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Blue Health Intelligence®

# Innovations in Predictive Modeling

The Predictive Modeling Summit  
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# Today's Speakers

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# Navigating a sea of data in a rapidly changing healthcare landscape





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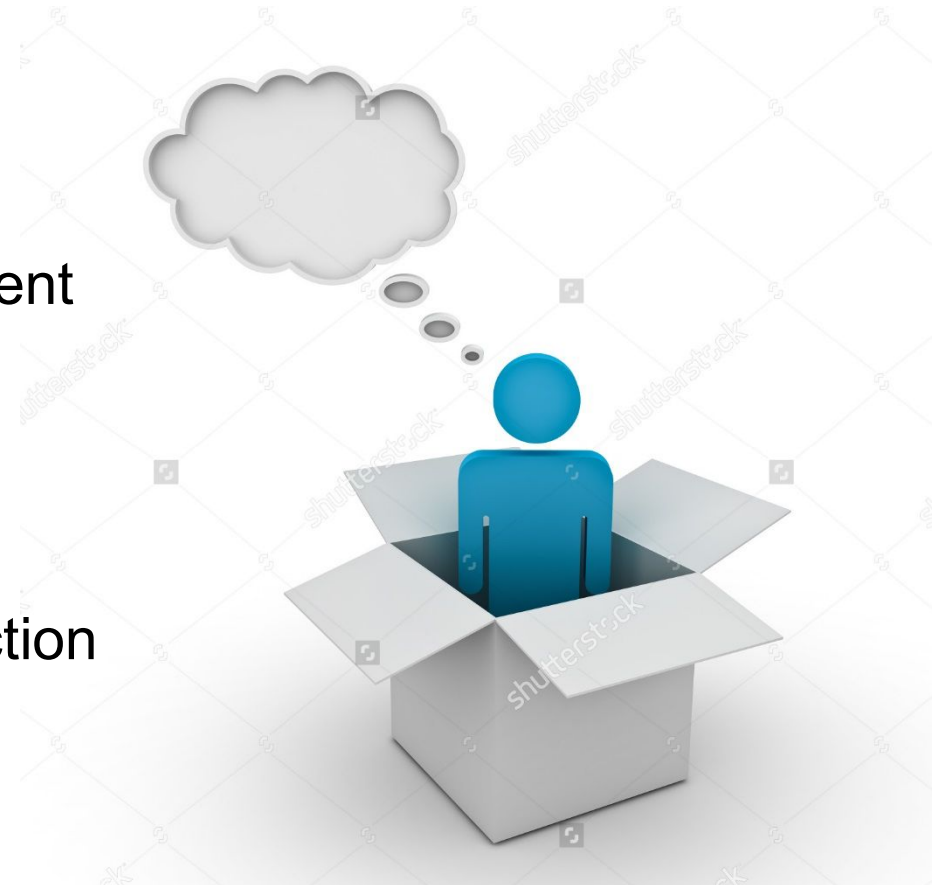
## Leading Health Intelligence and Analytics Resource

- **Business intelligence, analytics, and data** driving many national and local health initiatives
- Serving Blue Cross Blue Shield Plans and other Healthcare Clients
- Blue Cross Blue Shield Association Analytics Partner
- **Nation's largest healthcare claims database**
  - 165 million covered lives
  - Collected over 10 years
  - Covering every MSA in the US



# Challenges and Opportunities

- Financial Challenges
- Population Health Management
- Patient Safety and Quality
- Government Mandates
- Consumer Choice & Satisfaction
- Access to Care



# Solving Problems with Predictive Analytics

## ✓ Accurate Capture of Population Risk

- Ensure Accurate Risk Adjusted Payments
  - Medicare Advantage
  - ACA Individual & Small Group
- Better Manage Population Health



