Christopher Bartley, FSA, MAAA

Senior Actuary

CNO Financial Group, Inc.

Dennis Lu, FSA, FCIA

Senior Manager

Oliver Wyman Actuarial Consulting

Raymond McCollum, PhD

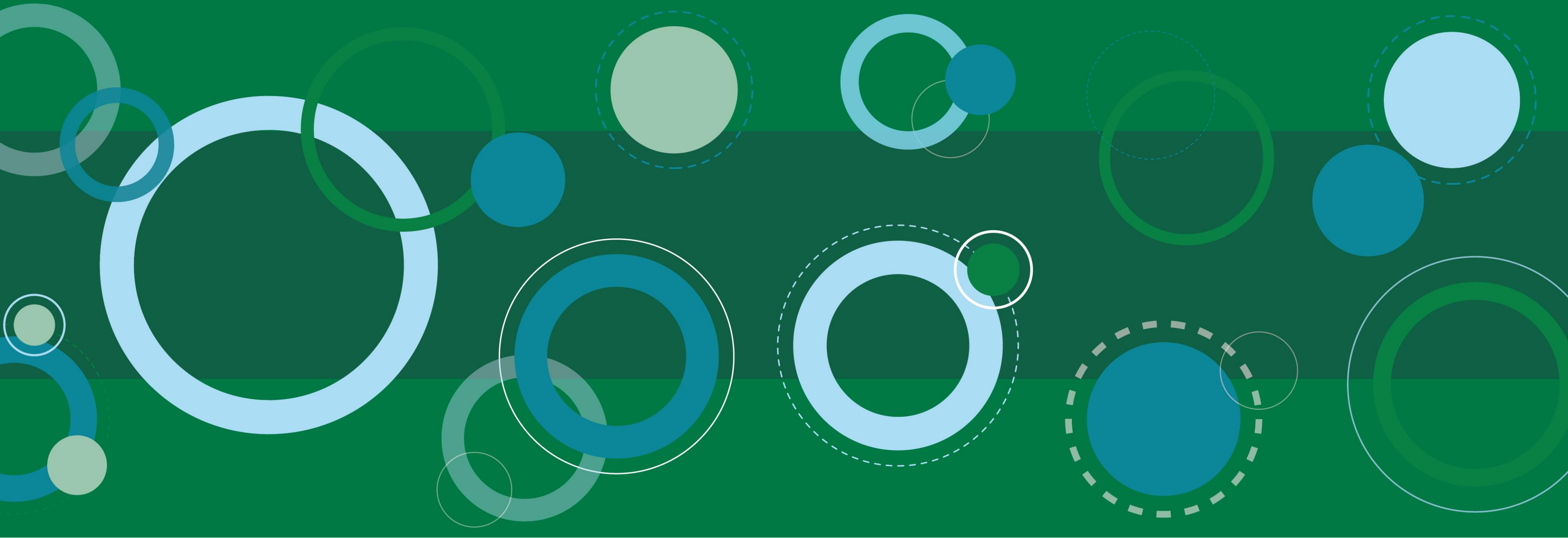*Vice President, Head of Group Insurance and Long-Term Care Data Science*

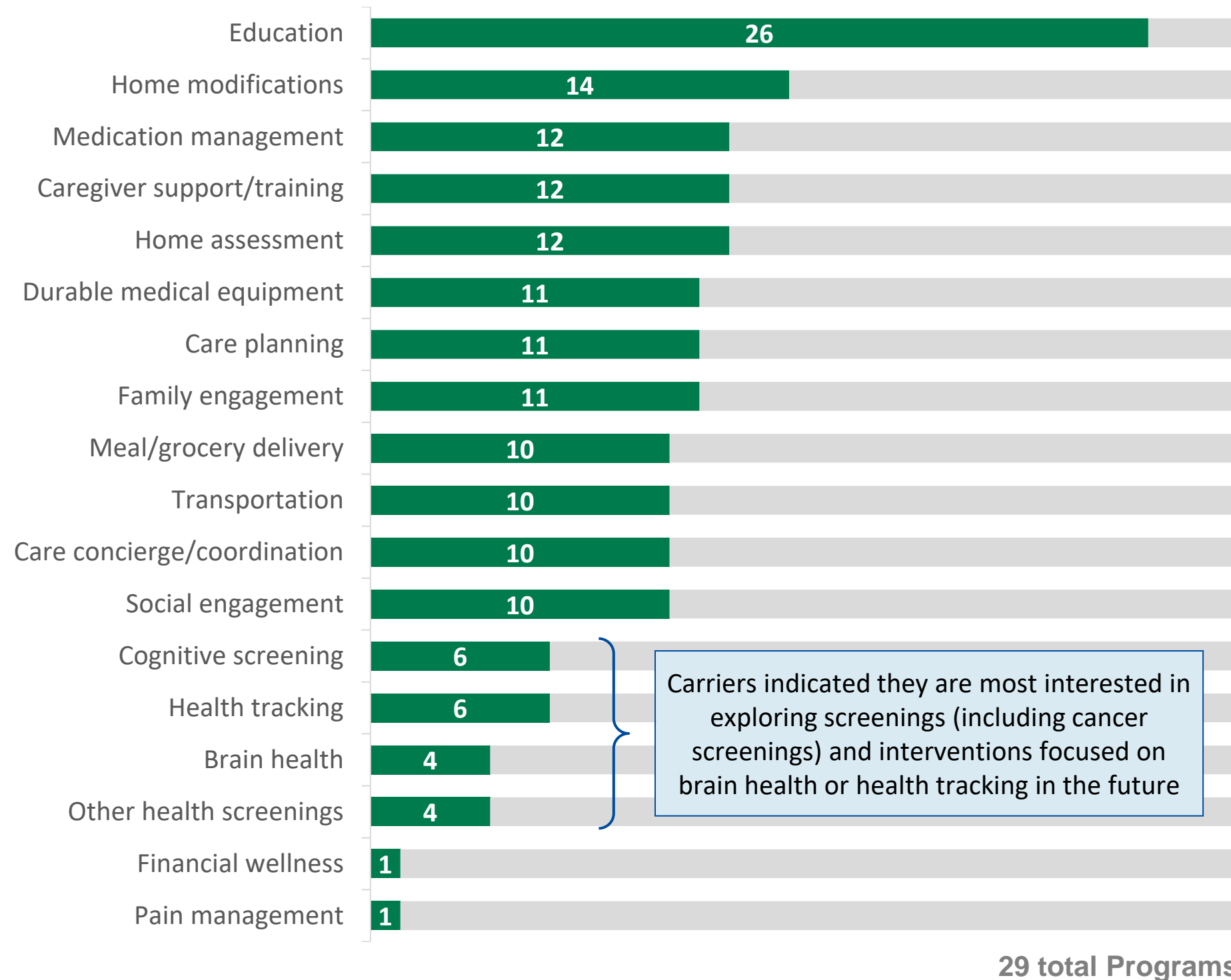Prudential Financial, Inc.

