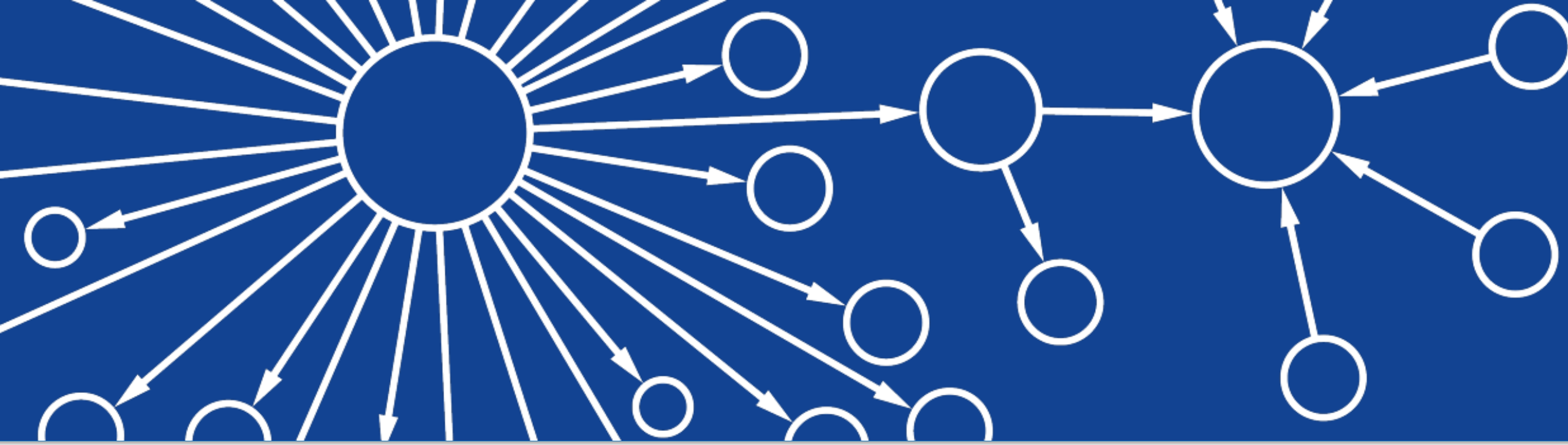

# AI in Quality Measurement


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THE QUEEN'S AWARDS FOR ENTERPRISE: 2014

BEST of SHOW WINNER Bio IT World 18

Linguamatics

# AI in Quality Measurement

- Interest in AI techniques such as NLP is exploding in healthcare. Such approaches hold promise for supporting quality measurement as part of workflows that augment human review and improve efficiency.
- Workshop topics:
  - Introduction to AI and NLP, advantages and disadvantages
  - Example quality measures:
    - Fall risk, Adult BMI assessment, ~~Comprehensive Diabetes Care~~, goal-based measures and *prior authorization/clinical review*
  - Discuss characteristics of quality measures that suit NLP

# Agenda

- Different types of AI and thoughts on applications
- Example applications of NLP
- Specific measures, deeper dive
  - Fall risk and NLP at MUSC
  - Goal based measurement, Person driven outcomes
  - BMI and opportunities for NLP
- Discussion and recommendations

# General discussion and potential outcomes

- Define challenges in quality measurements
- Share experiences of application of AI and NLP from the group
- Identify measures that would benefit from AI/NLP techniques
- Agree characteristics of measures that make them a good target
- Provide recommendations for NCQA and community

