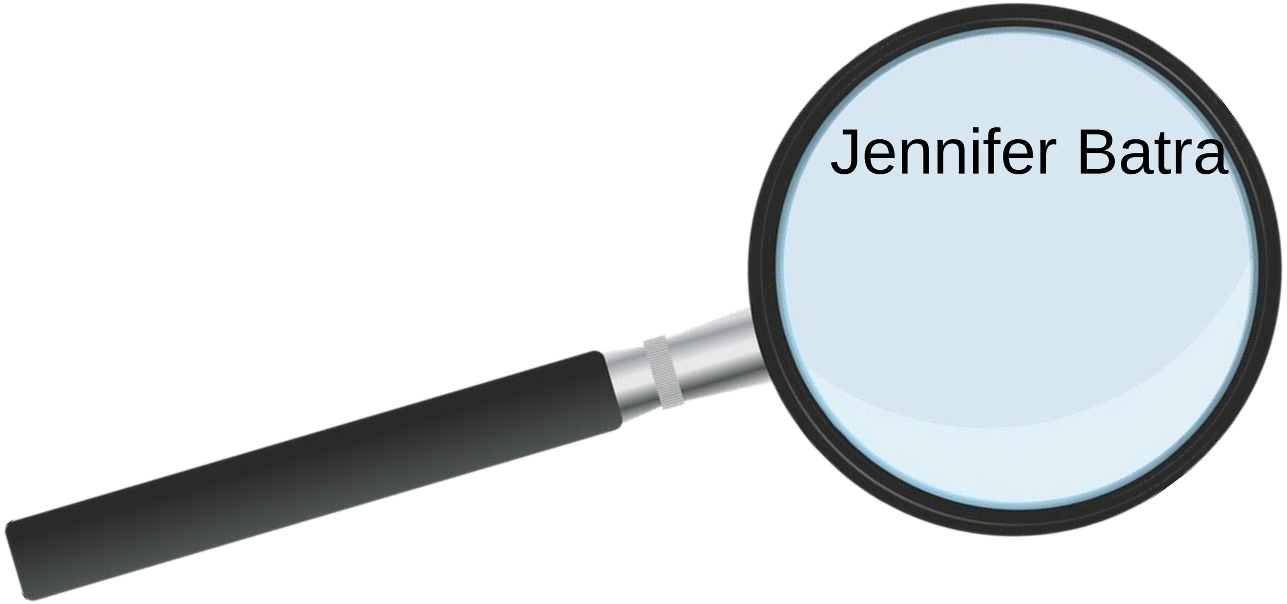
PARTNERSHIP BETWEEN ANALYTICS AND LTC OPERATIONS

Tools and Rules to Improve Your Game

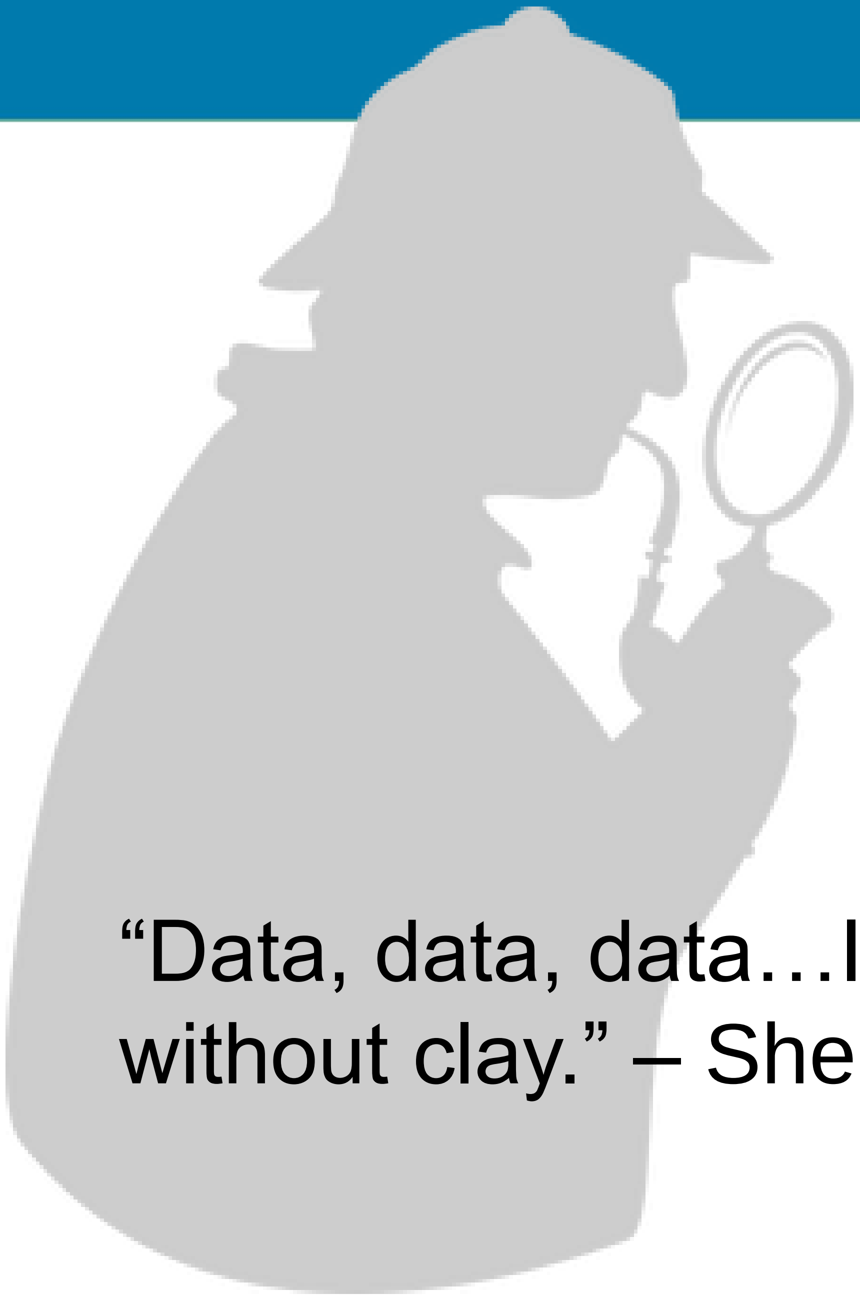
<u>Panelists</u>

- Jennifer Batra – Business Consulting Manager, Fuzion
- Lisa White – Director of LTC Reporting & Analysis, Bankers Life
- Jeff Ferrand – Chief Fraud Officer, Fuzion
- Charles Jenkins – Senior Claims Manager, CAN Insurance
- Kenneth Musselman, Ph.D., Strategic Collaboration Director, Regenstrief Center for Healthcare Engineering at Purdue University

BUILDING A PARTNERSHIP, ANALYTICS PLAN, AND UTILIZATION / INTERVENTION STRATEGIES



Jennifer Batra



"Data, data, data…I can't make bricks without clay." – Sherlock Holmes.