Tom Pyle, ASA, MAAA

Chief Actuary

Continental General Insurance Company

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SOCIETY OF ACTUARIES®

1. LTC Wellness Programs

LTC Wellness Programs: Interventions

What types of interventions are part of your company's Program(s)?[1]

Intervention	Count
Education	26
Home modifications	14
Medication management	12
Caregiver support/training	12
Home assessment	12
Durable medical equipment	11
Care planning	11
Family engagement	11
Meal/grocery delivery	10
Transportation	10
Care concierge/coordination	10
Social engagement	10
Cognitive screening	6
Health tracking	6
Brain health	4
Other health screenings	4
Financial wellness	1
Pain management	1

Carriers indicated they are most interested in exploring screenings (including cancer screenings) and interventions focused on brain health or health tracking in the future

29 total Programs

- **Interventions** are actions taken to mitigate certain risk factors or incentivize behavior change with a goal of improving health outcomes for participants

- On average, LTC carriers use **5-6 different types** of interventions for their wellness programs

- Recent LTC wellness programs (i.e., those implemented after 2020) **offer a wider range of interventions** compared to earlier wellness programs

Interventions that had the most positive impact on carriers' Program(s)[1,2]:

Financial results
1. Care concierge/coordination
2. Caregiver support/training
3. Cognitive screening *[tie]*
4. Other health screening *[tie]*
5. Home modifications

Policyholder satisfaction
1. Durable medical equipment
2. Education
3. Care planning *[tie]*
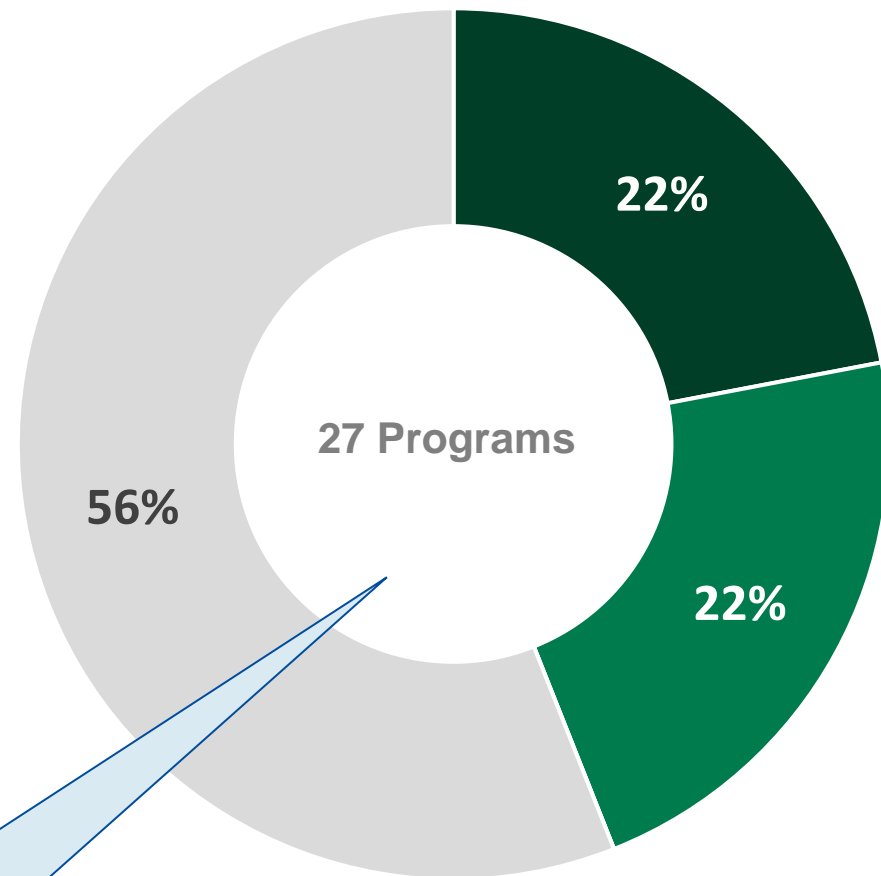4. Caregiver support/training *[tie]*
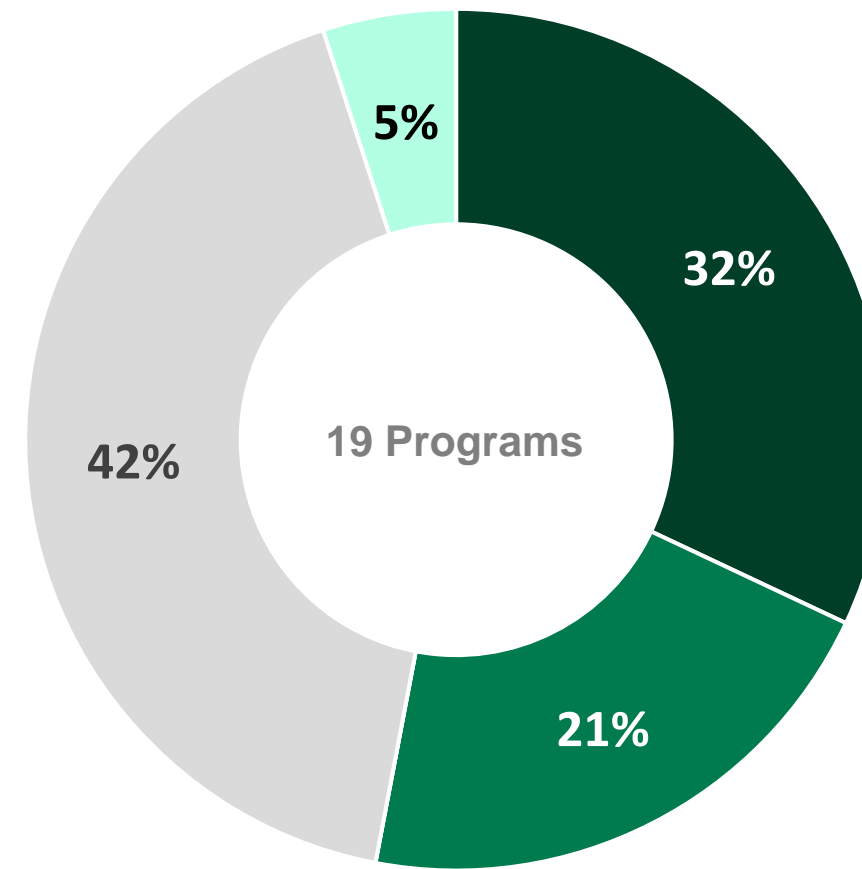5. Care concierge/coordination

LTC Wellness Programs: Outcomes

How is your company's Program(s) performing thus far based on the primary metrics and key approach(es) you are using for measurement?[1]

Based on policyholder metrics

27 Programs

- 22% (Positive)
- 22% (Neutral)
- 56% (Too soon to tell)

Based on financial metrics

19 Programs

- 32% (Positive)
- 21% (Neutral)
- 42% (Too soon to tell)
- 5% (Other)

