# Using Technology and Data Analytics to Improve Depression Care among Patients with Diabetes

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CENTER FOR HEALTHCARE ENGINEERING & PATIENT SAFETY
UNIVERSITY OF MICHIGAN

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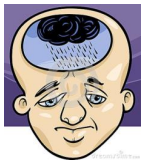
  - National Institute of Mental Health

# Symptoms of Depression

Emotions

- Sadness
- Guilt
- ……



Thoughts

- Suicidal ideation
- Self-criticism
- …

Behavior

- Withdrawal from social interaction
- Loss of interests in daily activities
- ……

Physical Condition

- Chronic fatigue
- Unexplained pain
- ……

Source: Mental Health First Aid, mentalhealthfirstaid.org

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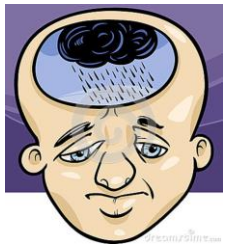
- Chronic fatigue
- Unexplained pain
- ……

Source: Mental Health First Aid, mentalhealthfirstaid.org

# Negative Impacts of Depression

- Depression makes health outcomes worse, increases healthcare utilizations and cost, and elevates suicide risk[1-4]

Emotions

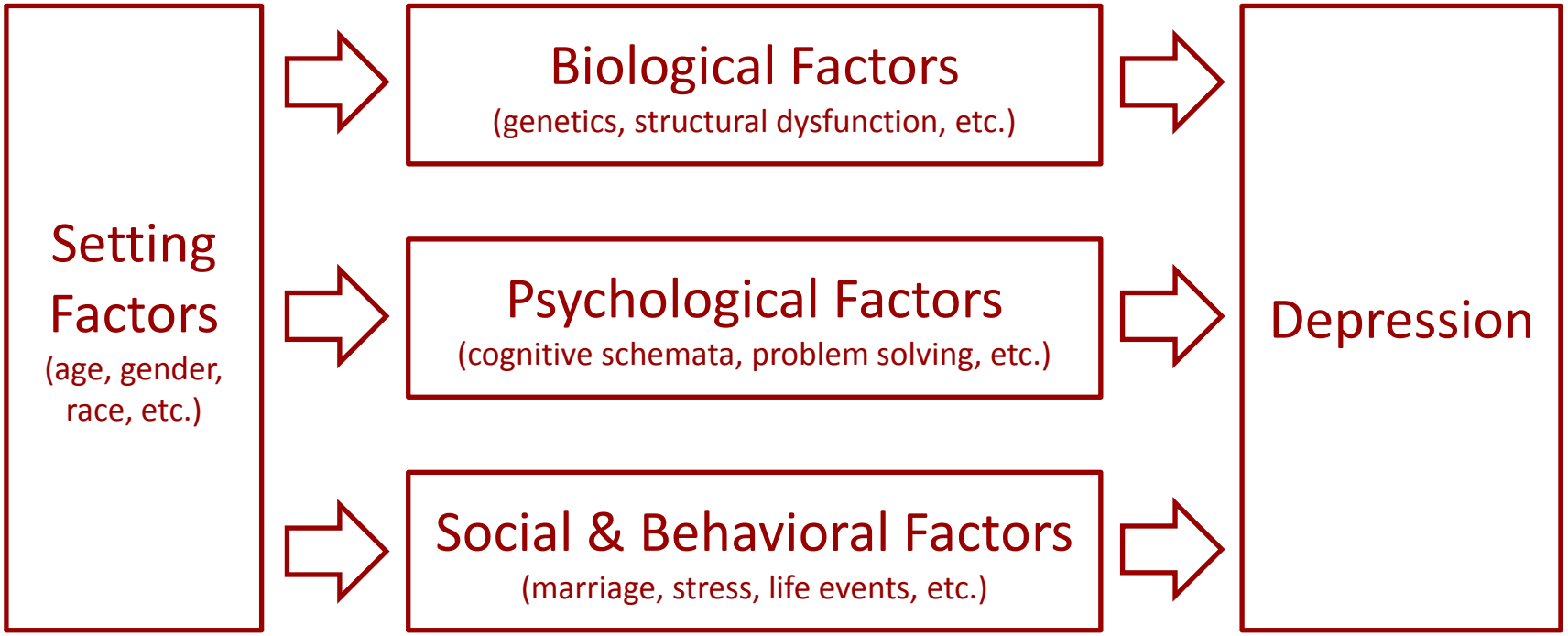


Thoughts


Behavior

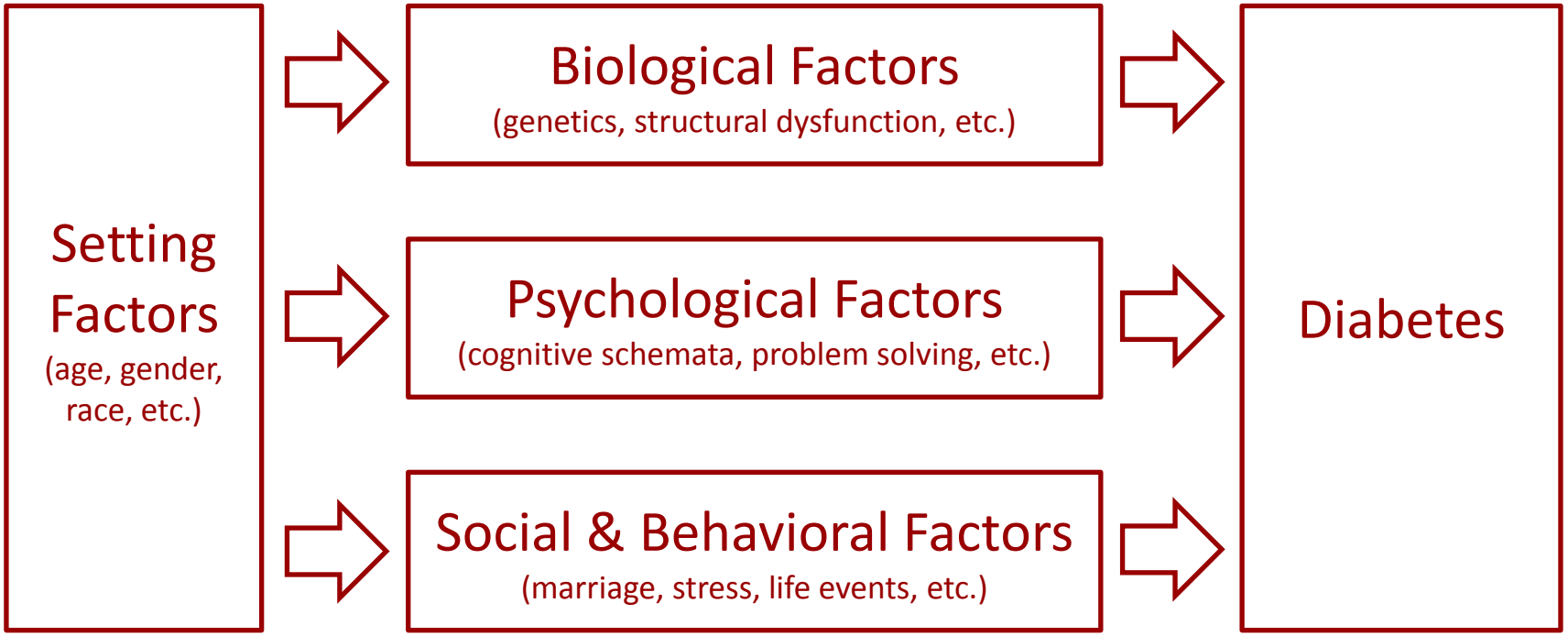
Physical Condition

# Multiple Risk Factors Affecting Depression




Source: Dobson, K. S., & Dozois, D. J. (Eds.). (2011). *Risk factors in depression*. Academic Press.

