What is ACCORDS?
Adult and Child Center for Outcomes Research and Delivery Science

ACCORDS is a ‘one-stop shop’ for pragmatic research:
• A multi-disciplinary, collaborative research environment to catalyze innovative and impactful research
• Strong methodological cores and programs, led by national experts
• Consultations & team-building for grant proposals
• Mentorship, training & support for junior faculty
• Extensive educational offerings, both locally and nationally
## ACCORDS Upcoming Events

<table>
<thead>
<tr>
<th>Date</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 26, 2024</td>
<td><strong>ACCORDS/CCTSI Community Engagement Showcase</strong></td>
</tr>
<tr>
<td>May 20, 2024</td>
<td><strong>Statistical Methods for Pragmatic Research</strong></td>
</tr>
<tr>
<td></td>
<td>Planning a Pragmatic Effectiveness Trial with a Factorial Design by Targeting the Posterior Distribution Variance</td>
</tr>
<tr>
<td></td>
<td>Presented by: Keith Goldfeld, DrPH, MS, MPA/MURP</td>
</tr>
</tbody>
</table>

Last seminars for the 2023-2024 academic year!

*all times 12-1pm MT unless otherwise noted*
Innovations in Pragmatic Research Methods

From Data to Equity, Policy, and Sustainability

June 5 - 6, 2024 | 10am-3:30pm MT

Registration is open now at www.COPRHCon.com

Registration Fees waived for students, staff, and faculty of CU SOM, CHCO, and CCTSI members at affiliate institutions
Opportunities and Challenges in the use of AI and ML for Population Health Informatics

Michael Matheny, MD, MS, MPH
Opportunities and Challenges in the use of AI and ML for Population Health Informatics

Michael E. Matheny, MD, MS, MPH

Director, Center for Improving the Publics’ Health Through Informatics
Professor, Departments of Biomedical Informatics, Medicine, and Biostatistics
Vanderbilt University Medical Center

Associate Director for Data Analytics, VINCI
Associate Director, Advanced Fellowship in Medical Informatics
Tennessee Valley Healthcare System VA

Twitter: @MichaelEMatheny
Email: michael.Matheny@va.gov, michael.Matheny@Vanderbilt.edu, michael.Matheny@vumc.org
Disclosure

- I have no conflicts of interest in the presentation of any materials, software, or algorithms presented in this presentation.

- All funding I have received in the last 3 years are research grants and contracts from VA ORD & HSR&D, NIH NHLBI & NIDDK, FDA, NIH-VA-DoD Joint funding, and a medical device public-private partnership (NESTcc [FDA U01])
Learning Objectives

• Define and discuss some of the challenges AI & ML algorithms are facing in development and implementation in healthcare

• Recognition and discussion of key issues in the use of AI/ML over time within observational data

• An overview and lifecycle framework for implementing AI in healthcare will be discussed

• Examples of real-world use cases for AI implementation will be highlighted in management of patient populations
Growth in Complexity of Medical Knowledge

Page Length:
~50 in 2004
~190 in 2019

Reference Count:
~80 in 2004
~800 in 2019

High Variability In Clinical Care

Artificial Intelligence to the rescue.......
Clinical Decision Support

- AI can improve the specificity of alerts and reminders by considering a much larger number of patient and contextual variables (Joffe et al., 2012).

- AI can provide probability thresholds that can be used to prioritize alert presentation and determine alert format in the user interface (Payne et al., 2015).
Healthcare Predictive Models are Ubiquitous

- Selected Systematic Reviews Over the Years
  - Post-catheterization AKI, 63 new models, 20 externally validated
  - Diabetes, 49 new models
  - General cardiovascular risk models, 363 new models, 473 external validations
  - Lung Cancer, 31 new models, 3 external validation studies

.... But (Successful) Implementations are not
TRIPOD & PROBAST (and –AI)

Summary of Risk of Bias assessment:

- Participants: 64% Low, 18% High, 18% Unclear
- Analysis: 91% Low, 9% High, 0% Unclear
- Outcome: 100% Low, 0% High, 0% Unclear
- Analysis: 73% Low, 18% High, 9% Unclear
- Analysis: 6% High, 94% Unclear

**BMJ Open**

Protocol for development of a reporting guideline (TRIPOD-AI) and risk of bias tool (PROBAST-AI) for diagnostic and prognostic prediction model studies based on artificial intelligence.