Policyholder metrics

- Policyholder engagement
- Policyholder satisfaction
- Policyholder behavior
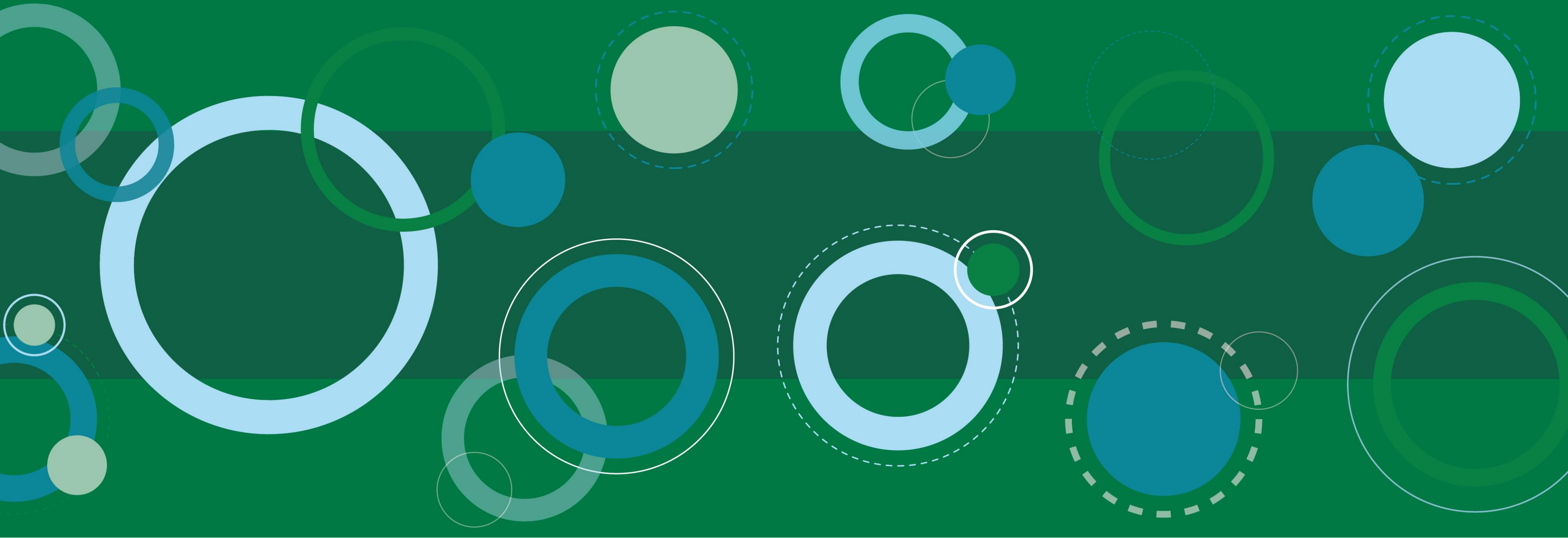
Financial metrics

- Claim incidence
- Benefit utilization
- Paid claims
- Starting site of care
- Care setting transfers

Legend: ■ Positive ■ Neutral ■ Negative ■ Too soon to tell ■ Other

Larger number of respondents as most programs are measuring policyholder metrics, but less are measuring financial impact.

- **Outcomes** are wellness program results based on specific measurement metrics and approaches.
- It is still too soon to assess performance on about 50% of Programs (down from 70% in our 2022 survey)

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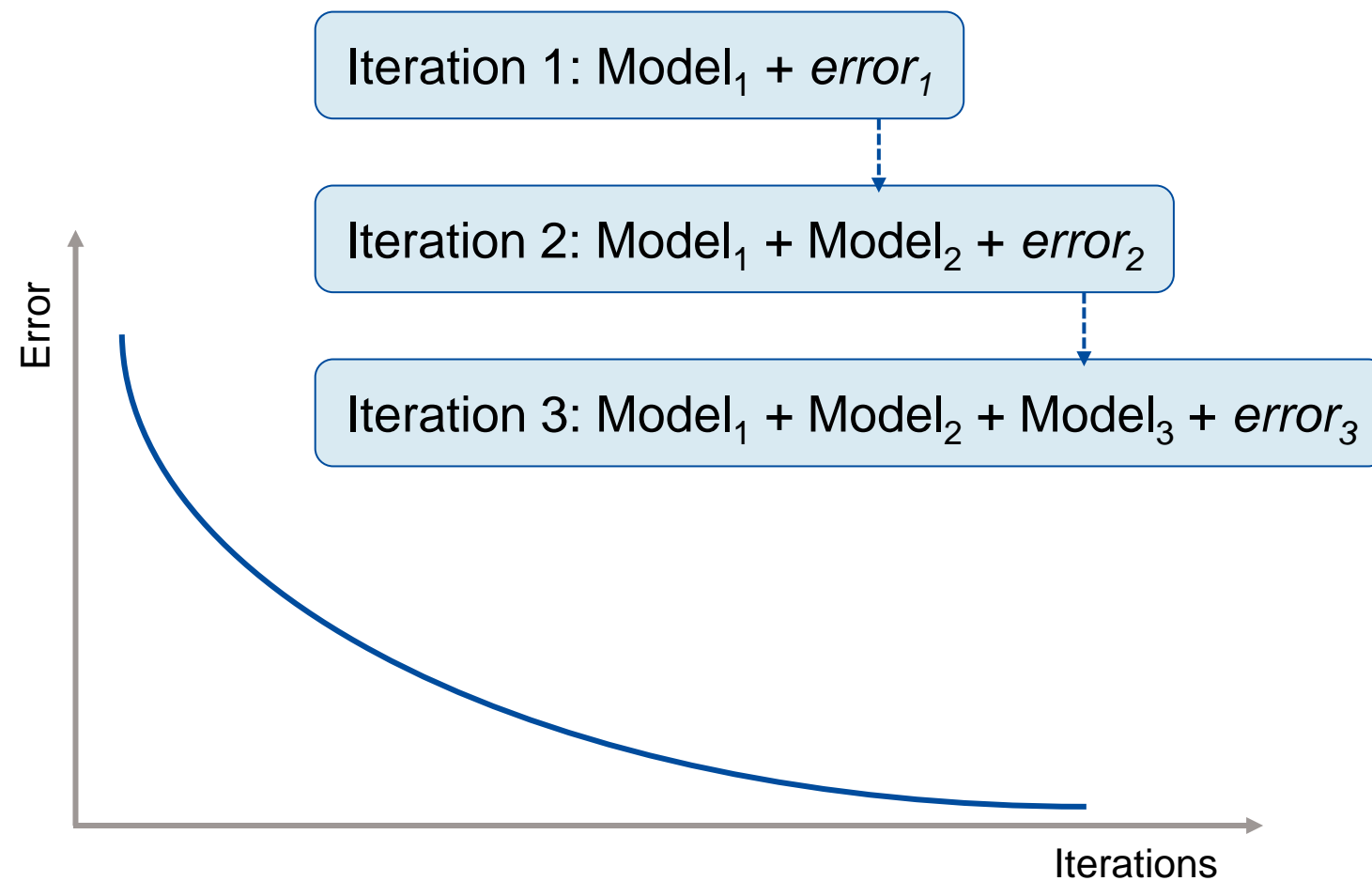
SOCIETY OF ACTUARIES

2. Leveraging Predictive Analytics

Predictive Analytics: Gradient Boosting Machine

Gradient Boosting Machine ("GBM")