Claims Costs
90%

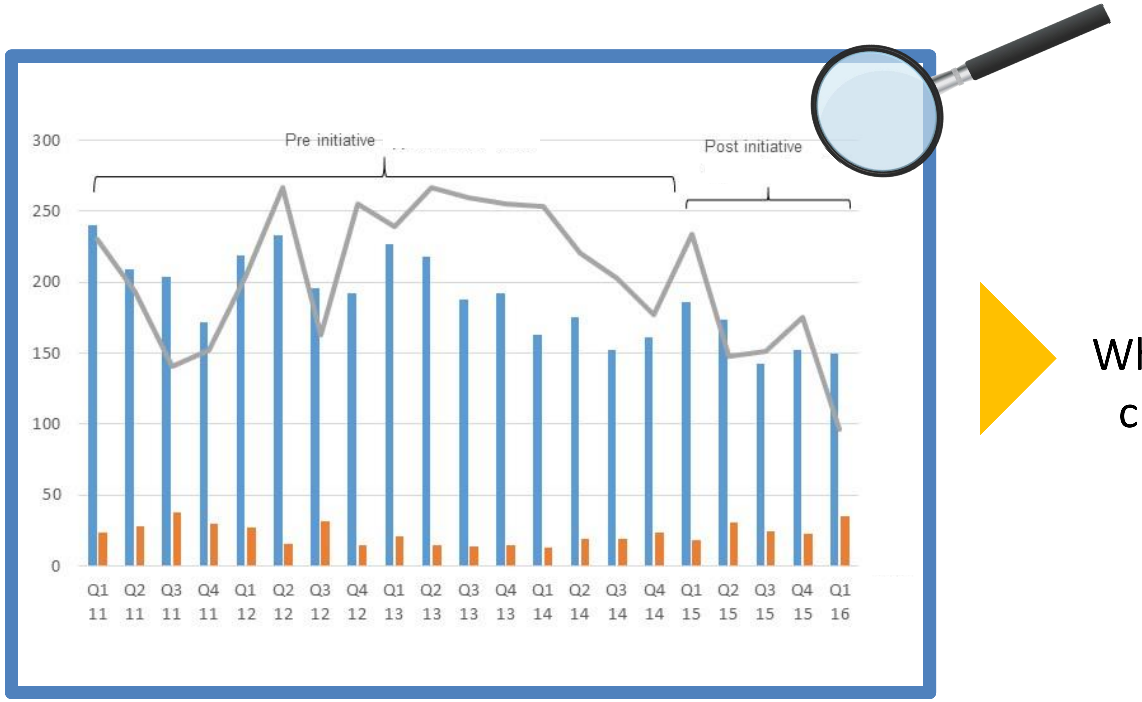
Administrative Costs
10%

Step 1
What is important?

- What drives UW performance?
- What drives complaints?
- What drives customer service calls?
- Are there multiplier effects?

Step 2

What is my performance base rate and…
...post initiative effects?



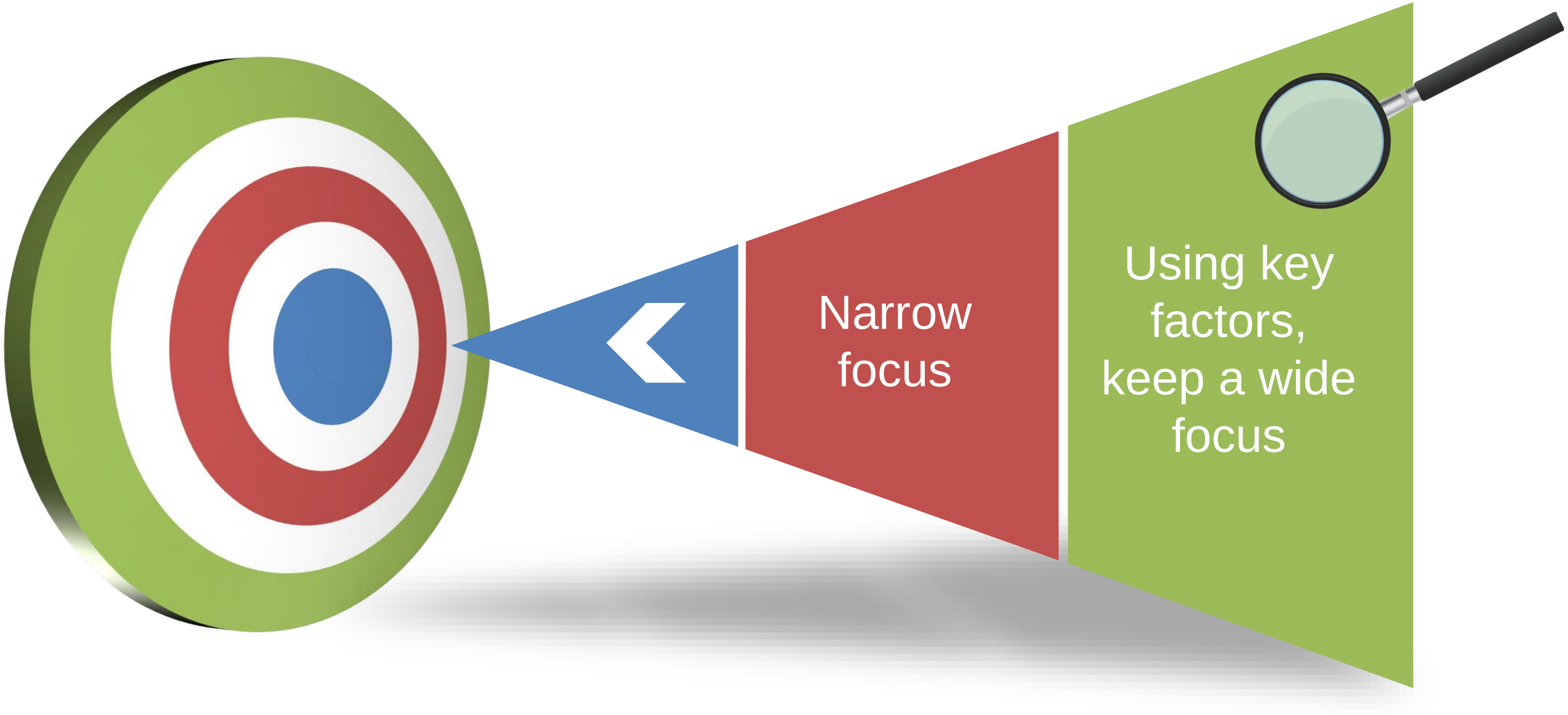
Step 3
What is the impact of a change in base rate?

FRAUD DETECTION

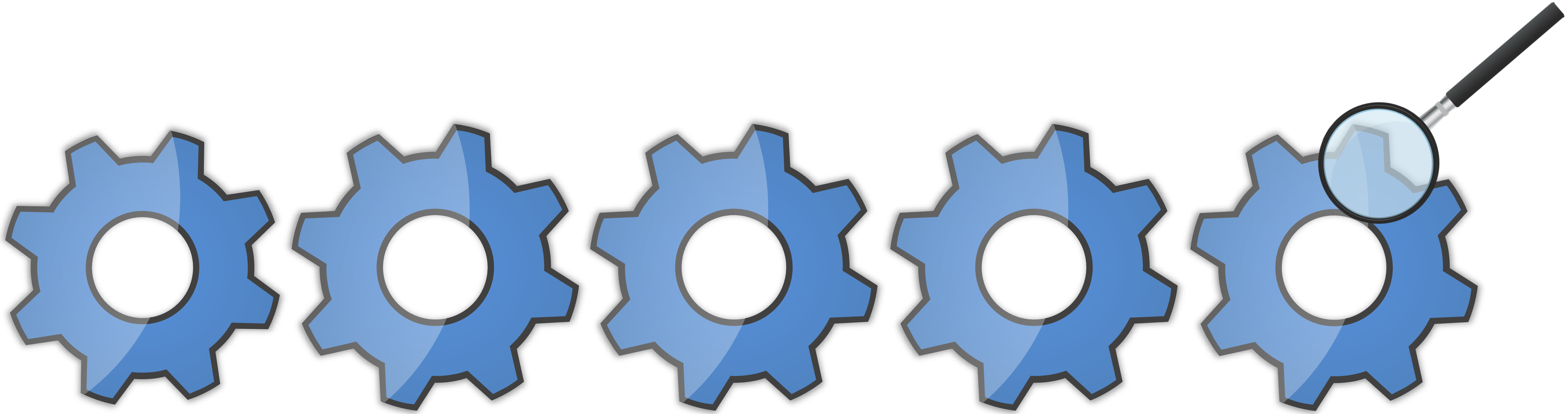
Research and Planning

- Idea generation
  - Intra-departmental brainstorming
  - Research
- Risk tolerance
- Information Availability
- Resource Availability
- Data mining planning
  - Identify Key Factors
  - Prioritize Models

So how do we use data to find fraud?