---

Nagendran, et al. BMJ 2020; 368:m689
Challenges In Modeling Bias

Healthcare Utilization

Clinical Outcomes

Fig. 1. Number of chronic illnesses versus algorithm-predicted risk by race. (A) Mean number of chronic conditions by race, plotted against algorithm risk score. (B) Fraction of Black patients at or above a given risk score for the original algorithm (“original”) and for a simulated scenario that removes algorithmic bias (“simulated”: at each threshold of risk, defined at a given percentile on the x axis, healthier Whites above the threshold are replaced with less healthy Blacks below the threshold, until the marginal patient is equally healthy). The x symbols show risk percentiles by race; circles show risk deciles with 95% confidence intervals clustered by patient. The dashed vertical lines show the auto-identification threshold (the black line, which denotes the 97th percentile) and the screening threshold (the gray line, which denotes the 55th percentile).
AI/ML Are Susceptible to Data Shifts

<table>
<thead>
<tr>
<th>Model</th>
<th>Event Rate Shift</th>
<th>Association Shift</th>
<th>Case Mix Shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic regression</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>L1 penalized regression</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>L2 penalized regression</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>L1-L2 penalized regression</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Random forest</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Neural network</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
</tbody>
</table>

Susceptibility – ★ High ★ Moderate ★ Low

ALL Models are susceptible to Event Rate Shifts

DL/NN Models were less susceptible to Case Mix Shifts

Need for Algorithms with Sub-Population/DEI Awareness

Example for Prediction of Developing Diabetes (Screening Threshold)

Gartner Hype Cycle for Artificial Intelligence

2019

- Deep Learning
- Machine Learning
- Natural Language Processing

2023

- Generative AI

Expectations:
- AI General Intelligence
- AI General Intellige
ChatGPT & Large Language Models

... are not immune to these issues!

- Limited response to queries that require information after the training data ended
- Continual evolution of LLMs create variation in accuracy.
- 10’s of thousands of hours spent in training updates to remove inappropriate, biased, and derogatory responses from ChatGPT in later versions

---

Implementation Challenges

• Integration into workflow at the right time for the right purpose
• Visualization of information and recommendations in alignment with objective
• Engaging all the relevant stakeholders for the task
• Translating prototypes into clinical production modules
NAM AI/ML Modeling Lifecycle

Learning Health System

User Centered Design

Implementation Science

Human-Computer Interaction

https://nam.edu/artificial-intelligence-special-publication/
What I Had Spent Years Learning...

Maintain, Update, or De-Implement
Monitor Ongoing Performance
Implement AI System in Target Setting
Identify or Reassess Needs
Describe Existing Workflows
Define the Desired Target State
Acquire or Develop AI System
What is the most important parts for clinical success?
A Cluster-Randomized Trial of Team-Based Coaching Interventions to IMPROVE Acute Kidney Injury Among Patients Experiencing Cardiac Catheterization

Real World Example #1

Brown

Matheny

Solomon
Cardiac Catheterization AKI Mortality Risk

1.2 Million angiography procedures each year

AKI results in 10-15% of cases

**Major AE (Adverse Events):**
Death, ESRD, Stroke, AMI

**All AE (Adverse Events):**
Death, ESRD, Stroke, AMI, CABG, surgical or cath revascularization, CHF, pacemaker,

*Subramanian et al, J Med Econ 2007;10(2)119-134*
Post-Procedural AKI Risk Mitigation Evidence

- While some trials were non-significant, general trend towards:
  - Reducing contrast volume in procedure
  - Encouraging patient hydration
  - Routine monitoring of kidney function before and after
  - Other medication optimization strategies (diuretics, etc)
Department of Veterans Affairs

172 Medical Centers
1,138 Outpatient Sites

~9 Million Veterans served yearly
Risk-Adjusted AKI Performance for National VA Cath Labs (Yearly)
Where’s The Gap?