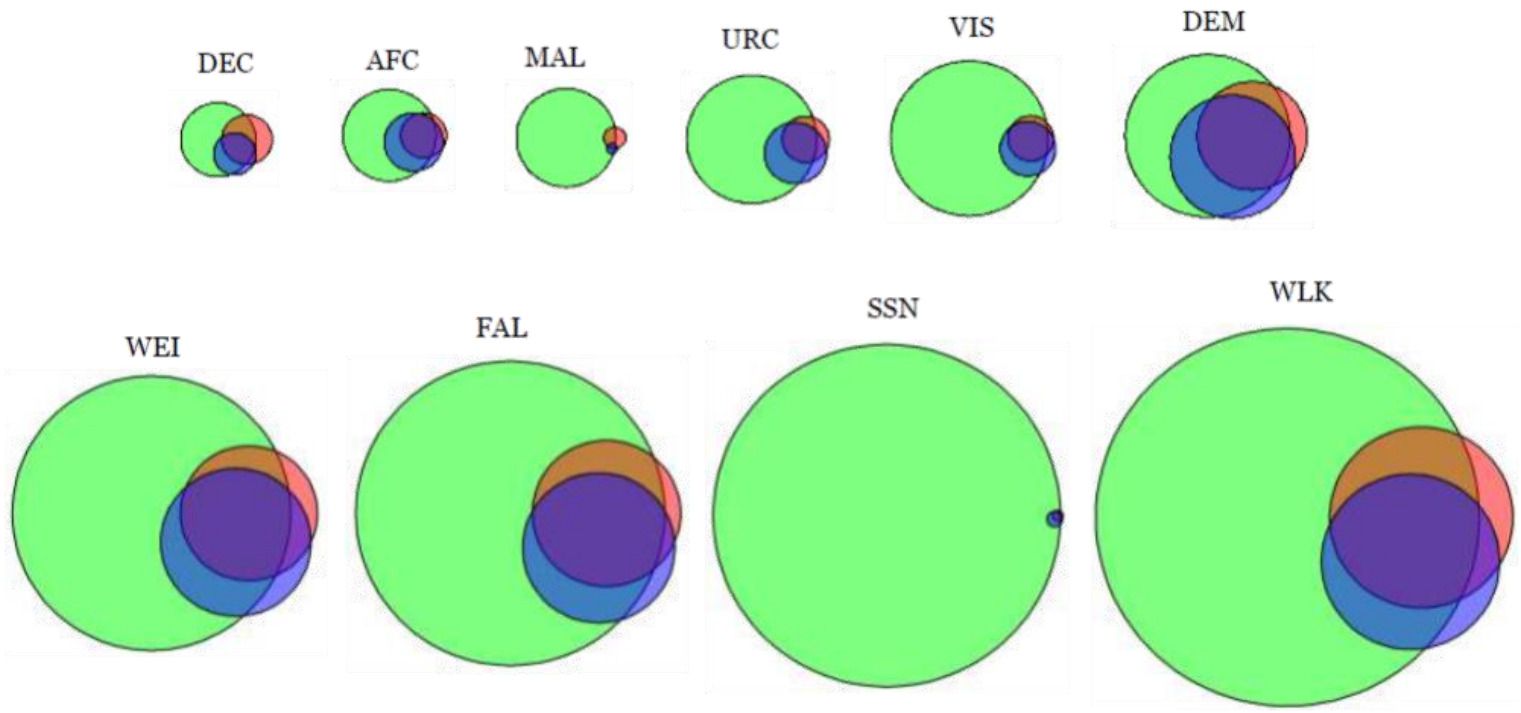
- Sessions on day 1 ONLY

# $15.4B annually to report quality measures



Casalino et al *Health Affairs* 2016

# Key clinical concepts are "locked" in free text




Added value of free text represented by the Venn diagram
Circle sizes represent the number of patients identified by each methodology/data-source
*Green: EHR Free Text; Blue: EHR Structured; Red: Insurance Claims*

| | |
|---|---|
| DEC | Ulcer |
| AFC | Stool incontinence |
| MAL | Malnutrition |
| URC | Urin. incontinence |
| VIS | Visually impaired |
| DEM | Dementia |
| WEI | Weight loss |
| FAL | Fall risk |
| SSN | Social support |
| WLK | Walking difficulty |

Johns Hopkins CPHIT 2016

# Artificial Intelligence vs Augmented Intelligence

- Artificial Intelligence
  - the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages
- Augmented Intelligence
  - *The concept of augmented intelligence is not to replace humans, but rather to capitalise on the combination of algorithms, machine learning, and data science to inform human decision-making abilities.*
  - *Information Age*

# Examples of AI

## Well known

NETFLIX

amazon

## Healthcare

IBM Watson

Large volumes of structured features and outcomes to model with



Linguamatics

# Supervised and Unsupervised Machine Learning

- Supervised
- Most commonly used - data scientist acts as a guide to teach the algorithm
- Training data is already labeled with correct answers
- For example, a classification algorithm will identify tumors after being trained on a dataset of labeled radiology images
- Examples include: linear and logistic regression, multi-class classification, and support vector machines.

- Unsupervised
- More closely aligned with what some call true artificial intelligence
- No labeled data, algorithms identify their own patterns
- For example, language translation from Google
- Examples include k-means clustering, principal and independent component analysis, and association rules

# What is Natural Language Processing?

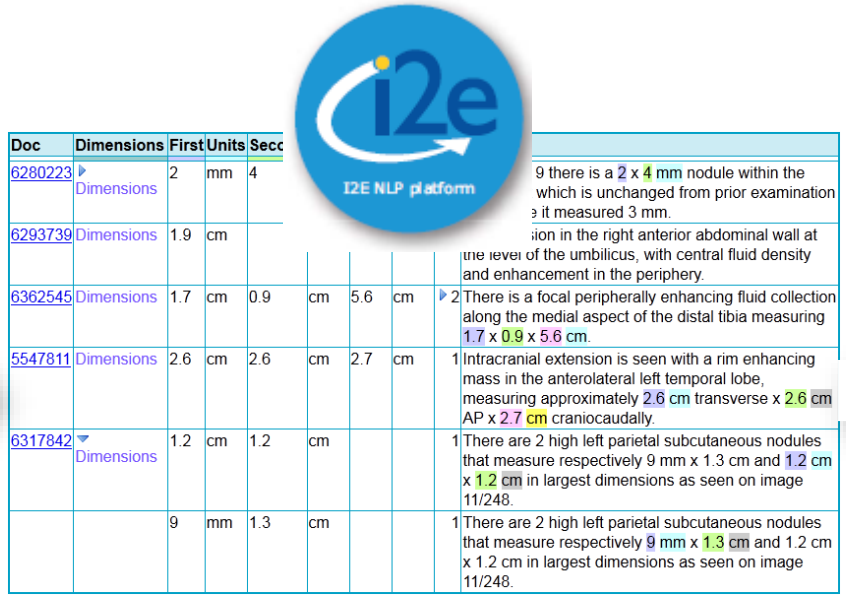
- Extraction of concepts from the free text ("unstructured" data) of clinical reports or clinician progress notes
- More than "key word" search;  Not "speech-to-text"
- Specific concept using ontologies and context:
  - "copd" vs "chronic obstructive pulmonary disease"
  - Family history of, ruled out, no evidence of
- General concepts:
  - "negative" sentiment in customer service or call center notes
- Value concepts:
  - ejection fraction, BMI

# NLP Turns Text into Discrete Data

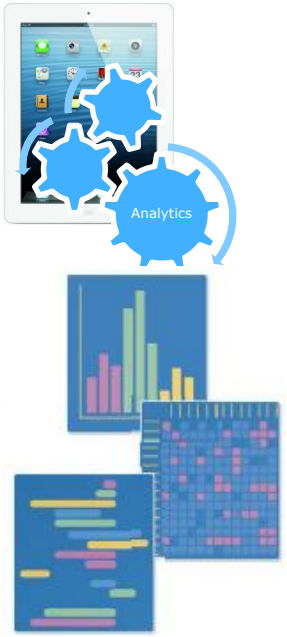
Turn text

Into structured data using sophisticated queries

To drive analytics


| Doc | Dimensions | First | Units | Secc | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 6280223 | Dimensions | 2 | mm | 4 | | | | | 9 there is a 2 x 4 mm nodule within the which is unchanged from prior examination e it measured 3 mm. |
| 6293739 | Dimensions | 1.9 | cm | | | | | | ion in the right anterior abdominal wall at the level of the umbilicus, with central fluid density and enhancement in the periphery. |
| 6362545 | Dimensions | 1.7 | cm | 0.9 | cm | 5.6 | cm | 2 | There is a focal peripherally enhancing fluid collection along the medial aspect of the distal tibia measuring 1.7 x 0.9 x 5.6 cm. |
| 5547811 | Dimensions | 2.6 | cm | 2.6 | cm | 2.7 | cm | 1 | Intracranial extension is seen with a rim enhancing mass in the anterolateral left temporal lobe, measuring approximately 2.6 cm transverse x 2.6 cm AP x 2.7 cm craniocaudally. |
| 6317842 | Dimensions | 1.2 | cm | 1.2 | cm | | | 1 | There are 2 high left parietal subcutaneous nodules that measure respectively 9 mm x 1.3 cm and 1.2 cm x 1.2 cm in largest dimensions as seen on image 11/248. |
| | | 9 | mm | 1.3 | cm | | | 1 | There are 2 high left parietal subcutaneous nodules that measure respectively 9 mm x 1.3 cm and 1.2 cm x 1.2 cm in largest dimensions as seen on image 11/248. |