# Multiple Risk Factors Affecting Diabetes



# Comorbid Depression & Diabetes

# Facts about Comorbid Depression and Diabetes

- Approximately 30% of patients with diabetes are suffering from depression, twice as likely as the general population[5].
- Most patients with diabetes receive care from primary care providers, and many of them want to receive mental care in the primary care settings[6].
- About 45% of diabetic patients with depression are undiagnosed[7]
- Overall, only 25% of patients with mental conditions receive effective care[6]

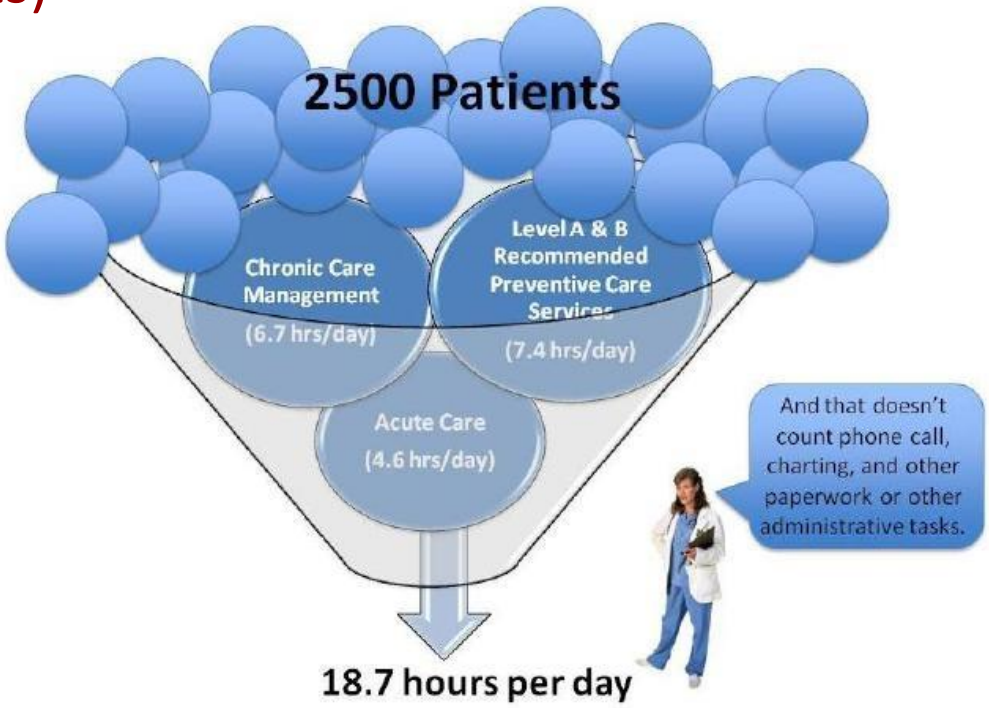
# Collaborative Care Model

- Principles of collaborative care
  1. Patient-centered team care
  2. Population-based care
  3. Measurement-based treatment to target
  4. Evidence-based care
  5. Accountable care
- Collaborative care is supported
  - Over 70 clinical studies have shown it is effective for most mental conditions compared to usual primary care
  - 2008 Mental Health Parity Act

Source: IMPACT: Improving Mood – Promoting Access to Collaborative Treatment. http://aims.uw.edu/collaborative-care/principles-collaborative-care