GBMs are a type of machine learning ensemble technique, which use an iterative process to automatically train a series of decision tree-based models, where each iteration improves on the prediction of the prior iteration by modeling the error of the prior iteration
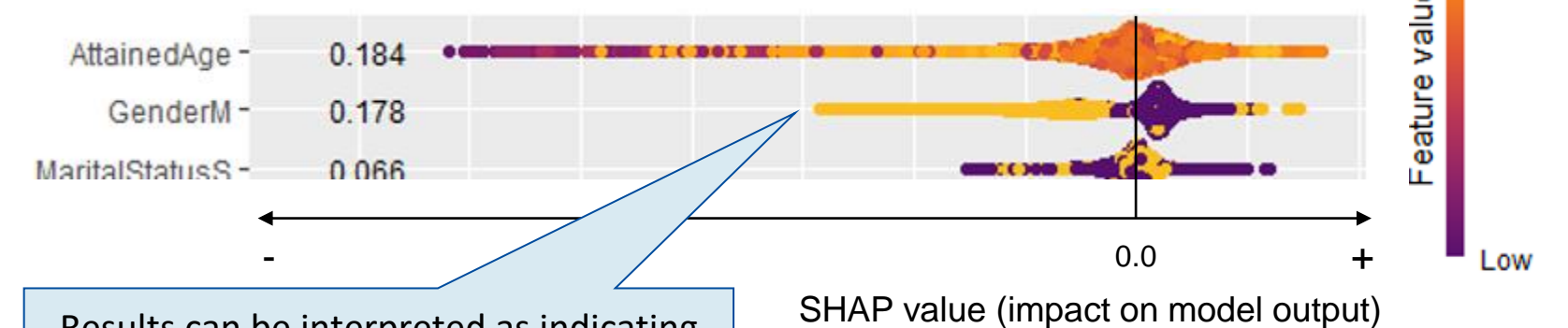
Iteration 1: $Model_1 + error_1$

Iteration 2: $Model_1 + Model_2 + error_2$

Iteration 3: $Model_1 + Model_2 + Model_3 + error_3$

Error

Iterations

SHapley Additive exPlanations ("SHAP")

- SHAP values provide a unified measure of feature importance by considering the contribution of each feature to the prediction

- SHAP analysis uses a GBM to rank variables based on their relative importance

- A SHAP importance plot visualizes the impact of each feature on the model's predictions, allowing us to identify the most influential features

Variables are converted to indicator features (i.e., 0 or 1), except attained age, where "1", indicating "true", is a "high" feature

Drivers ranked by Mean(|SHAP|)

High

AttainedAge –	0.184
GenderM –	0.178
MaritalStatusS –	0.066

Feature value

Low

SHAP value (impact on model output)

Results can be interpreted as indicating that being "male" reduces the prediction of the variable being modeled

Predictive Analytics: Home to Facility Transitions Case Study

Approach: We trained a GBM on illustrative data for claimants that started their claim in a home setting and subsequently received facility care services to identify policy attributes that may be predictors of the likelihood of transitions to facility care

SHAP analysis for likelihood of transition from home care to facility care setting:

Drivers ranked by Mean(|SHAP|)
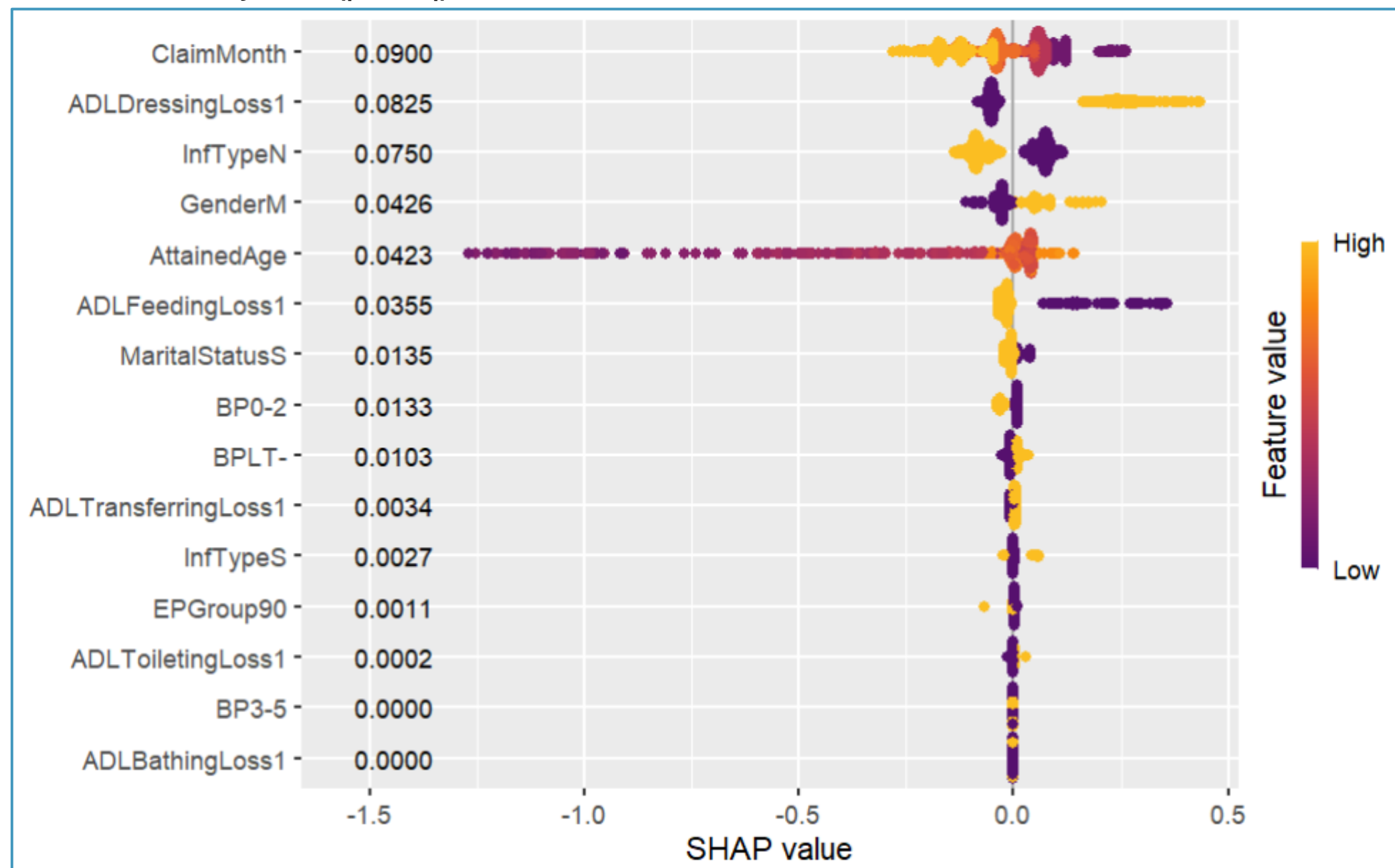
Driver	Attribute(s) with _higher_ likelihood of transitioning from home care to facility
Claim month (since incurral)	Early and middle claim months
Starting ADL loss - Dressing	Claims that initiate due to claimants' inability to perform Dressing ADL
Inflation type	Policies with inflation protection
Gender	Males
Attained age	Older attained ages (85+)
Starting ADL loss - Feeding	Claims that initiate due to claimants' inability to perform Feeding ADL
Other variables	Not interpretable, weak predictors

Predictive Analytics: Falls, Factures and Accidents Case Study

Approach: We used diagnosis codes from illustrative claim data to determine the proportion of approved claims related to falls, fractures, or accidents and then trained a GBM on this engineered "proportion" field to identify policy attributes that may be predictors of a policyholder's likelihood of claiming because of a fall, fracture, or accident

SHAP analysis for likelihood of claims being related to falls/fractures/accidents