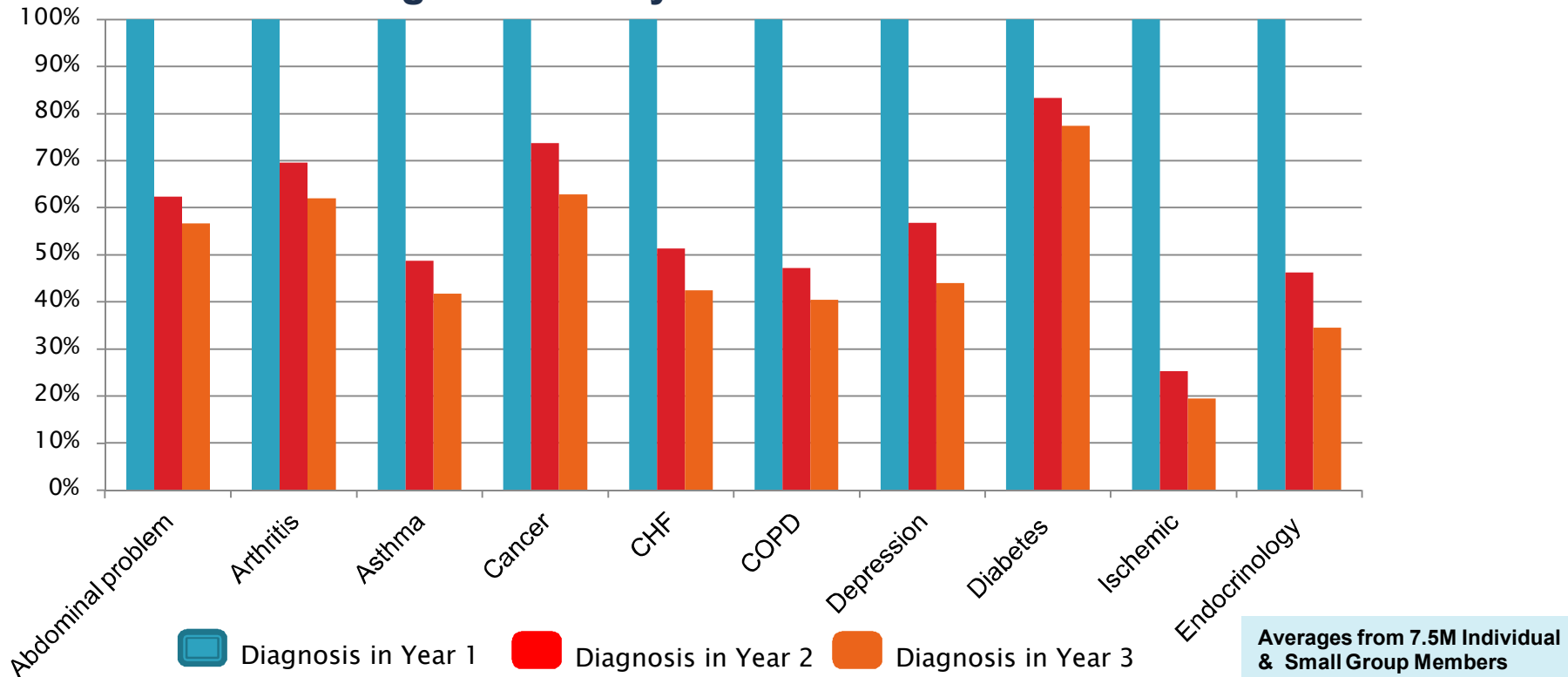
## ✓ Greatest Impact at a Lower Expense

## ✓ Flexibility and Transparency

# Risk adjusted payments depend on accurate and complete diagnosis coding on medical claims

*Physicians may not document the complete spectrum of applicable diagnosis codes during an office visit, particularly for members with chronic conditions.*

## Coding Persistency for Chronic Conditions



# Tracking the Status of Population Risk Capture

## Commercial On/Off Exchanges



- ✓ Capture each member's risk status—day 1 of the benefit year—and every month after
  - ✓ Persistent Coding & Management of Chronic Conditions
  - ✓ Capture of new and changing conditions and risk factors

## Medicare Advantage



- ✓ Match the right interventions with the right members at the right time
- ✓ Close gaps in care and diagnosis coding



# Examples of Predictive Analytics

- Predicting consumer health risk and identifying gaps in care and diagnosis coding
- Targeting consumers for intervention
  - Predicting the probability a consumer will engage with a “managing” healthcare provider on their own without intervention
  - Predicting which gaps in diagnosis have the greatest, or least, likelihood to close on their own without intervention

# The Business/End-User Perspective

## Predictive Model Disciplines

**Are analytics actionable and relevant to daily operations?**

**Are analytics trusted and accepted by business users**

**Does “what the data says” contradict real world experience?**

- Build with the business process in mind with clear acceptance criteria
- Present results and model performance in a manner that is understandable and transparent
- Conduct iterative reviews with business users, clinicians, and others to refine model results

# Diagnosis Gap Identification Models

Why would a serious medical condition not be found?