Patient shows a dilated cardiomyopathy with ejection fraction measured at 30%



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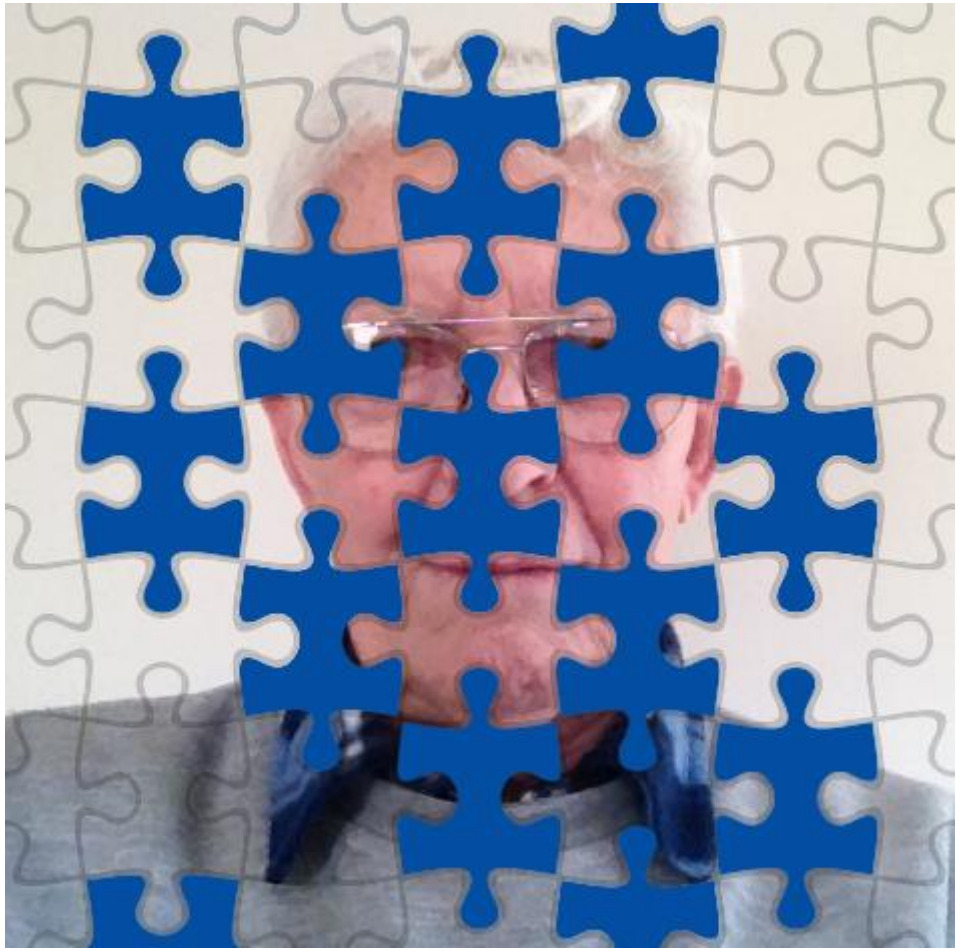
# The View With Structured Data

Claims:
Age: 74
Gender: Male
Heart attack
Pace maker fitted
Hospitalized with DVT
Plavix



Limited understanding of disease severity and member social determinants of health and life style factors

# NLP Insights into Disease Severity and Social Determinants

**Claims:**
**Age: 74**
**Gender: Male**
**Heart attack**
**Pace maker fitted**
**Hospitalized with DVT**
**Plavix**

Clinical notes:
Ejection fraction: 50
BMI: 22
A1C: 6
No shortness of breath

Social and life style:
Non-smoker
Red wine drinker
Wife recently deceased
Lives with sister in law



Linguamatics

# Types of NLP

- Rule based
- Analyst writes rules to extract values
- Ideally use data driven approaches to assess variability of language
- Manual process requiring effort to craft each rule
- Have transparency, good for healthcare

- Machine learning
- Focus on supervised approach, need to extract specific features
- Requires expensive annotated data sets or gold standards
- Needs to be transferable across variable language
- Lots of NLP engines, requires skills to use

# Challenges and Recommendations in NLP

- Annotated data
  - Used for evaluation, expensive process. HEDIS and other quality measures evaluations provide ready made training data
- NLP skills
  - In short supply but more options that enable use of NLP
- Transparency
  - Machine learning models lack transparency, rules better for this
- Workflow
  - Need to integrate with existing workflows, minimize impact to reviewers
- Data quality
  - PDF medical records can be terrible, use of OCR improving. More availability of EHR records securely sent to health plans and payer (SES)
- Data variability
  - Language varies across hospitals so need to preprocess and assess variability at scale

# CHF & COPD NLP helps close care gaps and add revenue

- NLP review efforts identified otherwise undocumented CHF or COPD patients across all payers
- Eligible for disease management and quality metric denominators

- **Manual chart review identified 1 care gap from 1000 patients**
- **NLP enriched review identified 1 care gap from 6 patients**

| qID | NYHA Class | Ejection Fraction | Type | ACE/ARB | ACE/ARB Dosage | Beta Blocker | Dosage | Hit | Doc |
|---|---|---|---|---|---|---|---|---|---|
| All | All | All | All | All | All | All | All | All | All |
| 1;2;3;4 | II | [30, 40] %<br>30-40% | | Ramipril<br>ramipril 10 mg/d. | 10 mg every 1d<br>10 mg/d. | Carvedilol<br>Coreg 25 mg b.i.d. | 25 mg every 12h<br>25 mg b.i.d. | ... dyspnea and an EF of 30-40%. ... 80 mg/d., Coreg 25 mg b.i.d., **NAME[VL0F8SMC] 325 ... 5 mg/d., ramipril 10 mg/d., and bumetanide 1 mg... appears to be NYHA class II and might benefit from implantation ... | P102_1503334.txt<br>cache |
| 1;2;3;4 | II | [40, 45] %<br>40-45% | | Lisinopril<br>Prinivil 20 mg/d | 20 mg every 1d<br>20 mg/d | Metoprolol Succinate<br>Toprol XL 25 mg/d | 25 mg every 1d<br>25 mg/d | ... decline in his EF of 40-45% postoperatively. ... MEDICATIONS: Prinivil 20 mg/d, Toprol XL 25 mg/d and warfarin. ... functional class at NYHA class II. | P102_1503107.txt<br>cache |
| 1;2;3;4 | II | [45, 50] %<br>45%-50% | | Lisinopril<br>lisinopril 40 mg | 40 mg every 1d<br>40 mg daily | Carvedilol<br>carvedilol 25 mg b.i.d. | 25 mg every 12h<br>25 mg b.i.d. | ... with recovered ejection fraction of 45%-50% status post primary prevention ICD ... continues to endorse NYHA class II functional limitations. ... current heart failure medications including carvedilol 25 mg b.i.d., lisinopril 40 mg daily. | M24Acro__2448.txt<br>cache |