• Numerous clinical trials, meta-analyses, and observational reports
• Lack of Implementation of Recommended Measures
• Paucity of:
  – implementation science
  – quality improvement initiatives
Study Objective

We sought to develop an integrated approach to quality improvement coaching and informatics information support for cardiac catheterization laboratories to reduce rates of AKI for patients following the procedure.

Integrate QI & Informatics to support process change
Operate at the clinical unit level (catheterization lab)
Inclusion criteria: Patients aged 18 or greater who undergo diagnostic coronary angiography or PCI.

Exclusion criteria: Patients with a history of dialysis (hemodialysis, peritoneal dialysis).

Primary Outcome: AKIN Stage 1 Acute Kidney Injury (+ 0.3 mg/dL or 50% increase)
Intervention: Virtual Learning Collaborative

**Baseline Data**
- 2017-2019

**Pre-Work**
- 1 Month
- September 2019

**Action Phase**
- 18 Months
- 10-2019 to 03-2021

**Sustainability Phase**
- 19-36 Months
- 04-2021 to 10-2023

**Application Process**
- Review Toolkit
  - Initial PPT Due 10/4/19
- Educational Sessions
  - First Monday of month @2 pm ET

**Continuous Improvement and Spread**
- Coaching/Mentoring
  - Email, Phone
- Monthly Reports
- Baseline Team Questionnaire
  - Due 10/4/2019

**Meet and Greet Calls With Coaches**
- Coaching/ Mentoring
  - Email, Phone
- Coaching as Requested

**Final Summary Report**
- Due 11/2023

**Baseline Team Questionnaire**
- Due 10/4/2019

**Status Update and Follow-up Team Questionnaire**
- Due 5/1/2021

**Coaching Process**
- Brown
- Stabler
- Zubkoff

**QI Training**
- Pre-Work
  - 1 Month
  - September 2019

**Sustainability Phase**
- 19-36 Months
- 04-2021 to 10-2023

**Action Phase**
- 18 Months
- 10-2019 to 03-2021

**Baseline Data**
- 2017-2019
Intervention: Automated Surveillance Reporting

- We developed an automated tool that accesses:
  - Corporate data warehouse for EHR data
  - Registry data from CART-CL clinical tool
- Monthly Updates and analyses for each site
- Robust Patient Risk Adjustment
- Dashboard to provide:
  - Overall risk-adjusted Site level performance compared to all CART Sites
  - Risk-adjusted site level statistical process control analyses
  - Ability to access your site’s patient identifiable case level data to support QI

Figure 1. ASR Dashboard for the IMPROVE AKI Trial.
National VA Cath-Related AKI Risk Prediction

- Adult Coronary Angiography Cohort (n= 115,633) (2009-2013)

- Large Volume of Candidate Predictors: Demographics, Administrative Codes, Medications, Laboratory Tests, Registry Data, Contrast

- Outcome Was AKIN Stage 1+ 7 Day
  - Stage 1+: 13.9%
  - Stage 2+: 1.7%
  - CIN (0.5): 11.9%

LASSO (L1) logistic regression:
- AKI Any Stage AUC 0.75 (0.74-0.5)
- AKI Stage 2+ AUC 0.83 (0.82-0.84)

↓ # Predictors -> reduced model robustness

Externally Validated by NE cohort (27,905)