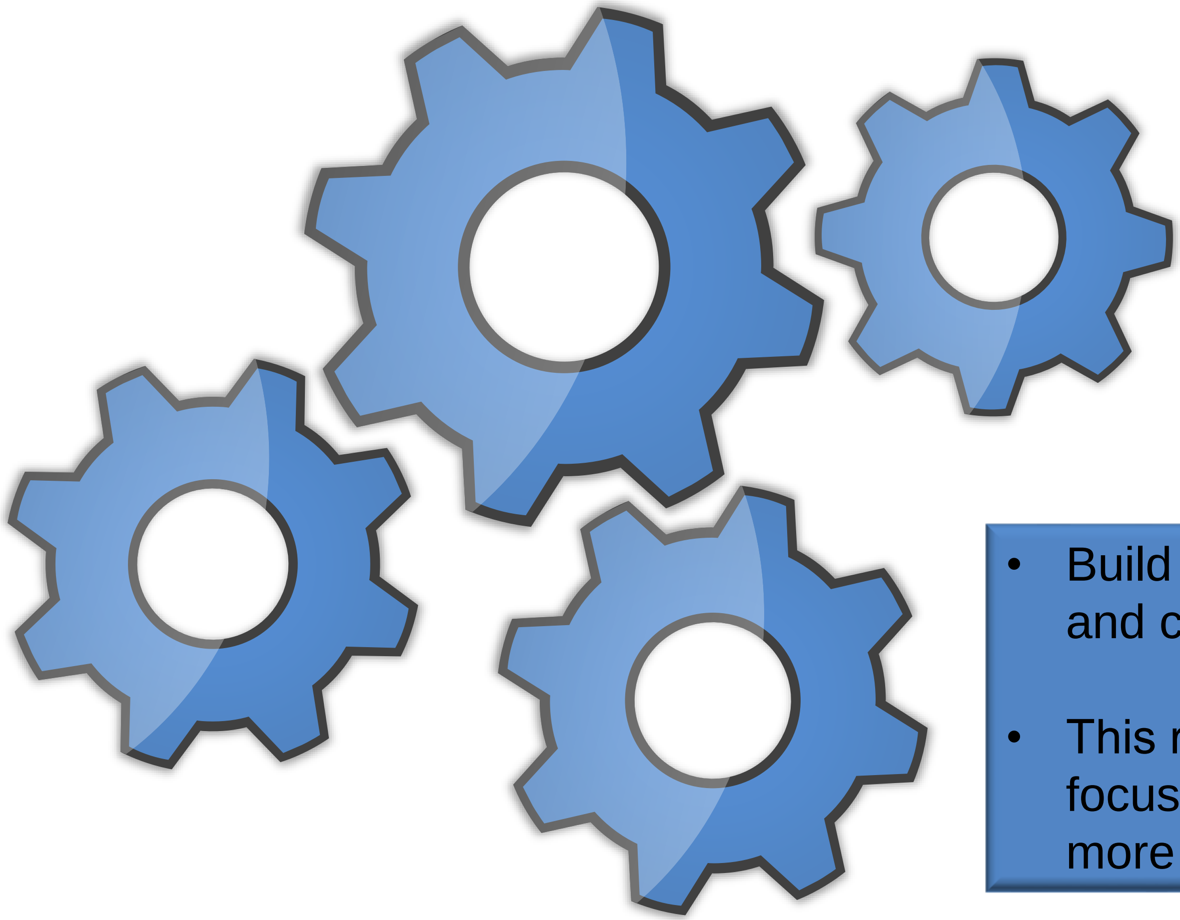


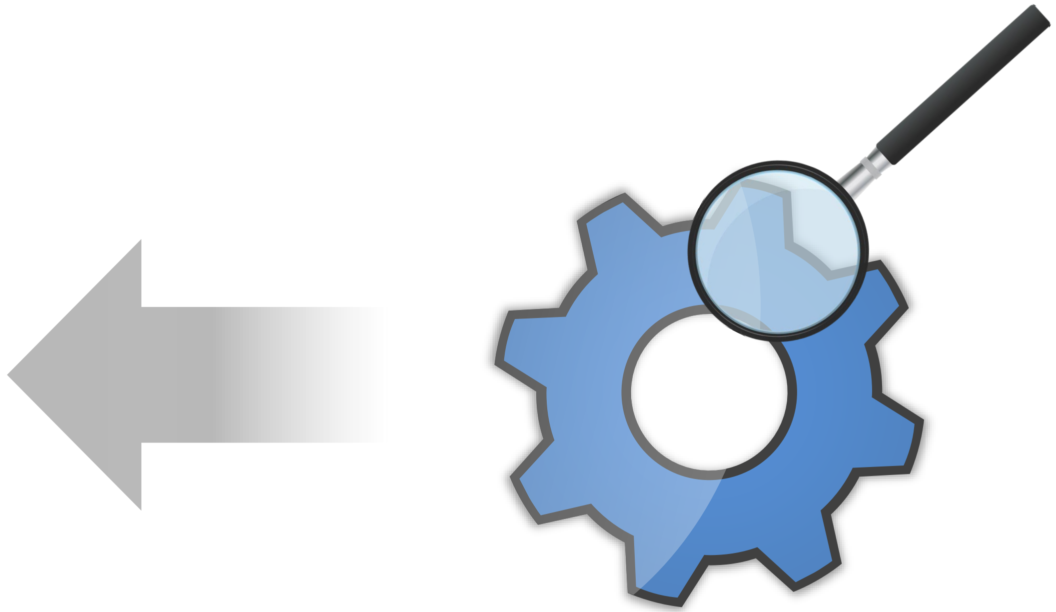
Data mining for key factors



Under Age 65	Contestable	Frequent ROB	Continuous Care	Complainers
• Simple • One factor to start	• Simple • New claims – policy age 2 yrs	• Complex • Often restore benefits	• Complex • Provider with no days off	• Complex • Vocal about payments