# Fall Risk

Linguamatics

# Identifying Falls Risk Screenings Not Documented with Administrative Codes Using Natural Language Processing

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# Background

- Falls are a leading cause of injury in the elderly population and a significant risk factor for morbidity and mortality
- 35-40% of healthy people over 65 fall at least once each year
- Over 50% of seniors (≥ 80) fall annually
- Over 20% of falls cause a serious injury (hip fracture, brain trauma)
- 55% of all deaths due to unintentional injury among the elderly came from falling
- $31 billion estimated direct medical costs for fall injures in the U.S. annually
- Over 50% of the elderly patients who fall do NOT discuss with their providers

# Standards of falls screening

- The American Geriatrics Society and British Geriatrics Society: providers should ask all elderly patients at least annually if they had a fall or had no fall during the prior year (2001)
- CMS: falls risk screening is a core quality of care measurement

  Primary Care Providers (PCP) can receive reimbursement for falls risk screening through voluntary participation in the Physician Quality Reporting System (PQRS)
- MACRA MIPS: a law offering value-based alternative payments for reimbursing physician services (2015)
- Falls risk screening remains a high priority measure in 2017

# Current approach for falls screening measures

- Reporting the percentage of patients aged 65 years and older who had a risk screening for falls within the prior 12 months
- Using CPT codes to define the numerator and denominator exception
- Limitation: may not completely or accurately reflect falls screening activities that providers performed during their practice
- Potential improvement: using Natural Language Processing (NLP) to identify falls screening from clinical notes

# Objectives

- To develop an NLP approach to identify documented falls risk screening in clinical notes for patients lacking coded falls risk screening data
- To evaluate the NLP algorithm performance against a gold standard -- domain expert manual review
- To demonstrate an NLP approach could accurately identify more falls risk screening in electronical health records (EHR) than the quality measure based on administrative codes alone

# Methods

- Study setting: Medical University of South Carolina (MUSC)
  - An academic medical science center serving Charleston, South Carolina, and surrounding areas
  - MUSC EHR: Epic (outpatient since 2012, inpatient since 2014)
  - MUSC Research Data Warehouse (RDW): a copy of Epic data for clinical research
- Data source
  - Cohort: a sample of 144 MUSC Medicare outpatients who had **NO** coded falls risk screening data in 2015
  - Progress notes and consult notes collected during 2015 (n= 1,558)

# Method (Con't)

- Falls Risk Screening Measure (CMS193v3): report the percentage of Medicare patients (≥ 65 Yrs) who were screened for falls risk during the measurement period

AHRQ Agency for Healthcare Research and Quality
Advancing Excellence in Health Care
United States Health Information Knowledgebase

Feedback / Help | Search Meaningful Use

USHIK Home | Standards | HITSP | Common Formats | Meaningful Use | All-Payer Claims | Draft Measures | Child EHR Format

**Falls: Screening for Future Fall Risk**
CMS139v3

Versions: CMS139v1, December 2012 EP • CMS139v2, June 2013 EP • CMS139v3, July 2014 EP • CMS139v4, June 2015 EP • CMS139v5, April 2016 EP

Compare Versions

At A Glance | Downloads/Resources | Population Criteria | Data Criteria | Supplemental Data Elements | Reporting Stratification | Metadata | References

Percentage of patients 65 years of age and older who were screened for future fall risk during the measurement period.

| | | | |
|---|---|---|---|
| ID | 139 | Measure Population: | Not Applicable |
| NQF | 0101 | Measure Observations: | Not Applicable |
| Version | 3 | Measurement Period | January 1, 20xx through December 31, 20xx |
| Release Package | July 2014 EP | Transmission Format | TBD |
| GUID | bc5b4a57-b964-4399-9d40-667c896f31ea | Scoring | Proportion |
| Eligibility | Eligible Professionals | Type | Process |
| Domain | Patient Safety | Measure Set | None |
| Improvement Notation | A higher score indicates better quality. | Measure Steward | National Committee for Quality Assurance |

**Initial Patient Population:** Patients aged 65 years and older with a visit during the measurement period

**Numerator:** Patients who were screened for future fall risk at least once within the measurement period
***Exclusions:*** *Not Applicable*

**Denominator:** Equals Initial Patient Population
***Exceptions:*** *Documentation of medical reason(s) for not screening for fall risk (eg, patient is not ambulatory)* ***Exclusions:*** *None*

**Denominator**: Medicare outpatient
**Denominator exception:**
- non-ambulatory
- wheelchair

**Numerator**: 3288F and 1100F (CPT codes)

# Develop NLP lexicon

| Domain expert (initial terms) | NLP informatician (lexicon) |
|---|---|
| fall | Enhanced “falls” terms: spelling variants, acronyms, and abbreviations |
| AMPAC (Activity Measure for Post Acute Care) | Modifiers: “evaluation,” “associated symptoms,” “risk screen,” “history of,” etc. |
| ADLs (Activities of Daily Living measures) plus “fall” | Negation: |
| nonambulatory | • lab value decreases (Hgb fall, bone density fall, etc) |
| | • vital sign reduction (weight fall, BP fall,etc) |
| | • seasons (last fall, in the fall,etc) |
| | • problems(fell on ice, fall with fracture, etc) |
| | • others(fall asleep, drain fall, fell out) |
| | • nonambulatory (wheelchair bound, bed bound) |
| | **! Note: regular negation actually indicates a fall screening (eg, “no fall”, “denied falls” )** |

