

Anecdotal evidence suggests that inpatient providers (physicians, nurses, discharge planners) currently make informal predictions of readmission that affect discharge planning. Such predictions are not new: providers have tried to predict other outcomes, such as mortality and length of stay, in several settings (e.g., intensive care unit, emergency department), with varying success.[5–10] However, the accuracy of informal predictions of hospital readmission is unknown. Several algorithms have also been developed in recent years to predict hospital readmissions, but their use has been limited, because they require information not typically gathered during clinical care, their models are complex and difficult to use, and/or because they are not accurate. A few studies have compared providers with algorithm-based tools to predict readmission and mortality in other settings,[9] but it remains unknown how well providers' predictions of readmission for general medicine patients compare with published algorithms or how the predictions of multiple disciplines compare with one another.

To reach the ultimate goal of preventing readmissions, identifying the highest risk patients is the first of a multistep process. Providers would next need to speculate on the reason for readmission before then targeting an effective

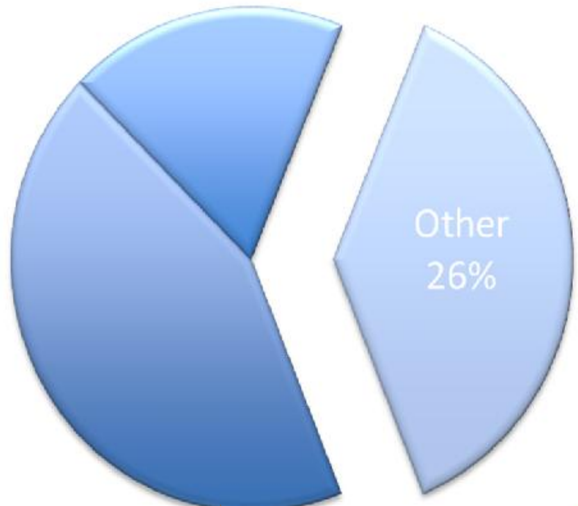
Predictive Modeling – End of Life

The Problem:



6% of Medicare Beneficiaries die annually.

Second to last year of life represents 13% of the total Medicare FFS spend.



Last year of life represents ~30% of the total Medicare FFS spend.

Predictive Modeling – End of Life

Over-medicalized death is defined as:

- ✓ Chemotherapy for cancer patients within 14 days of death;
- ✓ Unplanned hospitalization within 30 days of death;
- ✓ More than one emergency department (ED) visit within 30 days of death;
- ✓ ICU admission within 30 days of death; or
- ✓ Life-sustaining treatment within 30 days of death.

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Predictive Modeling – End of Life

Based on a Logistic Regression Model, an EOL risk score is calculated for each member of the population:

- Risk scores range in value from 0.0-1.0.
- Model is based on the following member attributes (121 in all):
  - Age and gender;
  - Race;
  - Zip (and zip-derived measure of poverty);
  - Clinical Grouper Flags (65 HCCs);
  - Certain acute DRGs;
  - Baseline admission count(s);
  - Baseline readmission count(s);
  - Baseline ER visit count(s);
  - Baseline admission via ER indicator;
  - Baseline dollars spent for healthcare resources.