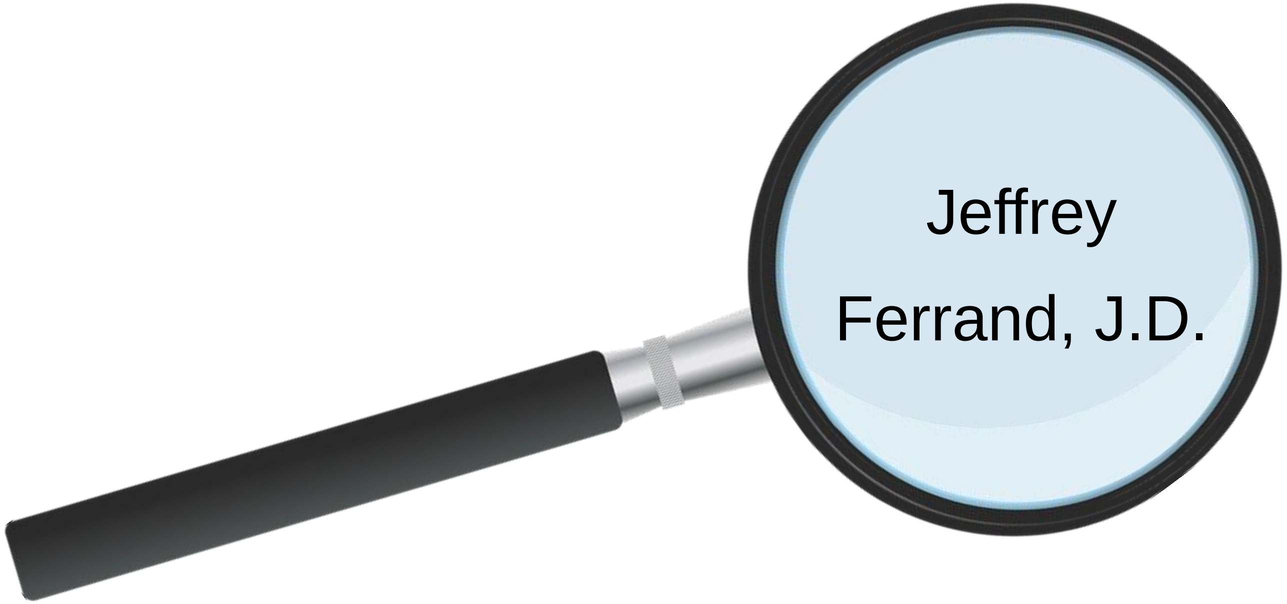
Future state





- Build a model that combines all key factors and creates a final score
- This result of the “scored” model would focus operations staff on the cases that are more likely to be fraudulent

ANALYTICS TO BUILD FRAUD MITIGATION PROGRAM AND SUCCESS WITH RESTORATION OF BENEFITS

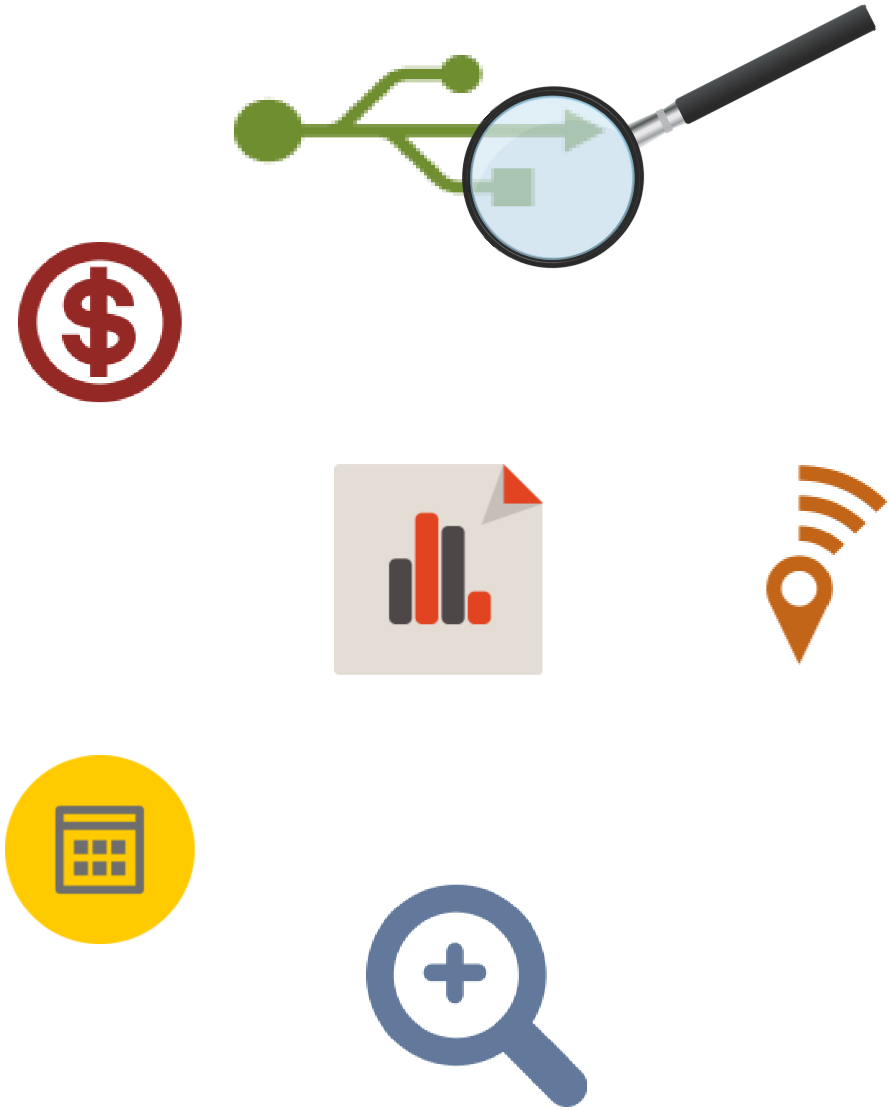


Foundation for a Successful Fraud Mitigation Program:

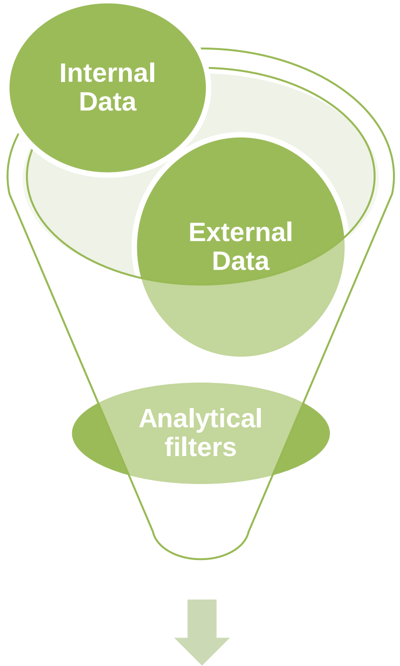
1. **Referral Engagement and Training**
2. **Investigative Strategies and Tools**
3. **Integration of Analytics and Modeling**

Analytics-Driven Fraud Program

- ✓ Automated Referrals
- ✓ Financial Impact
- ✓ Business Strategy
- ✓ Earlier Identification
- ✓ Focused Efforts