# NLP performance evaluation

- Formal evaluation by gold standard (domain expert manual chart review)
- Performance measures
  - Precision: proportion of true positives to the total number of algorithm-identified cases
  - Recall: proportion of true positives that are retrieved by algorithms
  - F-measure: a harmonic mean of precision and recall

    (F-measure =2* precision * recall/(precision + recall))
- Summary the reasons for false positives and false negatives

# Results

- Lexicon: 38 terms of falls risk screening, 26 pre-negation, 35 post-negation

| Terms relevant to falls risk screening | | Pre-negation | | Post-negation | |
|---|---|---|---|---|---|
| fall | 113 | fracture fall | 13 | fall at | 40 |
| falls | 47 | this fall | 6 | fall in | 35 |
| falling | 29 | in the fall | 6 | fall on | 28 |
| Fall Risk | 24 | from fall | 5 | fall + year | 20 |
| fell | 18 | last fall | 4 | fall asleep | 18 |
| fall risk | 15 | h/o | 2 | fall fracture | 4 |
| Fallen | 13 | would fall | 2 | fell out | 4 |
| Fall | 13 | something fall | 2 | fell down | 3 |
| LE AMPAC | 12 | fractures fall | 2 | fall off | 2 |
| denies any falls | 11 | tripped fall | 2 | fall break | 2 |
| No falls | 8 | weight fall | 1 | fell against | 1 |
| AM-PAC Raw Score | 4 | Tripped fall | 1 | fall back to sleep | 1 |
| fell | 3 | Indication fall | 1 | fall broke | 1 |
| Denies falling | 2 | tissue fall | 1 | fall broken | 1 |
| No recent falls | 2 | fever fall | 1 | | |
| Denies any fractures or falls | 2 | Pessaries fall | 1 | | |
| History of falls | 2 | level fall | 1 | | |
| Falls risk scale score | 1 | every fall | 1 | | |
| Risks for falls | 1 | indicated fall | 1 | | |
| risk of fall | 1 | ejection fraction | 1 | | |
| No risk of fall | 1 | | | | |

# I2E algorithm performance

- NLP: identified 62 cases of falls risk screening from 144 patients
- Gold standard (domain expert manual review): identified 64 cases
- In common: 59 true positives, 77 true negatives

| | **NLP algorithm** | |
|---|---|---|
| **Domain expert** | positive | negatives |
| positives | 59 (TP) | 5 (FN) |
| negatives | 3 (FP) | 77 (TN) |

**Precision** =TP/(TP + FP)= 59/(59+5)=59/64=0.92
**Recall** =TP/(TP+FN)=59/(59+ 3) =59/62 = 0.95
**F-measure** = 2*precision*recall/(precision +recall)
=2*0.92*0.95/(0.92+0.95)=0.93

# Examples of misclassification

**False Negatives**

No falls but reports some near falls at home
She denies any trauma or falls in the last 6 months,
One week ago, she tripped and fell on her knees her
Denies falls or fractures, urinary stones, heat...
She denies any trauma or falls in the last 6 months,

**False Positives**

chest pain related to the fall and movement; but nothing
...
the fall - she has no recollection of events
Fell around 10/12, tripped and fell

# Discussion

- I2E algorithms accurately identified 59 patients who had a falls risk screening documented in their clinical notes – (40% more than coded data)
- Several similar studies (focus on falls event detection) with modest performance
  - Toyabe: NLP identification of inpatient falls in progress notes
    - injurious inpatient falls, F-score 0.91
    - Inpatient falls, F-score 0.12
  - Shiner: falls detection from progress note (specificity: 0.80; sensitivity: 0.44)
- Detecting "falls screening" poses more challenge than detecting a "fall incident"
  - providers usually do not use "fall risk" or "fall screening" to document such a activity; they often use "fall" (236 "fall" mentions vs 42 "fall risk" mentions)
- Negation eliminates false positive and may introduce false negative, high specificity preferred for quality reporting

# Conclusions

- Information about falls risk screening can be commonly found in clinical notes for patients lacking such screening recorded by coded data
- The current quality reporting based on coded data only may underestimate the providers' performance
- Using both structured coded data and clinical narratives for quality reporting is necessary