Post-Cath AKI Prospective Model External Validation

Single Center
Greece
2015-2018
1,297 pts
Liberal: 16.5%
Strict: 1.9%

Fig. 1. c-statistic values of models investigated for contrast-induced acute kidney injury (CI-AKI) in PCI (percutaneous coronary intervention) patients. a Liberal CI-AKI criterion (an increase ≥25% or ≥0.5 mg/dL in pre-PCI serum creatinine 48–72 h after PCI). b Strict CI-AKI criterion (an increase ≥0.5 mg/dL in pre-PCI serum creatinine 48–72 h after PCI).
Model Maintenance Key Challenges

...with variable external performance, we needed a plan...

• Electronic Health Record – generates data in a certain way
• Data Encoding Variation Between Sites
• Retrospective warehouse data <> real-time production EHR data
• Data Drift Over Time

...and surprise, a huge issue in the middle of our active intervention...

• The Pandemic!!! (12 of 18 months of active intervention)
A Framework for Dynamic, Data-Driven Model Updating

Predictive analytics system

New patient observation → Active model → Prediction → Clinical application

- Dynamic calibration curve
- Adaptive window monitor
- Test-based model updates

Prediction error → Drift detection alert → Recommended updating window

Updating method | Forms of miscalibration corrected
--- | ---
Intercept correction recalibration | Systematic over/underprediction
Linear logistic recalibration | Over/underfitting
Flexible logistic recalibration | Complex miscalibration varying across the range of probability
Model refitting | Complex miscalibration due to differences in predictor-outcome associations

We incorporated a risk model surveillance framework to sustain the model.

Monthly performance May 2018 – February 2020

Davis SE, Brown JR, Dorn C, Westerman D, Solomon RJ, Matheny ME. Circ Cardio Qual & Outcomes 2022
AKI Trial Result for All & CKD within 7 Days

- Among 20 Centers in 18-month intervention phase:
  - 4,517 patients
    - 510 with AKI (~12%)
  - 1,314 patients with pre-existing CKD
    - 214 with AKI (~19%)
  - Population characteristics of study sites by 4 intervention groups were approximately balanced.

In all patients, the VLC+ASR intervention cluster had a substantial reduction in AKI when compared to TA alone.

Adjusted Odds Ratio =0.54; 0.40, 0.74)
Unresolved Challenge: Interpretation of Data Analytics

• Analytic Framework Grounded in Engineering Statistical Process Control (Adapted for Healthcare)

• Even with direct team education, barriers to understanding for interpretation of process control charts

• In qualitative evaluation, most useful parts were case list and providers having a more transparent ML model with variable weights that they could cross-reference with case list
Risk-Adjusted Sequential Probability Ratio Testing Explanation

- Formal framework for incorporating $\alpha$ and $\beta$ error of analyzing accumulating data.

- Specify Odds Ratio of event rate elevation detection desired (clinically relevant detection instead of just statistically relevant detection).

- Account for patient case-mix variation through risk adjustment (national model).

Control Limit that confirms an outlier signal using the risk adjustment model for a given:
- Odds Ratio
- alpha error (Type I)
- beta error (Type II)

Cumulative log-likelihood ratio always starts at 0
Accumulates per individual case
Positive deflection indicates the outcome was observed
Negative deflection indicates that outcome was not observed
Importance of System & Clinical Champions

**Clinical**
- Nephrologist
- Cath Lab Nurse Manager
- Cath Lab Manager
- Cath Lab Director
- Interventional or Diagnostic Cardiologists
- Nurse managers from units

**VA-Specific**
- QMO/Chief Quality Lead
- Patient Safety Manager/Officer
- Clinical Applications Coordinator (CAC)

**Day-to-Day Leadership**
- System Leadership
- Technical Expertise

**VA Clinical Assessment Reporting and Tracking (CART) Program Partnership**
ImproveAKI Conclusions

• Clinical
  – Combination of VLC with ASR significantly reduced AKI.
  – Combined VLC with ASR team-based coaching intervention may be an effective, scalable intervention to establish aggressive prevention protocols to prevent AKI.