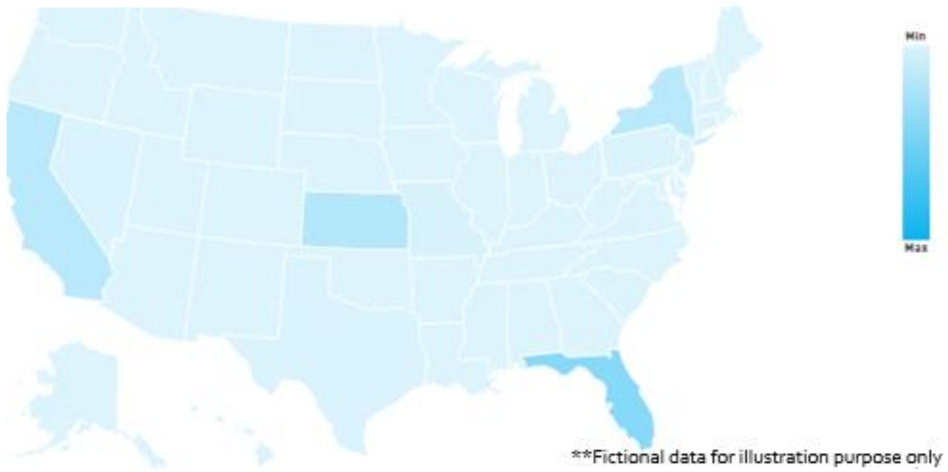
Analytics-Driven Fraud Program



Screened Referrals

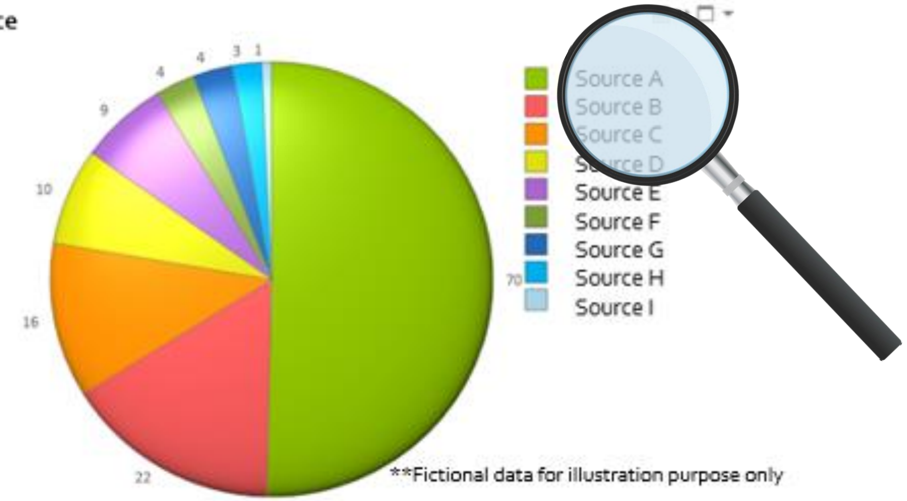
- Red flags / business rules
- Predictive modeling
- Anomaly detection
- Text mining
- Link analysis
- Data visualization

Analytics-Driven Fraud Program: Data visualization



**Fictional data for illustration purpose only

Referrals by Source



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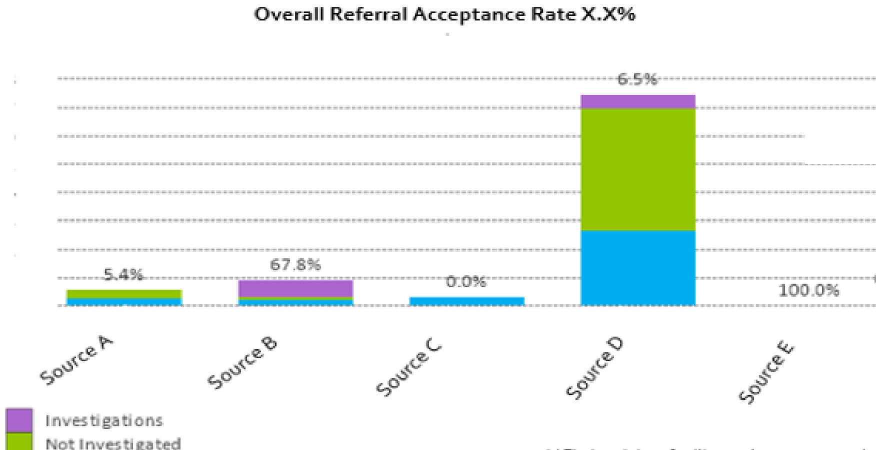
Investigations by Referral Source



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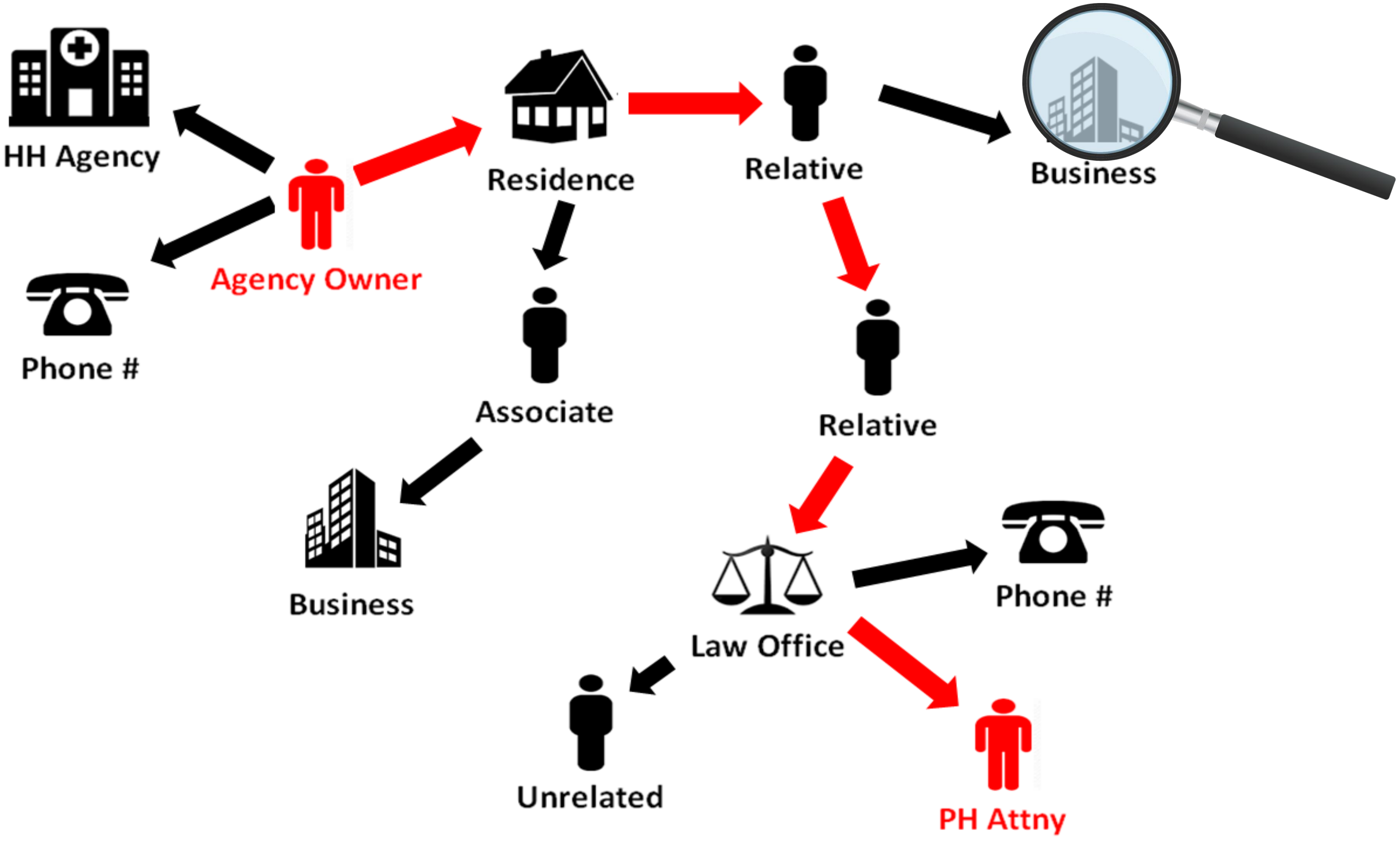


HH Agency
Residence
Relative
Business
Agency Owner
Phone #
Associate
Relative
Business
Phone #
Law Office
Unrelated
PH Attny