# Person-driven Outcomes

Linguamatics

# Person Driven Outcomes

NCQA Digital Health Summit
November 14, 2018

# Agenda

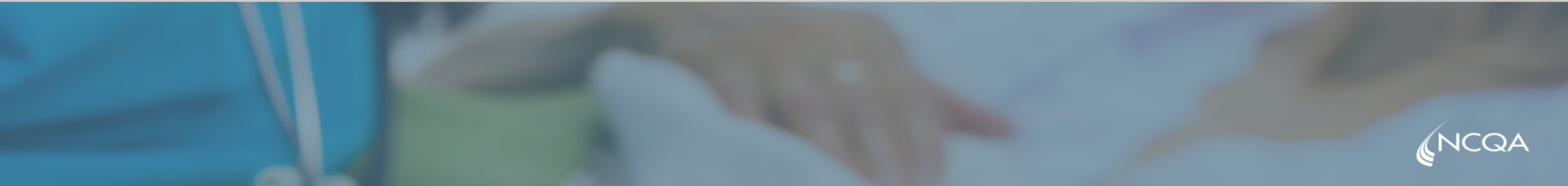
REVIEW OF PERSON DRIVEN OUTCOMES

HOW WILL NLP AFFECT WHAT WE CAN LEARN FROM THIS PROJECT

NCQA

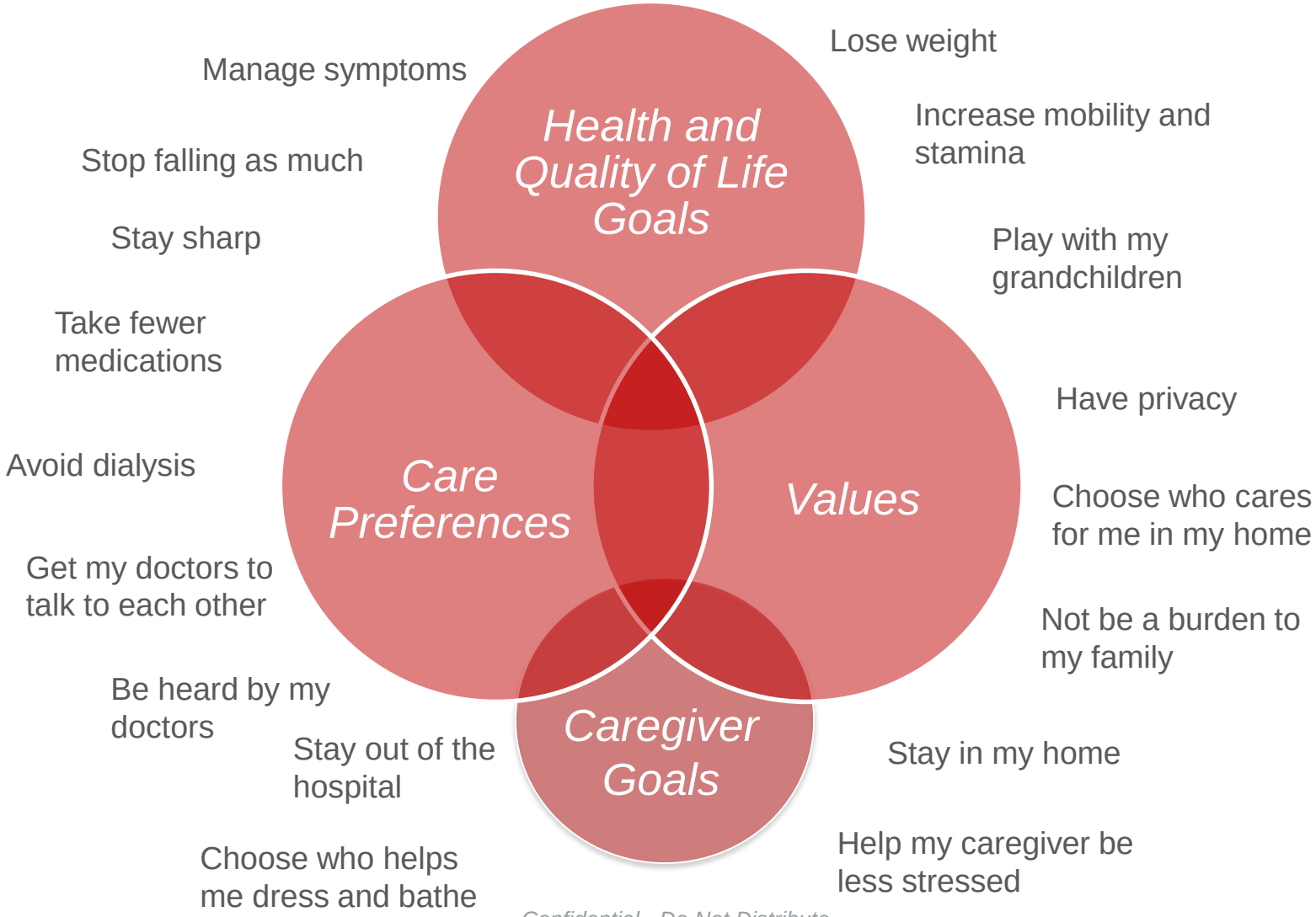
*Person Driven Outcomes*

# Review of Person Driven Outcomes



# What Matters Most?

***Person-Driven Outcomes:*** *Measurable, individualized and prioritized outcomes to guide care and evaluate quality*



# Step 1: Elicit what is important

< Patient Baseline | Goal Inventory | Switch inventory type

**Top 3 Goals**

Select up to three goals that the patient would like to work on in the next three months. You can add a custom goal using the button below.

Add custom goal

- Stay out of the hospital or emergency department
- Get specific care, service or equipment (e.g., wheelchair, transportation services, doctor's appointment)
- Be physically active (e.g., walking, swimming, do physical or occupational therapy)
- Care for myself (e.g., dressing, bathing, cooking, shopping, finances)
- Do recreational activities (e.g., hobbies, community events, travel, volunteer)
- Avoid accidents such as falls
- Socialize with friends and family
- Practice religious or spiritual life

# Step 2: Determine how it will be measured

Patient Goal Inventory | Goal Questionnaire

What is the patient or caregiver's goal you will be working on? ?

Avoid accidents such as falls

Do you want to measure this goal using a Patient Reported Outcome Measure? Some examples of goals that may be measured well with Patient Reported Outcome Measures are mental healh related (depression, anxiety, cognition), symptoms (dyspnea, fatigue, and sleep), or physical function.

YES - Use PROM

NO - Use Goal Attainment Scaling

Continue

# Step 3a: Measure the Outcome

*Goal Attainment Scaling*

Goal Questionnaire | GAS Questionnaire

What outcome did you identify as most important? What is the participant's SMART goal?

Sleep better through the night

Is this a maintenance or improvement goal?

- Maintenance
- ✓ Improvement

Expectation Scale

| Much less than expected (-2) | Where are you now? (-1) | **Expected (0)** | Somewhat better than expected (+1) | Much better than expected (+2) |
|---|---|---|---|---|
| Wake up 3-4 times a night and not fall asleep until after midnight | Wake up 3-4 times a night | Only wake up once a night | Not wake up at all during the night | Not wake up at all during the night and get a full 8 hours of sleep |

# Step 3b: Measure the Outcome

*PROMs*

Patient selects the Person Reported Outcome Measure that captures the outcome of most importance to them

< Goal Questionnaire PROM Questionnaire

**What area do you want to work on? What category describes your goal?**

- Physical Function
- Mobility
- Depression
- Depression (PHQ-9)
- Anxiety
- Anxiety (GAD-7)
- Anger
- Pain Interference with Daily Activities
- Pain Behavior (behavior in response to pain)
- Fatigue
- Dyspnea Severity
- Sleep Related Impairment
- Cognitive Function
- Ability to Participate in Social Activities
- Satisfaction with Social Role
- Social Isolation
- Emotional Support