Drivers ranked by Mean(|SHAP|)
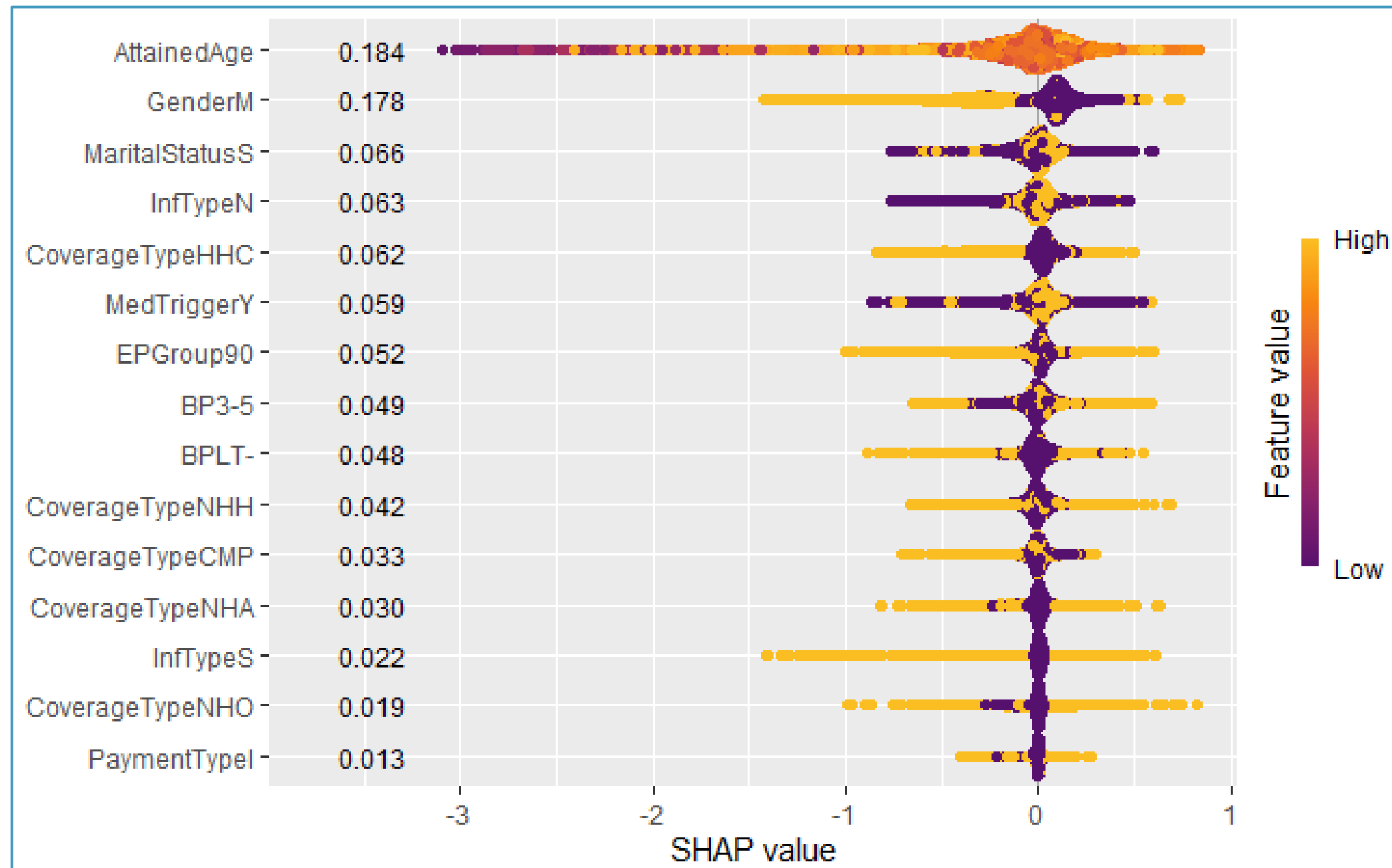
Driver	Attribute(s) with __higher__ likelihood of claims related to falls/fractures/accidents
Attained age	Middle ages (75-85)
Gender	Females
Marital status	Single policies
Inflation type	Policies __without__ inflation protection
Other variables	Not interpretable, potentially overfitting

Predictive Analytics: Analysis Deep Dive

Analyzing Factors of Wellness
- Adoption
- Adherence

Analyzing Wellness Results
- Improvement
- Recovery

Statistics versus Data Science
- Large Data
- Removing Distributions

Using Data to Gain Best Data
- Enough Data
- Sequential Design of Experiments

Predictive Analytics: Factors Driving Wellness

Wellness Programs may help avoid or delay claims
- Improve health outcomes
- Provide financial benefit

Likelihood of Joining (Adoption)
- Not just healthy policyholders
  - Suggest the program at its maximum potential impact
  - Claims expected between 2-5 years
  - On the trajectory towards a claim
- Highest risk individuals stand to benefit the most
  - Account for chronic diseases and similar factors
  - Employ the use of XGBoost and SHAP values

Likelihood of Remaining (Adherence)
- Analysis of the time to event using Statistical Distribution Fitting
  - Enables the analyst to predict the duration a policyholder will stay with the program
- Tailor the program length based on predictions
  - Long Term versus Short Term programs

Wellness Programs

Predictive Analytics: Factors Driving Wellness

Wellness Programs need to target the right policyholders

How Much Difference Can Wellness Make in the Policyholder's Life

- Analysis based on specific conditions
- Different diagnoses have varying improvement probabilities
- Explore the relationship between conditions and daily living activities
- Identify the policyholders who would most benefit from the program
- Consider analyzing each Activity of Daily Living (ADL) individually?

Recovery or Improvement Probability

- Conditions that wellness programs significantly improve
- Determine the duration that the program can delay the onset of eligibility for Long-Term Care (LTC) benefits
  - Should align with the probability of the policyholder remaining in the program
  - Analyze long-term trends
- Cost-effectiveness of the programs
  - Decisions should be based on individual policies
  - Compare the cost of keeping individuals at home versus other care options

Wellness programs

Predictive Analytics: Analysis Quality

Analysis Techniques old verse new.
There is NO difference!

Data Science

- Contemporary data sets consist of thousands, even millions, of data points, a substantial increase from Fisher's time when 30 data points were considered a lot!

- Despite asymptotic distributions like t-test, Z-test, and chi-Square not being crucial, the rest of the statistical theory remains applicable!

Traditional Statistics

- Traditional distributions, such as Chi-squared and t-tests, were utilized to answer queries if many data points were available.