• Informatics
  – Maintaining Risk Models Are Challenging & Require Significant Infrastructure
  – Summarizing Complex Clinical Data For Intuitive Clinician Interpretation is HARD
Real World Example #2

A Randomized Trial of a Personalized Clinical Decision Support Intervention to Improve Statin Prescribing in Patients With Atherosclerotic Cardiovascular Disease (PCDS Statin)
Statin and high-intensity statin (HIS) use remains low in patients with atherosclerotic cardiovascular disease (ASCVD).

In PCDS statin study, we evaluated whether patient context-aware reminders could improve HIS use in ASCVD patients.
Formative Work: Qualitative Study on Patient & Clinician Perspectives

- 21 adult Patients with ASCVD
- 20 prescribing clinicians: cardiologists, primary care physicians, primary care nurse practitioners, and clinical pharmacists
- Recorded interviews, transcribed, coded, with discrepancy resolution

Study Objective

We sought to develop a system to support providers in improving rates of HMG CoA Reductase (statin) prescribing among patients with known cardiovascular disease.

Develop patient context aware clinical summaries
Minimize provider burden and maximize workflow integration
Implementation in Two VA Healthcare Systems

Inclusion criteria:
- Patients aged 18 or greater with cardiovascular disease (administrative codes)

Guideline Education
(27 primary care clinics)

Randomization
(August 2021)

Intervention sites

Usual care sites,

Weekly data processing,
synchronous/asynchronous reminders,
guideline resources on an intranet portal

Patient dashboard displaying clinician compliance with statin therapy

End of the study
(11/31/2022)

Exclusion criteria:
- Provider Opt-Out
- Not seen last 2 years
- Patient not on active provider panel
Outcomes

• Pre-post change in High Intensity Statin use between intervention and usual are sites.
Canary NLP Tool Adaptation to VA

## Canary NLP Tool Adaptation to VA

Evaluation of Addition of NLP for detection reasons for a patient with ASCVD to not be on a high-intensity statin

<table>
<thead>
<tr>
<th></th>
<th>Structured Data Only</th>
<th>Structured + Canary VA NLP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>0.69 (0.60 – 0.76)</td>
<td>0.89 (0.81 – 0.93)</td>
</tr>
<tr>
<td>Specificity</td>
<td>1.00 (1.00 – 1.00)</td>
<td>0.94 (0.92 – 0.96)</td>
</tr>
<tr>
<td>PPV</td>
<td>1.00 (1.00 – 1.00)</td>
<td>0.84 (0.69 – 0.90)</td>
</tr>
<tr>
<td>NPV</td>
<td>0.90 (0.87 – 0.93)</td>
<td>0.96 (0.93 – 0.98)</td>
</tr>
<tr>
<td><strong>AUC</strong></td>
<td><strong>0.84 (0.81 – 0.88)</strong></td>
<td><strong>0.91 (0.91 – 0.93)</strong></td>
</tr>
<tr>
<td>True Positives</td>
<td>91</td>
<td>117</td>
</tr>
<tr>
<td>False Positives</td>
<td>0</td>
<td>22</td>
</tr>
<tr>
<td>True Negatives</td>
<td>380</td>
<td>358</td>
</tr>
<tr>
<td>False Negatives</td>
<td>41</td>
<td>15</td>
</tr>
</tbody>
</table>

Reminders sent to their primary care clinicians 2-7 days before patient’s visit (synchronous reminders) or outside of the patient’s primary care visit (asynchronous reminders).