# Step 4a: Feedback and Reporting

*Patient Facing Reports*


December 18, 2017

**Personal Report** for Jane Doe

**Goal:** I will remain mentally stable and to feel depressed less than 2 days a week.

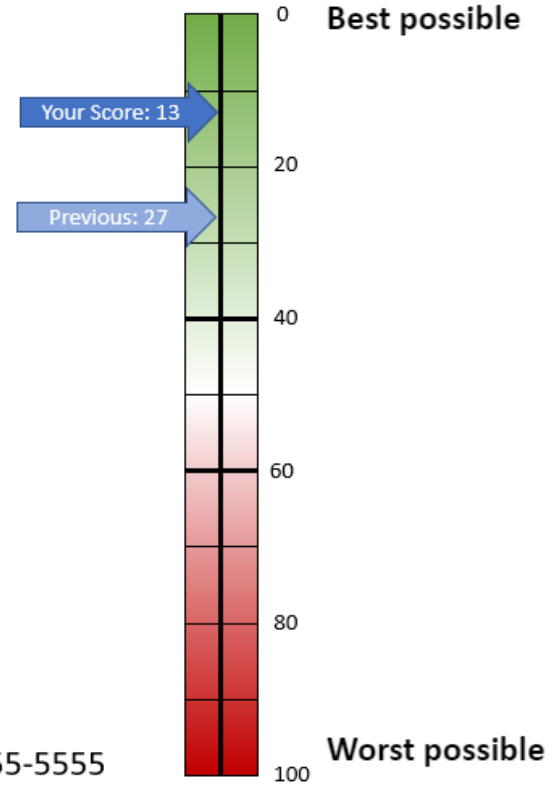
**Outcome:** Depression

**Score:** 13 (Lower scores are better.)

You would like to **improve** this score.

**Possible Barriers:** Trouble getting out of the house. Daughter may not be able to provide ride to psychiatrist appointment.

**Plan:** Become more involved in the community – join the church choir and carpool with others.
Continue regular appointments with psychiatrist. Get additional CountyRide vouchers for transportation.




**Next follow up:** 6 months **Care Manager**: John Smith **Phone Number**: 555-555-5555

# Step 4b: Feedback and Reporting

*Patient Facing Reports*

October 18, 2017

**Personal Goal Report** for Jane Doe

**Goal:** To go to Arizona the first of the year

COMMUNITY HEALTH PLAN of Washington™

This is a goal to **IMPROVE** At your last follow up you had done **SOMEWHAT LESS THAN EXPECTED**

| Much less than expected | Somewhat less than expected | Expected Level | Somewhat better than expected | Much better than expected |
|---|---|---|---|---|
| To experience delays in healing, and not be able to travel, as planned | To be back to baseline eventually, but not at rate of expectation | To be at baseline to travel by Jan 1, 2017 | To be back to baseline by Christmas 2016 | To be back to baseline by Thanksgiving 2016 |

**Barriers:** Concern that physical therapy will be too expensive

**Plan:**
Continue working with Physical Therapist
Do daily exercises as described by the Physical Therapist
Get patient qualified for lower-cost services (to overcome cost barrier)

**Next follow up:** 3 months **Care Manager**: John Smith **Phone Number**: 555-555-5555

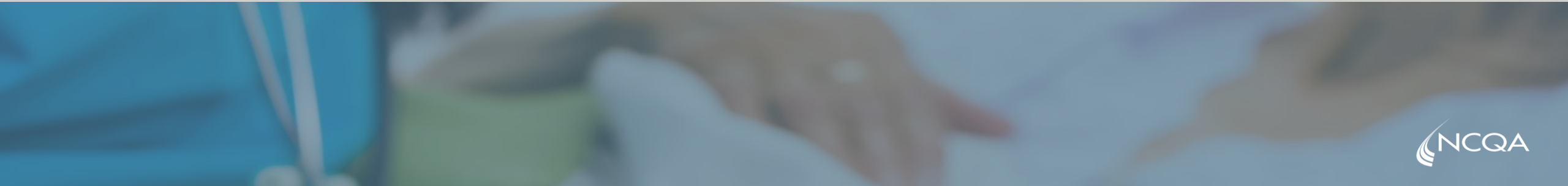
# Step 5: Measurement

| Clinician | % pts. with goal and plan documented in last 6 months | % pts. with follow-up on goal in last 6 months | % of pts. with goal achieved in last 6 months |
|---|---|---|---|
| Clinician A | 99 | 81 | 74 |
| Clinician B | 100 | 90 | 80 |
| Clinician C | 80 | 75 | 65 |
| Clinician D | 75 | 74 | 50 |

*Provide organizations with a way to track how well they are doing helping people to achieve what they say matters most*