- Modern data sets have thousands or millions of data points, eliminating the need for speculation.
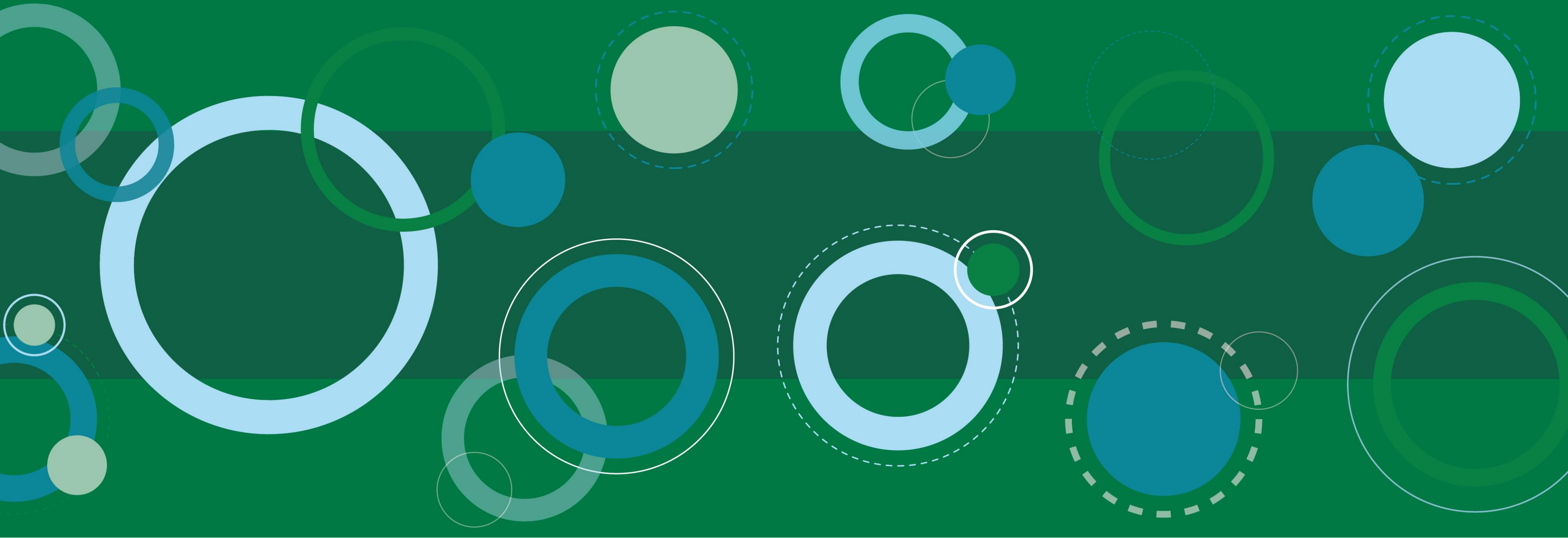
Predictive Analytics: Analysis Quality

Confidence Intervals

- Increased data leads to greater knowledge
  - Requires a method to quantify the data for each subject
  - For instance, there's a 95% certainty that a policy holder will stay in the program for 4 months, with a 90% probability of improvement
  - Simulation methods can be employed to calculate confidence intervals

Sequential Design of Experiments

- Even when researchers can't design an experiment, the Design of Experiments (DOE) remains useful in Data Science
  - DOE can identify areas where more data is necessary to enhance model accuracy
  - It can also highlight where data is weak and suggest solutions
- Techniques for Model Improvement
  - Mathematical methods can help improve model fitting
  - Additional data can be acquired, for instance, through surveys
  - New fields of data can be introduced, such as further blood tests
  - Existing data fields can be expanded, for example, to include older (100+) or younger (70-) age ranges
- The process should then be to improve, retest, and repeat this cycle for continuous enhancement.
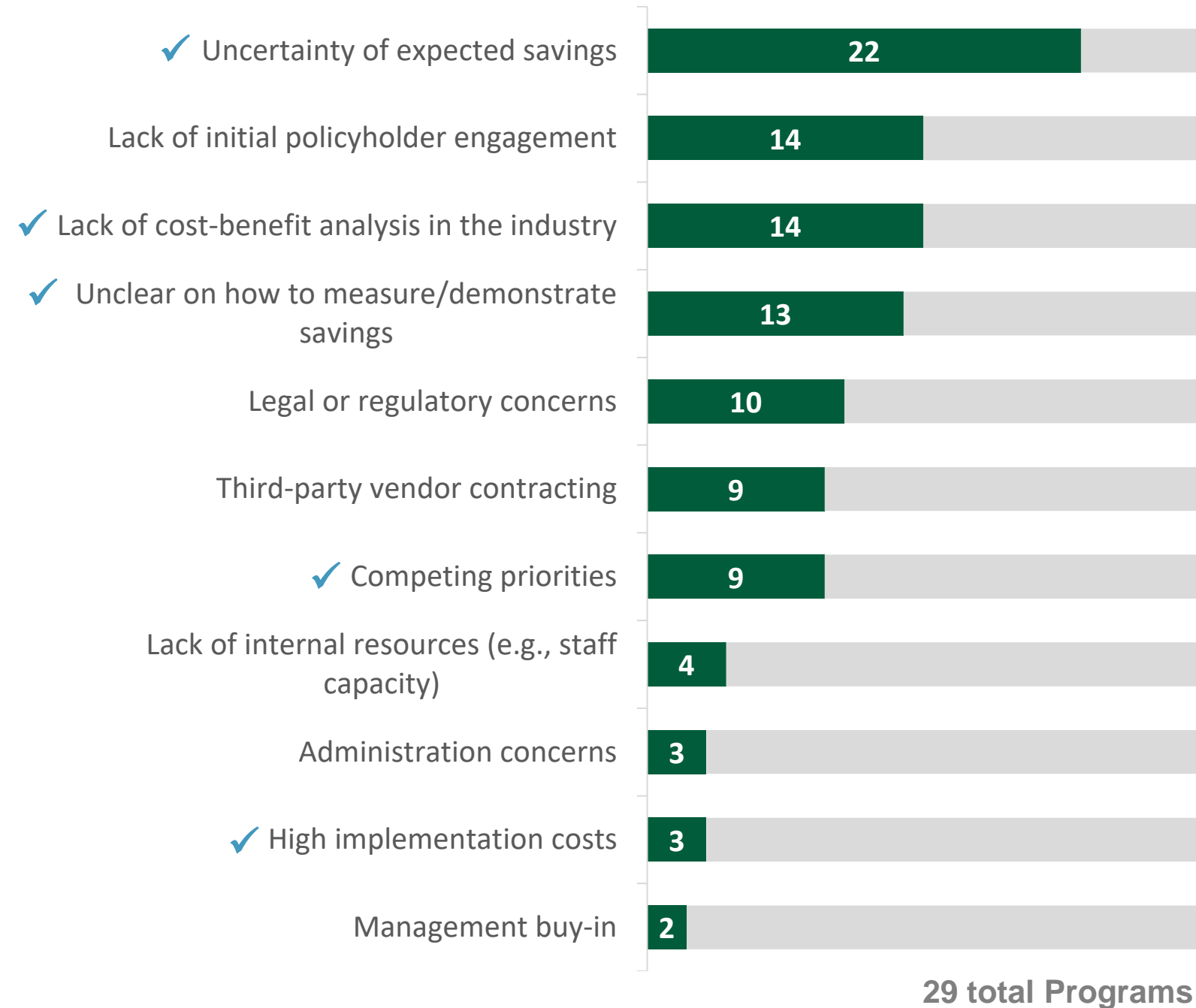
Improved Data → Confidence Intervals → DOE Simulations → Improved Data
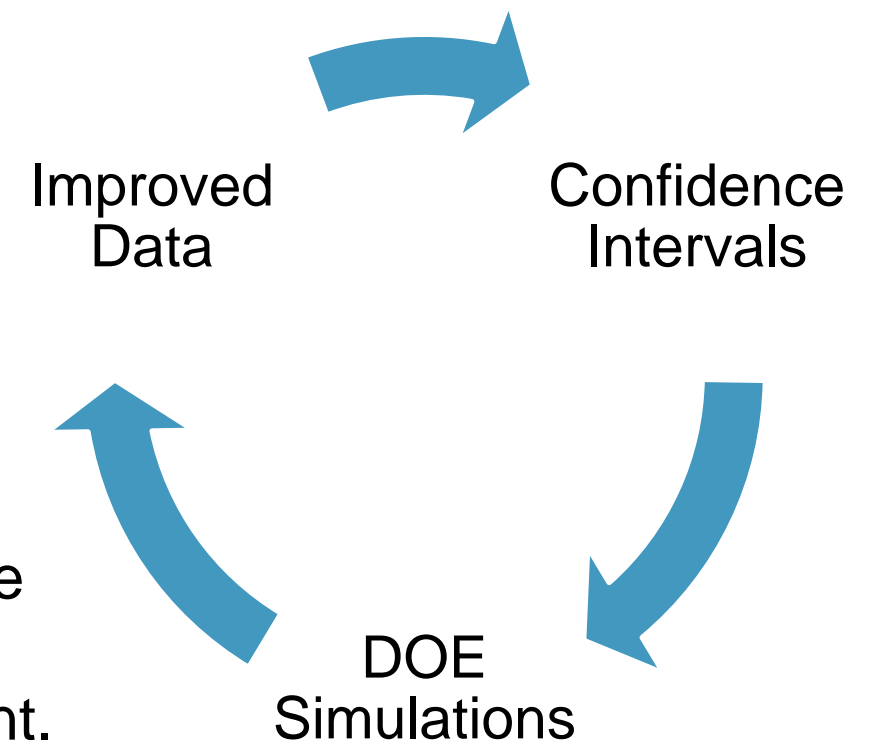
3. Lessons learned