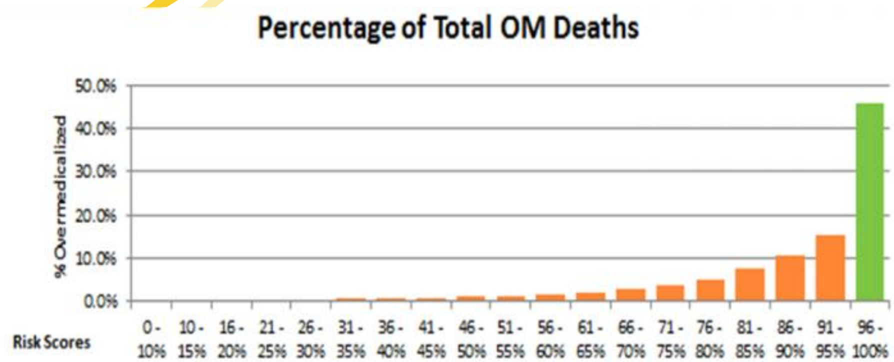
Predictive Modeling – End of Life

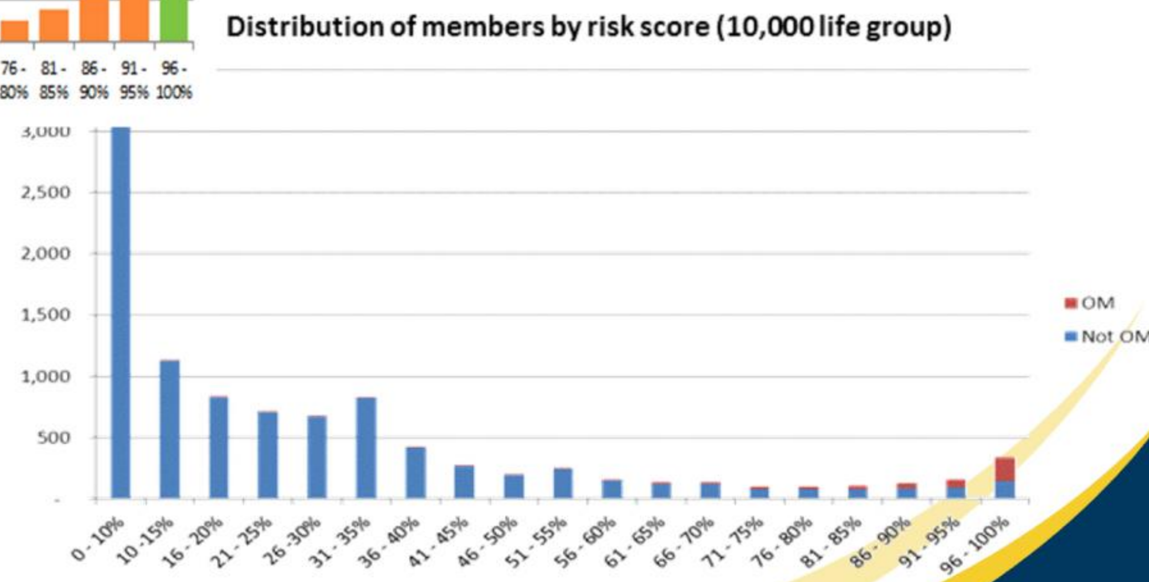
Variables that add the most to the weighting:

1. Acute Myocardial Infarction
2. Acute Leukemia
3. Craniotomy with major device implant
4. Cardio-Respiratory Failure & Shock
5. Metastatic Cancer & Acute Leukemia
6. Lung, Upper Digestive Tract and Other Severe Cancers
7. Septicemia or Severe Sepsis
8. Number of Admissions

Predictive Modeling – End of Life

Model Performance:





How Can Data Help Achieve the Triple Aim?

- What's in it for the healthcare consumer or provider? In healthcare, consumers don't get to make choices – providers and payers make choices for them.
- Traditional price tools aren't applicable to consumers, and decreased utilization can be negative to a provider.
- Value-based purchasing (by consumers and providers) and consumer-driven healthcare can help to bring healthcare into line with other industries. It is widely recognized that we need to pay for quality, not volume.