To reduce alert fatigue, our algorithms limited care summaries to <=3 unsigned alerts at all times.
Centrally-processed individualized statin-relevant care summary sent to each ASCVD patient based on presence or absence of SASEs. (structured data + NLP)

Information included date and type of ASCVD diagnosis, statin and dose, date of last fill, date and type of SASE, and guideline resources on HIS definition and SASE management.
Centrally-processed individualized statin-relevant care summary sent to each ASCVD patient based on presence or absence of SASEs. (structured data + NLP)

Information included date and type of ASCVD diagnosis, statin and dose, date of last fill, date and type of SASE, and guideline resources on HIS definition and SASE management.
Dear Clinician,

Our review shows that your patient suffers from atherosclerotic cardiovascular disease (ASCVD), coronary heart disease (CHD), ischemic stroke, or peripheral arterial disease (PAD). Our review also suggests that your patient is either not on a statin or the guideline-recommended intensity of statin therapy. Statin therapy in patients with ASCVD reduces the risk of recurrent cardiovascular events and mortality.

Our review also indicates that your patient could have suffered from one of the statin-associated side effects (SASEs). A great majority of patients with SASEs can tolerate some form of statin therapy (low dose of the same statin, a switch to another statin, or low dose of a long acting statin such as atorvastatin or rosvuastatin).

Guideline-Recommended High Intensity Statins
Rozuvastatin 20-40mg by mouth daily
Atorvastatin 40-80mg by mouth daily

If your patient is on statin therapy from a non-VA source, please add this statin as a non-VA medication.

We sincerely thank you for your time and consideration.
Usual Care – Primary Care Operational Dashboards
Randomization

Guideline Education
(27 primary care clinics)

Randomization
(August 2021)

Intervention sites
14 clinics, 117 clinicians,
18,427 patients

Weekly data processing,
synchronous/asynchronous reminders,
guideline resources on an intranet portal

Usual care sites,
13 clinics, 128 clinicians,
18,214 patients

Patient dashboard displaying clinician compliance with statin therapy

End of the study
(11/31/2022)
• 41.6% of patients in the intervention arm had a signal related to statin associated side effects in structured data or NLP.
• 4928 reminders sent to providers for 4,532 unique patients, representing 53% of the patients not on high intensity statins at baseline in the intervention arm.
• 73% of reminders were asynchronous, 27% were synchronous.
• Over time, 37 clinicians (31.6%) in intervention sites opted out.

31.6% of the clinicians in the intervention arm still elected to drop out during the study
  - competing demands
  - alert fatigue
  - iterative COVID-19 infection waves

Known Issues:
  - 2–3-day lag from data calculation to note generation (interval med fills, death, etc.)
  - Insufficient Primary Care Alignment: Did not count referral to lipid clinic or PSK9 inhibitor initiation
Primary Outcome

OR for HIS use with the intervention 1.06, (95%CI=1.02-1.11)

Between Group Δ = 3.8% (3.7-3.9%)

Outcome

Pre-post change in high intensity statin use in patients receiving care at usual care and the intervention sites (overall, among those who did not receive reminders, and among those who received reminders)

Number needed to remind = 10

Among Those Who Received Reminder

Initiated HIS

- Usual Care
- Intervention (overall)
- Intervention (No reminder)
- Intervention (+ reminder)
PCDS Statin Trial Conclusions

- Clinical
  - Patient context aware reminders led to significant increase in statin adherence.
  - ~10 reminders needed to be sent for a patient to be started on high-intensity statin

- Informatics
  - Alert Fatigue
    • reminders not sent to all eligible patients due to stringent algorithms to limit alert fatigue.
    • Further improvements to context are needed due to provider drop-out
  - Knowledge management a key issue for scalability of patient context aware CDS
Overall Conclusions

• AI and ML are increasingly being integrated into healthcare, BUT substantial challenges remain for the safe and effective clinical implementation of these technologies

• A rigorous AI/ML lifecycle approach that integrates:
  – Data science / AI / ML technical rigor
  – Human Factors / Human Computer Interaction
  – Implementation Science
    ... is critical to achieve demonstrable clinical impact in patient care
Acknowledgements