Lessons Learned: Overcoming Challenges

Most significant hurdles faced by companies when starting a wellness program[1]:

Challenge	Count
✓ Uncertainty of expected savings	22
Lack of initial policyholder engagement	14
✓ Lack of cost-benefit analysis in the industry	14
✓ Unclear on how to measure/demonstrate savings	13
Legal or regulatory concerns	10
Third-party vendor contracting	9
✓ Competing priorities	9
Lack of internal resources (e.g., staff capacity)	4
Administration concerns	3
✓ High implementation costs	3
Management buy-in	2

29 total Programs

✓ Top 5 most prevalent reasons why companies <u>without a Program</u> do not have one

Lessons learned from implementing an LTC wellness program[1]:
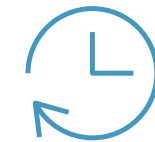
- Establish trust and improve your relationship with policyholders first
- Engagement is critical to measurable results
- Invest time upfront on data requirements and measurement frameworks
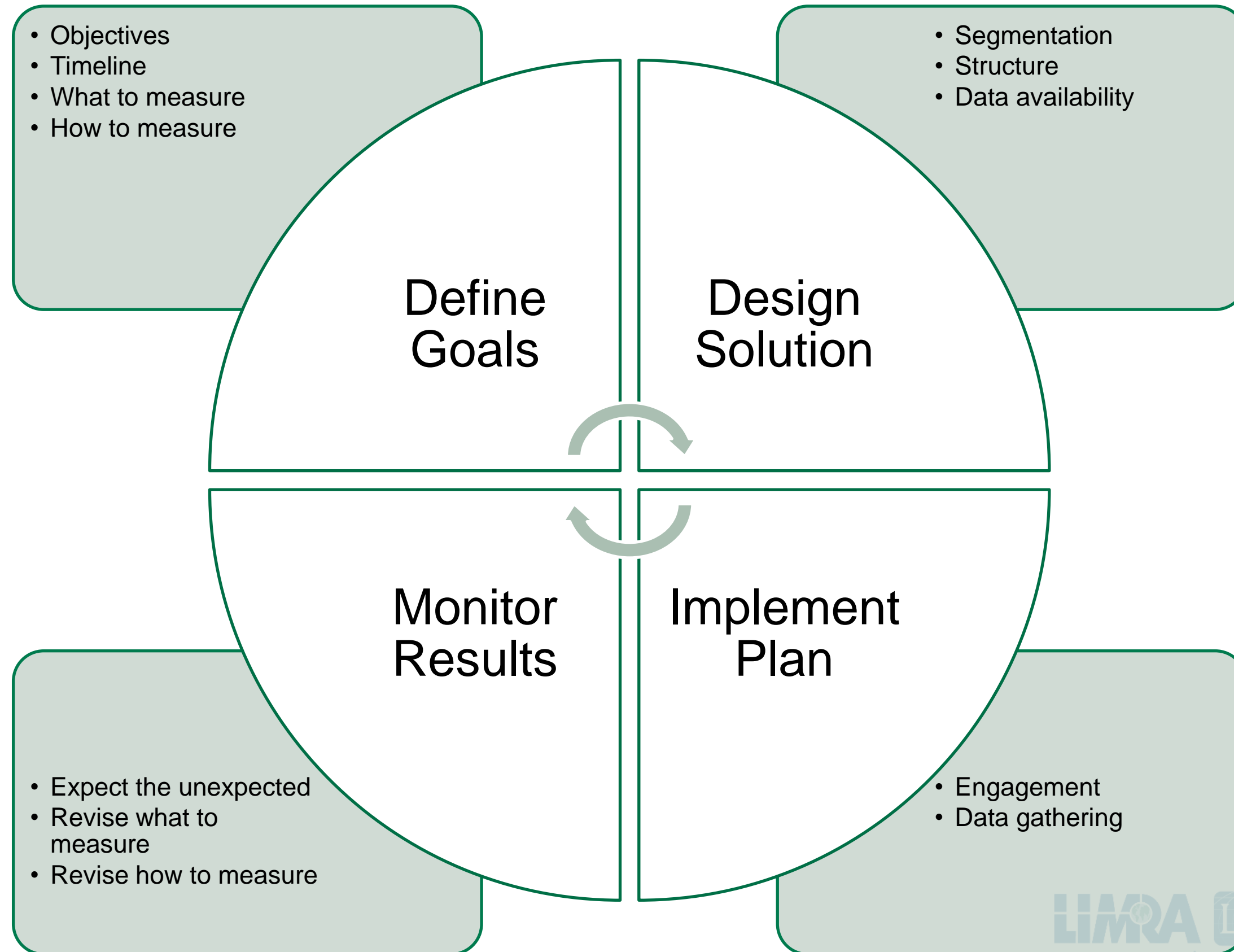- Results take time to emerge and can continue to evolve over time
- Spending money on the right policyholders is important
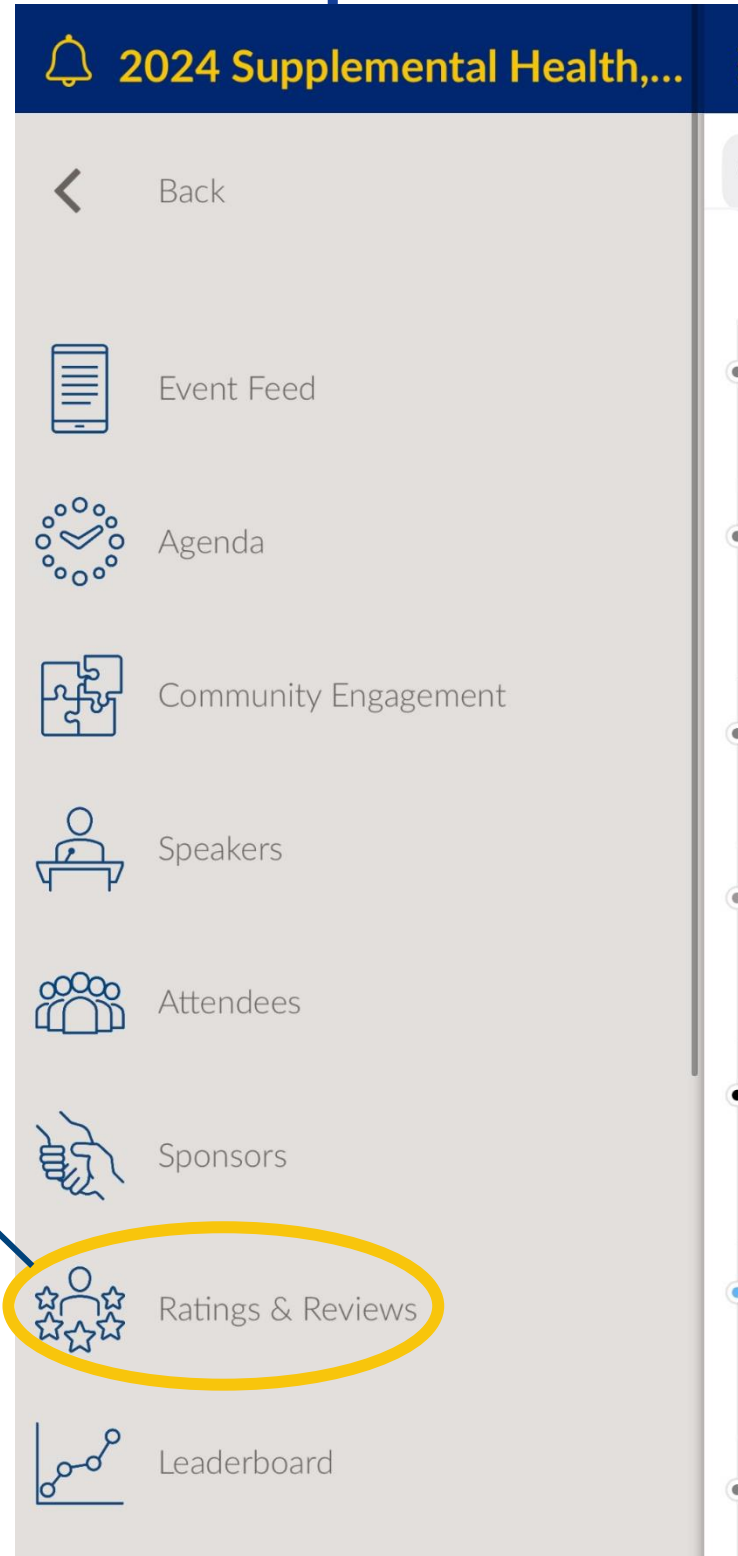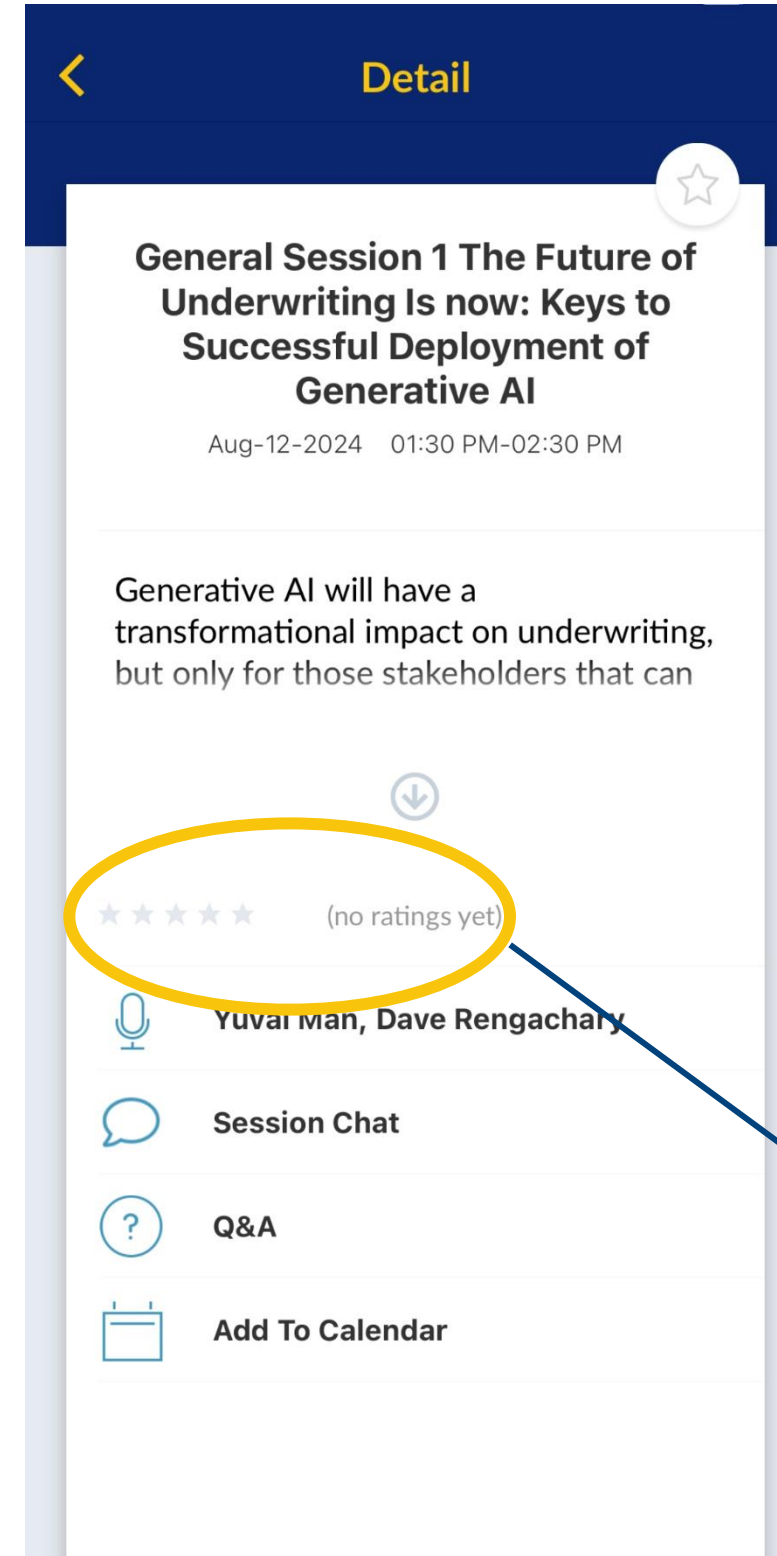- Even the smallest of interventions can make a difference

[1] Based on Oliver Wyman's 2023 LTC Wellness Program survey

Lessons Learned: Wellness Program Cycle

- Objectives
- Timeline
- What to measure
- How to measure

- Segmentation
- Structure
- Data availability

Define Goals

Design Solution

Monitor Results

Implement Plan

- Expect the unexpected
- Revise what to measure
- Revise how to measure

- Engagement
- Data gathering