USING ANALYTICS TO IDENTIFY RESTORATION OF BENEFITS FRAUD

Case Study Example

- **Problem:**
  - ❖Instances of questionable ROB claims

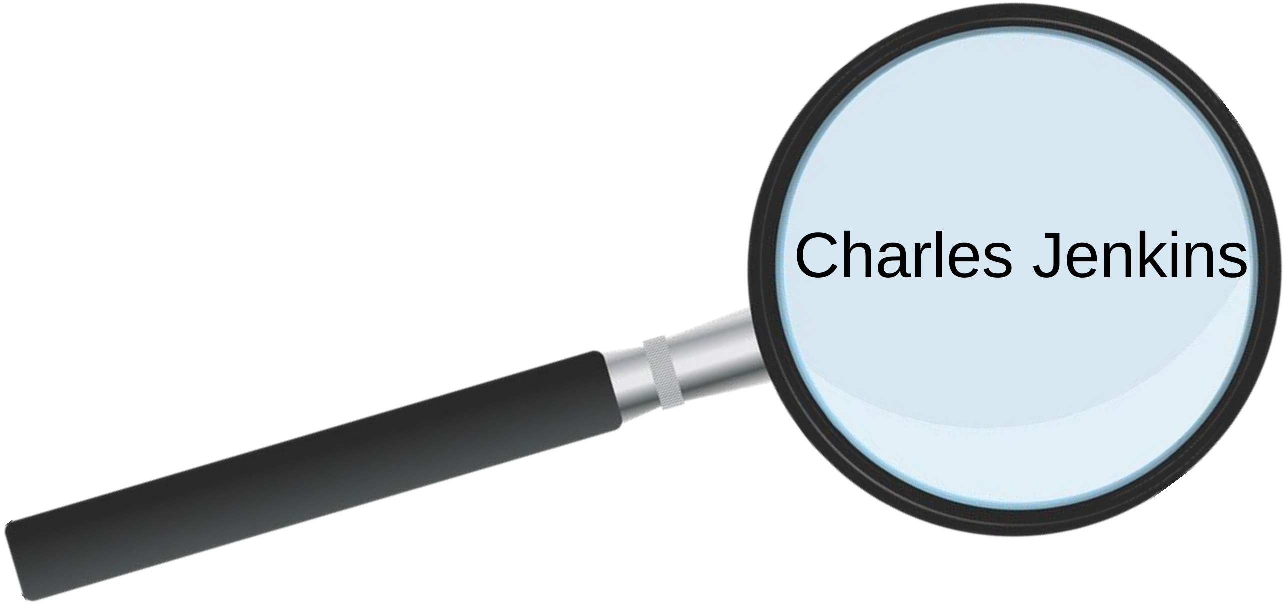
- **Intervention Strategy**:
  - ❖Develop analytics model to predict questionable ROB claims to trigger more detailed review

- **Result**:
  - ❖Increase in fraud identification and prevention of waste/abuse

Case Study Example

Case Study Example

WELLNESS



Wellness programs defined

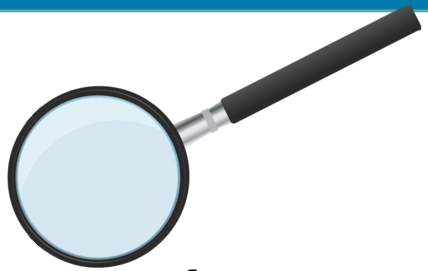
- Goal is to implement a wellness program which will have a positive effect on the customer and the business
- Program depends on expected length of claim
- Program can target short term and long term durational claims
- Program components include:

  - claim analysis
  - management
  - interventions based on predicted claim duration
  - assisting the customer in setting achievable goals for recovery or care
  - optimizing usage of benefits
  - minimizing waste

Foundations

- A Predictive Model with Targeted Criteria
  – What is the expected Incidence, Intensity, and Duration of a claim based on the right data points: *Age, primary diagnosis driving the claim, comorbidities, situs of care, prior level of function, ADL needs, support system, etc.* ?
  – Data analytics is crucial to creating the model through compiling data and ‘running the numbers’ on selected criteria to predict outcomes.
- Reliable Source of Data and Accurate Analysis
  – Are systems in place capable of capturing the appropriate data, preferably through automation?
  – Are tools in place that can analyze and report on the data, and identify claims based on the model?

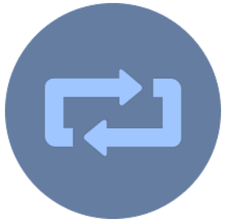
Implementation



- Identify cohorts: *Long Term, Short Term, Unknown*
- Develop strategies for each that will provide the best outcome for the customer
- Be clear on policy language understanding by the business and the customer
- Educate the customer and get them (voluntarily) actively engaged in setting and reaching goals
- Consider engaging the customer’s physician

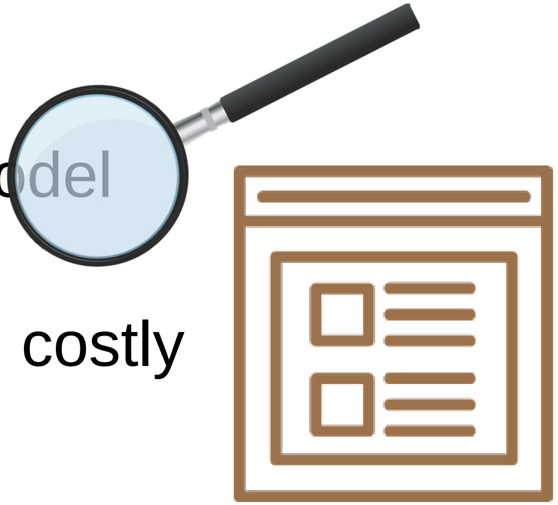
Monitoring and metrics

- Systems should be capable of capturing data from program implementation through end, not just for the initial prediction
- Ongoing data capture and analysis:
  - Monitor program effectiveness for the customer and the business
  - Provide information to modify, expand, improve, and refine the predictive model which:
    - strengthens the model
    - provides better outcomes
    - allows for dynamic adjustments as the demographics of the claim block change over time

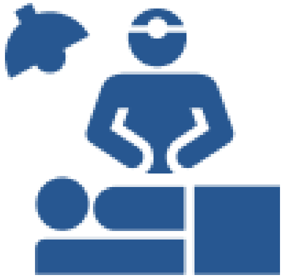


  - Track strategy success
  - Metrics and data for managing the day to day, run the business use as well as compiling information to identify trends that can be used cross functionally (claims, actuary, staffing, etc.)

Risks



- May take time to capture/acquire sufficient data to create a model and evaluate effectiveness
- Poor data sources and analysis can lead to an ineffective and costly program
- Claim cohort incorrectly identified which may impact ability to implement program and facilitate customer return to a level of independence
- Lack of interest or participation by customer to want to return to a higher level of function



Rewards

CUSTOMER

- A better claim experience for the customer through active engagement

- Added value for the customer
- Better health-related outcome for the customer
- Efficient utilization and potential preservation of benefits

BUSINESS

- Better reserving
- Effective claim cost management
- Historical data captured for future claim analysis and modeling

ANALYTICS-BASED INTERVENTIONS FROM THE HEALTHCARE INDUSTRY

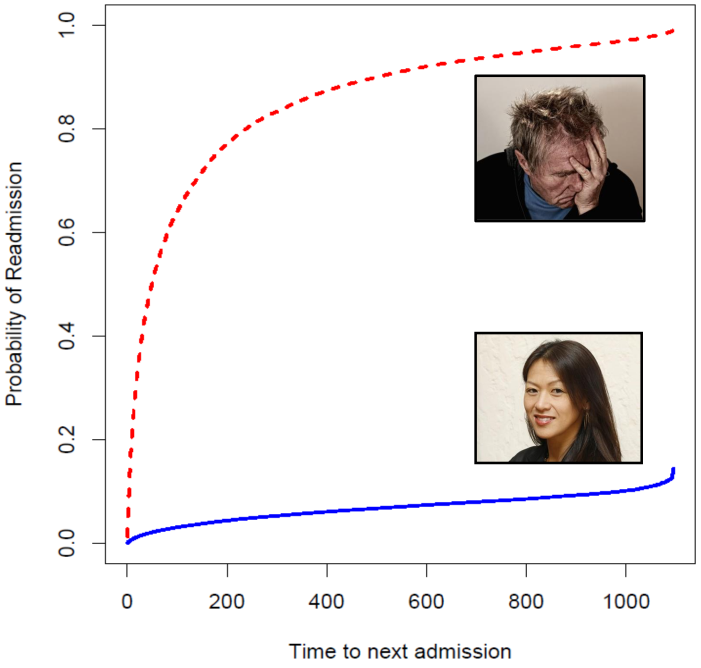
PREVENTABLE HOSPITAL READMISSIONS

Li is a **commercially insured** patient admitted with a **nervous system disorder**. She stayed in the hospital for **less than 24 hours** with a disease **severity level of 1**. She is **married** and is being **discharged to home**. She was in the **hospital 180 days prior**.