- Not recorded on the claim for billing
- Poor documentation
- Not actively treated
- Undiagnosed
- Newly developed



# Diagnosis Gap Identification Models

Putting together the puzzle pieces to find the disease

- Disease History
- Prescriptions
- Tests & Medical Procedures
- Practice Patterns
  - Providers seen and their specialties



# Gap Identification Models

## Key Steps

- Clinically meaningful groupings
  - There are too many distinct medical codes
- Separate modeling for some types of insurance and by broad age groupings
- Separate development and testing populations
  - Oversampling of some populations and conditions
- Combining evidence into a joint probability
  - Naïve Bayesian

$$\frac{(S/M)p_1 \dots p_n}{(S/M)p_1 \dots p_n + (H/M)q_1 \dots q_n}$$

# Engagement Model

Who is going to visit the doctor and when?

- Direct reminders to the best location
- Optimize and customize outreach



We chose a survival model

- It sounds counter-intuitive, but patient “survived” until he had an office visit



# Engagement Model

- Choosing candidate variables
  - Clinical condition (physician consultation)
  - Care seeking patterns
  - Demographics
- Selecting variables
  - Strength of relationship with office visit rate
  - Correlations between variables



# Engagement Model

## Survival Analysis Model with Categorical Variables

Real Office Visit Probability		Predicted Office Visit Probability									
		0% -10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	>90%
Survival Days	30	4.31	14.14	25.12	34.79	44.97	61.05	59.84	72.27		
	60		9.81	24.86	38.79	45.37	55.32	64.15	76.75	79.41	85.38
	90		9.78	17.58	38.81	49.88	55.2	66.01	74.84	84.99	88.34
	120		7.1	15.3	31.79	56.3	58	66.07	75.87	83.89	91.24
	150		4.76	16.25	27.38	49.61	61.71	66.31	76.07	84.86	92.31
	180		3.7	17.04	24.3	45.08	63.68	67.65	76.41	85.29	92.51
	210			18.08	24.59	42.17	64.47	69.81	76.21	85.46	92.48
	240			20.4	25.17	41.23	63.15	70.79	76.66	85.8	92.66
	270			18.96	26	38.99	62.07	71.83	76.7	85.86	92.83
	300			20.07	26.83	38.4	61.06	73.07	76.91	85.8	92.97
	330			18.82	27.82	37.29	59.91	73.89	77.33	85.87	93.08
	365			20.19	28.77	36.29	60.06	74.23	77.83	86.01	93.18

How well did we predict and what are our blind spots?



# Gap Closure Model

- Predict the likelihood that a diagnosis will turn up naturally in near future claims without any intervention to encourage it
- Predictive variables:
  - Risk Score Model (Child, Adult)
  - Condition (Diabetes, COPD/Asthma, etc.)
  - Age and Gender
  - Time since gap opened (months)
  - Gap identification methods (Prior Year, Drug, Procedure, etc. )
  - Number of office visits
  - Actuarial value of coverage
  - Rural/Urban



# Gap Closure Model

- Modified Decision Tree with Preference
- Generated rules to classify gaps into high or low likelihood of natural closure
  - The majority of results were neither high nor low
- Rather than voting or averaging, we applied a deliberate preference favoring rules which did classify as high or low



# Modeling Process – The Build Essentials

- Define the business problem
- Define the knowledge space
  - What do we know; what can we know
- Choose the right tools
  - Build with the business process in mind
  - Type of model, data definitions, success measures
- Let the data speak then validate against real-world experience
  - Exploratory analysis of distributions and relationships
  - Iterative reviews with business users and clinicians
- Build trust and acceptance with business users

# Modeling Process – The “Go Live”

- Hand-off to Development
  - Content, format, operational workflow
- Assist the business to articulate value and performance
- Build in performance monitoring
- Continuous improvement

# Wrap Up

**Questions?**

**Thank you!**