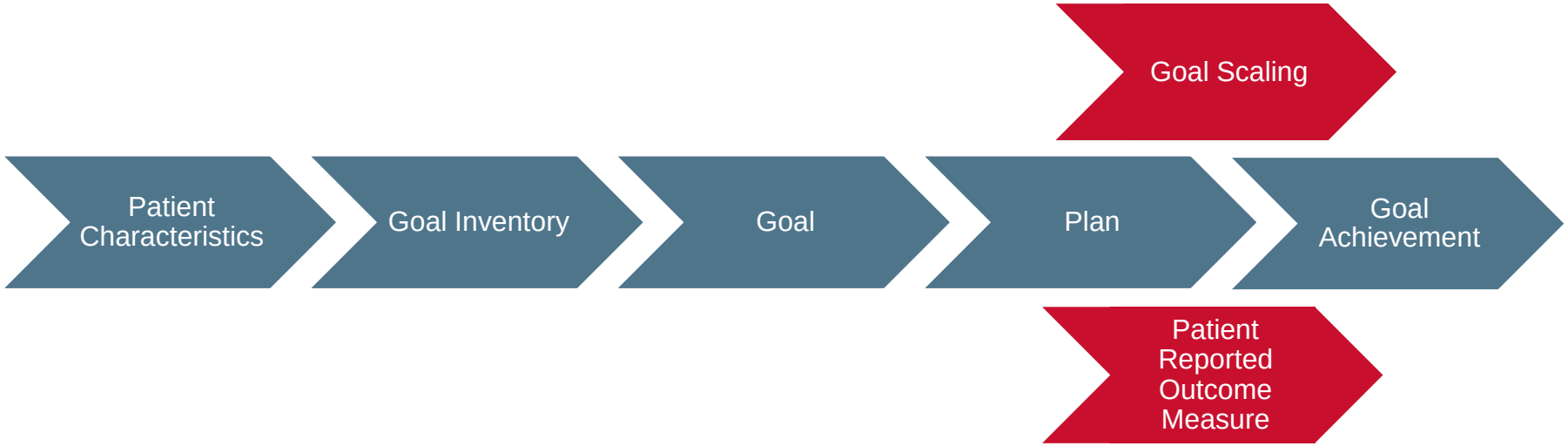
*Person Driven Outcomes*

# How will NLP affect what we can learn?



# Opportunities to Use NLP

*What can we learn?*




| SMART Goal selected for scaling | GAS - Much less than expected | GAS - Somewhat less than expected | GAS - Expected | GAS - Somewhat better than expected | GAS - Much better than expected |
|---|---|---|---|---|---|
| To walk with a cane again instead of walker | Require use of a wheelchair | Walk with a walker | Walk with a cane within next 3-6 months | Walk with a cane within next 1-2 months | Walk with a cane within the next month |
| To walk without any equipment, cane walker etc | Rely on equipment for walking most of the time | Walking with cane/walker when out of home and longer distances | Walk without equipment when out of home for daily activities | Rarely use equipment for walking unless very long distances | Never have to use equipment for walking |
| To be well enough to be able to mow his lawn in 6 months | To rely on others for lawn care | To mow lawn by next fall | To mow lawn by next summer | To mow lawn by next spring | To go shopping or similar activities without wheelchair by mid-winter |
| To be “normal” walk without equipment and have pain controlled as 5 out of 10. | To require use of a wheelchair at times and have pain rating 8-10 in 6 months. | To require use of a walker/cane and have pain rating 6-8 within 6 months. | To walk without equipment and occasionally use a cane with pain rating 5-6 within 6 months | To walk without equipment, occasionally a cane and have pain rating 4-5 within 6 months | To walk without equipment and report pain rating 0-3 within 6 months. |
| To resume “normal” life (driving, outings, visiting father) and to improve diabetes A1c from 10% | Not be able to drive, rely on others for some needs and have no change in A1c within 6 months. | Drive, meet with friend and family within 3 months and improve A1c to 9 by May 2017 | Drive, meet with friends and family within 2 months and improve A1c to 8 by May 2017 | Drive, meet with friends and family within 6 weeks and improve A1c to 7 by May 2017 | Drive, meet with friends and family within 1 month and improve A1c to 6.5 by May 2017 |

NCQA

*"I was made more aware of the time spent at the bedside, how much you can gain from that conversation, how much information you can gain to make the right referrals and to set that patient up for even a greater success…"*

*– Nurse care manager*

*"…we work together. I don't feel like she's giving…orders to have things done. I feel like…she's understanding of what he can do."*

*– Wife of 85-year-old male patient*

*Questions*

# BMI Measures

Linguamatics

# Measurement Applications for NLP

*Measure Case Studies - Weight Assessment and Counseling for Nutrition and Physical Activity for Children/Adolescents (WCC)*

Description:

The percentage of members 3–17 years of age who had an outpatient visit with a PCP or OB/GYN and who had evidence of the following during the measurement year.

**This measure has three rates**

- BMI percentile documentation*
- Counseling for nutrition
- Counseling for physical activity

*Because BMI norms for youth vary with age and gender, this measure evaluates whether BMI percentile is assessed rather than an absolute BMI value.

# Measurement Applications for NLP

*Measure Case Studies - Weight Assessment and Counseling for Nutrition and Physical Activity for Children/Adolescents (WCC)*

## Measure Specifications

Eligible Population: Patients aged 3–17 years as of December 31 of the measurement year.

Denominator: A systematic sample drawn from the eligible population

Numerator: **BMI Percentile**
BMI percentile during the measurement year as identified by administrative data or medical record review

Numerator: **Counseling for Nutrition**
Documentation of counseling for nutrition or referral for nutrition education during the measurement year as identified by administrative data or medical record review

Numerator: **Counseling for Physical Activity**
Documentation of counseling for physical activity or referral for physical activity during the measurement year as identified by administrative data or medical record review

# Measurement Applications for NLP

*Measure Case Studies - Weight Assessment and Counseling for Nutrition and Physical Activity for Children/Adolescents (WCC)*

**Definitions**

**Administrative Specification**

BMI Percentage Value Set
Nutrition Counseling Value Set
Physical Activity Counseling Value Set

**Medical Record Review: BMI Percentile**

Documentation must include height, weight and BMI percentile during the measurement year. The height, weight and BMI percentile must be from the same data source.

Either of the following meets criteria for BMI percentile:

- BMI percentile documented as a value (e.g., 85th percentile).
- BMI percentile plotted on an age-growth chart.

Only evidence of the BMI percentile or BMI percentile plotted on an age-growth chart meets criteria.

# Measurement Applications for NLP

*Measure Case Studies - Weight Assessment and Counseling for Nutrition and Physical Activity for Children/Adolescents (WCC)*

**Definitions:**

**Medical Record Review: Counseling For Nutrition**

Documentation of counseling for nutrition or referral for nutrition education during the measurement year as identified by administrative data or medical record review

Documentation must include a note indicating the date and at least one of the following:

- Discussion of current nutrition behaviors (e.g., eating habits, dieting behaviors)
- Checklist indicating nutrition was addressed
- Counseling or referral for nutrition education
- Member received educational materials on nutrition during a face-to-face visit
- Anticipatory guidance for nutrition.
- Weight or obesity counseling

# Measurement Applications for NLP

*Measure Case Studies - Weight Assessment and Counseling for Nutrition and Physical Activity for Children/Adolescents (WCC)*

## Examples from medical transcripts

The patient was given a healthy eatings article today and really stressed the importance of at least decreasing the amount of sugar intake as it is a perpetuator of inflammation.... 03/11/2018

She has been trying to work on nutrition and decreasing her saturated fat intake. ... 01/12/2018

Provide high protein diet education for patient and mother. ... 03/17/2018

Provide patient with new type 2 diabetes diet education. ... 02/13/2018

Provide gradual weight loss diet education, heart healthy nutrition education, and diabetes diet education. ... 06/04/2018

I will see her in my office in 3 to 4 weeks where I will give her some lifestyle modifications and dietary advice and disclose the findings of the scope to her. ... 10/23/2017

# Measurement Applications for NLP

*Measure Case Studies - Weight Assessment and Counseling for Nutrition and Physical Activity for Children/Adolescents (WCC)*

**Definitions:**

**Medical Record Review: Counseling for Physical Activity**

Documentation of counseling for physical activity or referral for physical activity during the measurement year as identified by administrative data or medical record review.

Documentation must include a note indicating the date and at least one of the following:

- Discussion of current physical activity behaviors (e.g., exercise routine, participation in sports activities, exam for sports participation)
- Checklist indicating physical activity was addressed
- Counseling or referral for physical activity
- Member received educational materials on physical activity during a face-to-face visit
- Anticipatory guidance specific to the child's physical activity.
- Weight or obesity counseling

# Thank You

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