4%

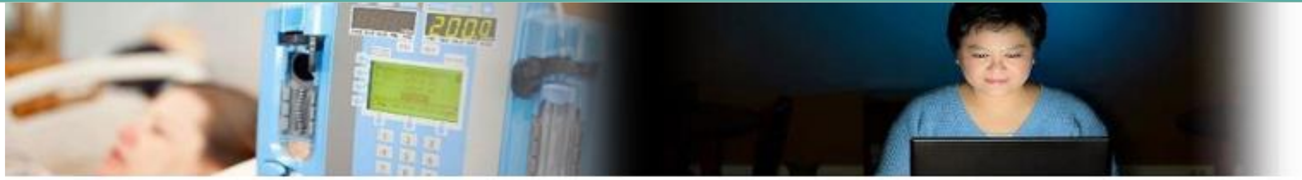
Risk of 30-Day Readmission

29%



Robert is a **Medicaid** patient admitted with a **blood disorder**. He stayed in the hospital for **6 days** with a disease **severity level of 3** having a **hospitalist** as his attending physician. He is **legally separated** and is being **discharged to home.** He was in the **hospital 15 days prior**.

Readmission: decision support app



Regenstrief Center for Healthcare Engineering

PURDUE UNIVERSITY Discovery Park

30-Day Readmission Risk Assessment

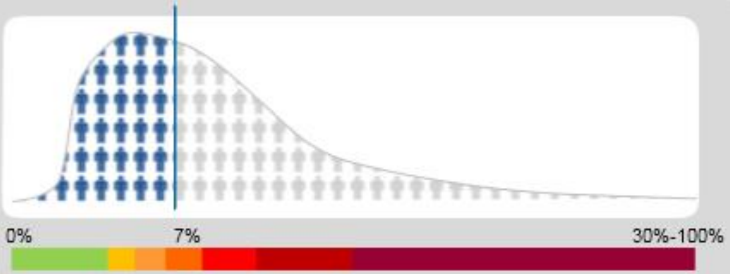
Name	Mary Stewart
Patient ID	4
Current Date	April 18, 2014 08:25 AM
Discharge Date	Saturday, April 19, 2014
Principal Diagnosis	16.10 Complications

Risk Rating:

Average

Preventable Readmission Risk 7%

More likely to be readmitted than 48% of patients



Recommended intervention(s):

- [x] Enhanced Discharge and Scheduled Follow-up ★★★

Other available intervention(s):

- [ ] Transition Coach ★★★★
- [ ] Post-Discharge Phone Call and Home Visit ★★★★
- [ ] Virtual Nurse ★★
- [ ] Medication Reconciliation ★★
- [ ] Language Assistance ★
- [ ] Teach-Back Discharge Plan ★

COMPANY WELLNESS

Mrank

A non-linear, non-weighted, pairwise comparison method*

Health Determinants				
BMI	A1C	LDL	Systolic	Diastolic
45	6.2	125	150	97
28.1	8.5	127	143	96
27	5.5	150	162	101
24.3 +	4.3 +	140 +	121 +	89
25.1	4.9	123	115	77
26.1	5.2	135	136	91
24.5	5.1	127	125	79
22	4.7	120	119	72
28	5.2	178	130	83 +
38	11.7	131	129	88

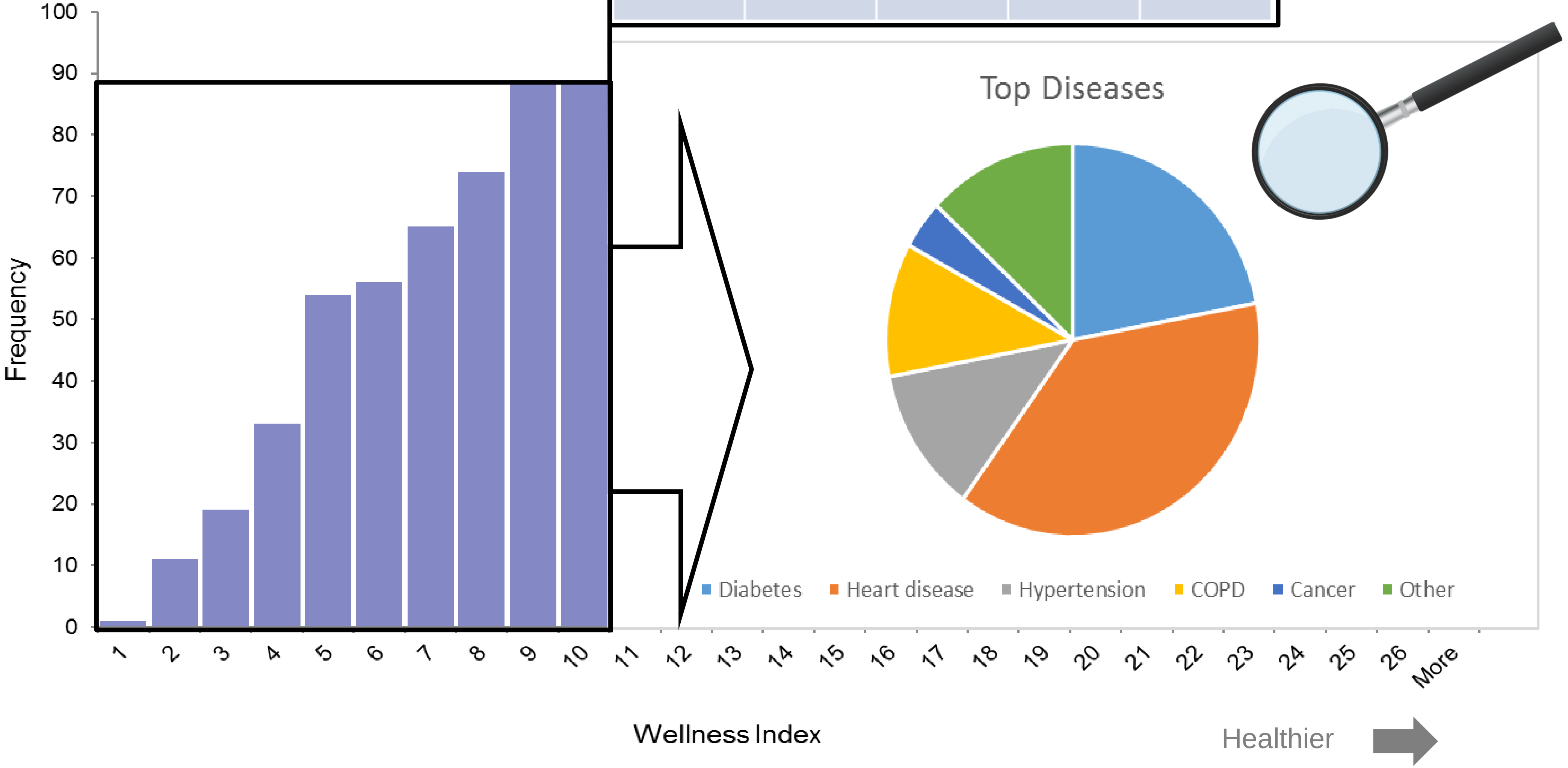
Data Matrix

* Huang, P. and Moh, T., "A non-linear, non-weight method for multi-criteria decision making," *Annals of Operations Research,* January 2017