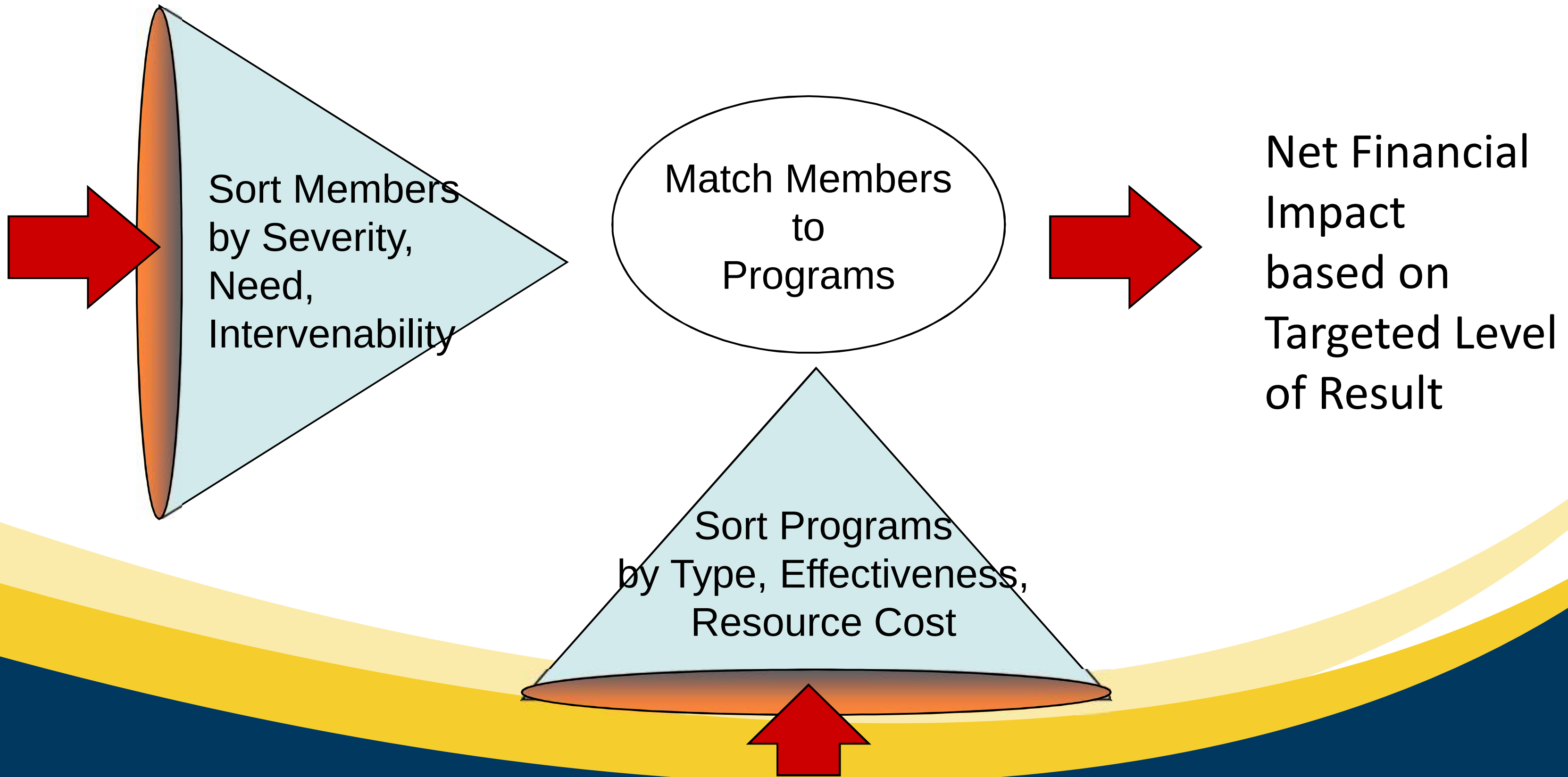
Opportunity Analysis

- Traditional Predictive Modeling ranks patients high to low in terms of a predicted outcome.
- Opportunity analysis adds another dimension: Intervenability*.

* My colleague, Dr. Geraint Lewis of the UK National Health Service prefers the word "impactibility." As Churchill said of the United States and Great Britain, we are two great nations separated by a common language, or with typical American directness, in the words of George and Ira Gershwin, "Tomato Tomato."

Opportunity Analysis

- Group members into Condition Categories, assign a program, and model the…
  - Program cost (resource requirements to achieve a targeted level of result); and
  - Program financial outcomes (what may be saved due to intervention).



Opportunity Analysis

More information:

QUALITY & GOVERNANCE

By Geraint Lewis, Heather Kirkham, Ian Duncan, and Rhema Vaithianathan

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How Health Systems Could Avert 'Triple Fail' Events That Are Harmful, Are Costly, And Result In Poor Patient Satisfaction

ABSTRACT **Health care systems in many countries are using the "Triple Aim"—to improve patients' experience of care, to advance population health, and to lower per capita costs—as a focus for improving quality. Population strategies for addressing the Triple Aim are becoming increasingly prevalent in developed countries, but ultimately success will also require targeting specific subgroups and individuals. Certain events, which we call "Triple Fail" events, constitute a simultaneous failure to meet all three Triple Aim goals. The risk of experiencing different Triple Fail events varies widely across people. We argue that by stratifying populations according to each person's risk and anticipated response to**

Geraint Lewis (geraint.lewis@nhs.net) is chief data officer of the National Health Service, in London, England.

Heather Kirkham is a manager in the Clinical Outcomes and Analytics Department at Walgreens, in Deerfield, Illinois.

Ian Duncan is the vice president in the Clinical Outcomes and Analytics Department at Walgreens.

9 Applying the Economic Model: The Example of Opportunity Anal

9.1 Introduction

In Chapter 8 we introduced the concept of the Risk Management ec planning care management programs by assessing the potential eco intervention or program. We have named this multi-dimension intervention planning **Opportunity Analysis** to highlight the fact th program sponsors on the idea that high-utilizing patients in a popul for simultaneously improving the quality of care while reducing net utilization. For a program to be successful requires discrimination between high-opportunity members, and other members that may be high cost or high risk, but represent a lesser opportunity for achieving the "Triple Aim," defined by former CMS Administrator Don Berwick MD as advancing the health of populations while simultaneously improving individual patients' experiences of care and reducing per capita health care costs [23, 161, 173]. Extending Berwick's work, we have defined the concept of the "Triple Fail," meaning those health outcomes that simultaneously exhibit three failures: they are costly, they represent a suboptimal health outcome and they result in a poor patient experience. Opportunity Analysis can be thought of as technique for identifying and preventing triple fail occurrences within populations [173].

Contact Information

Ian Duncan FSA FIA FCIA FCA MAAA

Dept. of Statistics & Applied Probability
University of California Santa Barbara
duncan@pstat.ucsb.edu
805-893-6023