**ImproveAKI Trial**
- NIH NIDDK Funding
- Clinicians and patients who participated in the study.
  - Jeremiah R. Brown, PhD
  - Richard Solomon, MD
  - Meagan E Stabler, PhD
  - Sharon E. Davis, PhD
  - Elizabeth Carpenter-Song, PhD
  - Lisa Zubkoff, PhD
  - Dax M. Westerman, MS
  - Chad Dorn, MS
  - Kevin C Cox, MS
  - Freneka Minter, PhD
  - Hani Jneid, MD
  - Jesse W. Currier, MD
  - S. Ahmed Athar, MD
  - Saket Girotra, MD
  - Calvin Leung, MD
  - Thomas J Helton, PhD
  - Ajay Agarwal, MD
  - Mladen I Vidovich, PhD
  - Mary E Plomondon, PhD
  - Stephen Waldo, MD
  - Kelly A Aschbrenner, PhD
  - James O’Malley, PhD

**PCDS Statin Trial**
- VA HSR&D Funding
- Clinicians and patients who participated in the study.
  - David J, Ramsey PhD.
  - Dax Westerman MS
  - Mark K. Kuebeler, MSC
  - Liang Chen, M.D., M.S.
  - Julia M. Akeroyd, MPH
  - Glenn T. Gobbel, DVM, PhD, MS
  - Christie M. Ballantyne, MD
  - Laura A. Petersen, MD, MPH
  - Alexander Turchin, MD, MS
  - Salim Virani, MD, PhD

**Current Primary Grant Funding:**
- VA HSR&D VINCI Resource Center
- VA HSR&D SDR MVP
- NIH NHLBI R-01
- NIH NIDDK R-01
- FDA NESTcc Devices Consortium
- FDA Sentinel Innovation Center
THANK YOU

@MichaelEMatheny

For more information contact:

michael.matheny@va.gov
michael.matheny@vumc.org
Results: Baseline, Action, Post-Intervention Phases

Table 3: AKI proportion before, during, and after action phase by intervention group and CKD status

<table>
<thead>
<tr>
<th>Population</th>
<th>Prior 12 Months</th>
<th>Action Phase</th>
<th>Post-Intervention Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N (%)</td>
<td>N (%)</td>
<td>Case-Mix Adjusted % [95% CI]</td>
</tr>
<tr>
<td>All Patients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All VA Sites</td>
<td>1630 (11)</td>
<td>2156 (12)</td>
<td></td>
</tr>
<tr>
<td>All Study Sites</td>
<td>416 (11)</td>
<td>510 (11)</td>
<td></td>
</tr>
<tr>
<td>Intervention Group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technical Assistance (TA)</td>
<td>67 (8)</td>
<td>110 (13)</td>
<td>14 [14 to 15]</td>
</tr>
<tr>
<td>ASR + VLC</td>
<td>73 (9)</td>
<td>88 (8)</td>
<td>9 [9 to 9]</td>
</tr>
<tr>
<td>CKD Subset</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All VA Sites</td>
<td>693 (19)</td>
<td>959 (19)</td>
<td></td>
</tr>
<tr>
<td>All Study Sites</td>
<td>187 (18)</td>
<td>235 (18)</td>
<td></td>
</tr>
<tr>
<td>Intervention Group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TA</td>
<td>36 (17)</td>
<td>42 (17)</td>
<td>20 [19 to 20]</td>
</tr>
<tr>
<td>TA + ASR</td>
<td>54 (18)</td>
<td>68 (23)</td>
<td>20 [20 to 21]</td>
</tr>
<tr>
<td>VLC</td>
<td>61 (20)</td>
<td>77 (19)</td>
<td>16 [16 to 17]</td>
</tr>
<tr>
<td>ASR + VLC</td>
<td>36 (15)</td>
<td>48 (14)</td>
<td>16 [16 to 17]</td>
</tr>
</tbody>
</table>