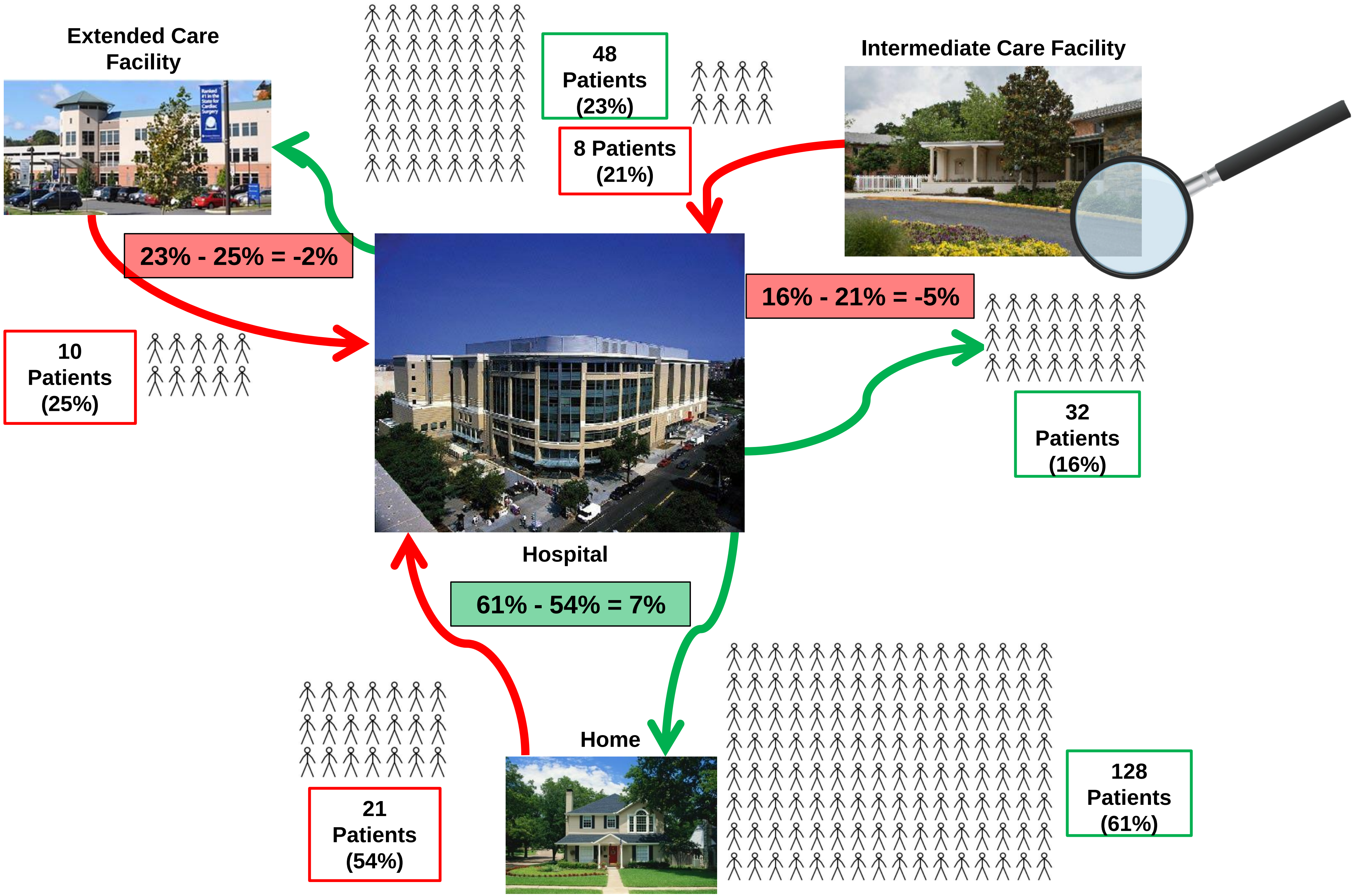
Company wellness

Population: 1,135

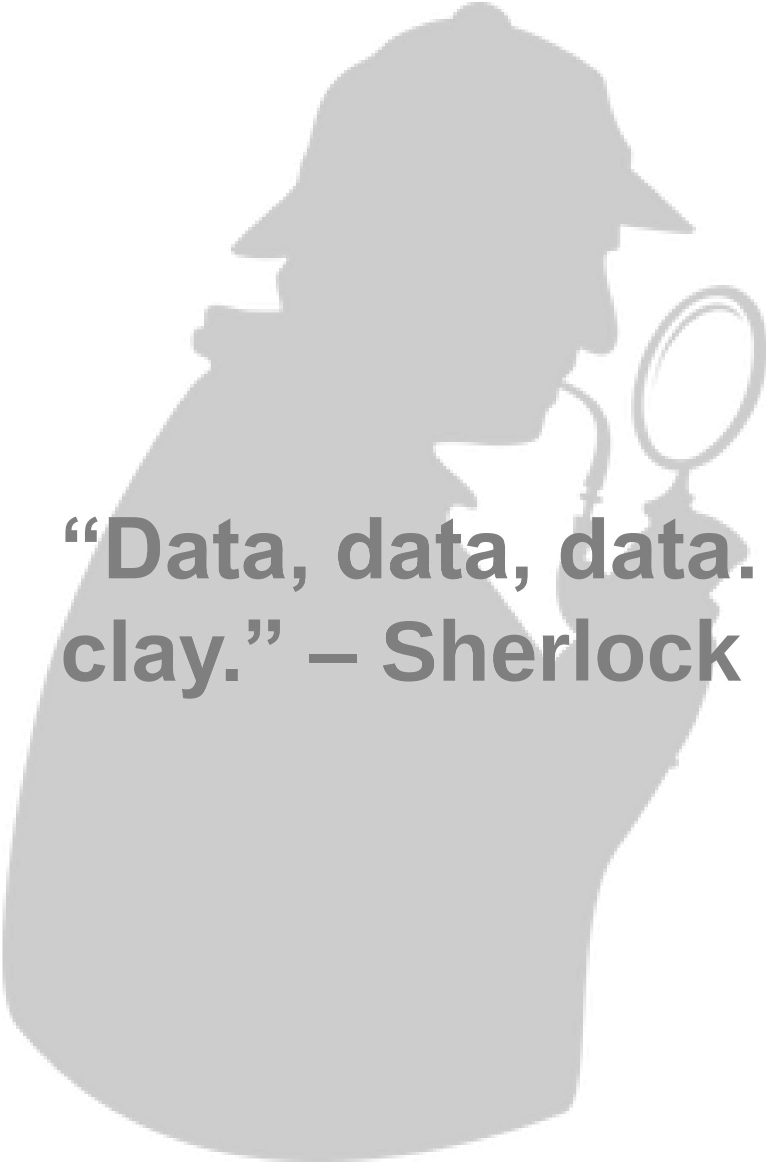
BMI	A1c	LDL	Systolic	Diastolic
25	5.7	130	120	80



CARE TRANSITIONS


Extended Care Facility
48 Patients (23%)
Intermediate Care Facility
8 Patients (21%)
23% - 25% = -2%
16% - 21% = -5%
10 Patients (25%)
32 Patients (16%)
Hospital
61% - 54% = 7%
Home
21 Patients (54%)
128 Patients (61%)

HAVE YOU DISCOVERED SOME CLAY TO MAKE YOUR BRICKS?



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