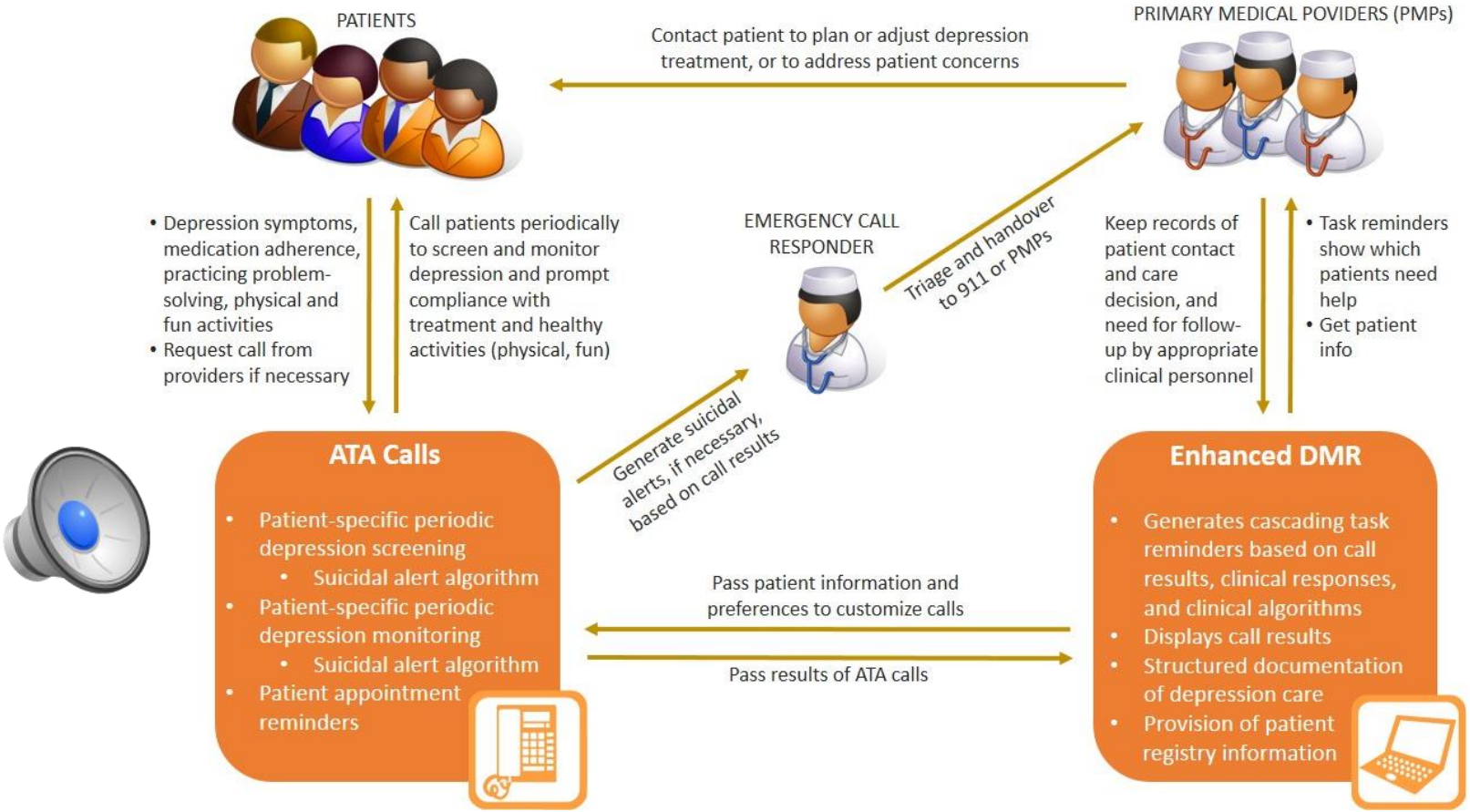
# Barriers to Collaborative Care

- Providers too much to do
  - especially for safety-net providers (10% expenses, 25% of patients)




Source: Agency for Healthcare Research and Quality, www.ahrq.gov

# Diabetes-Depression Care Adoption Technology (DCAT)




Source: Wu, S., Vidyanti, I., Liu, P., Hawkins, C., Ramirez, M., Guterman, J., … Ell, K. (2014). Patient-Centered Technological Assessment and Monitoring of Depression for Low-Income Patients. *The Journal of Ambulatory Care Management*, *37*(2), 138–147. doi:10.1097/JAC.0000000000000027

# DCAT Provider Task Examples

| Lookup | Patients | ESS Access | Reports | Resources | MedRecon Access | Sign Out |

Program: DCAT-Technology Enhanced

Tasks: Due + Overdue

Task Complete

Drag a column header here to group by that column

| # | | Stage | Days | Group | Task | MRUN | Name | Assigned |
|---|---|---|---|---|---|---|---|---|
| | ☐ | Overdue | 231 | Call patient to complete PHQ | PA - PHQ incomplete in DCAT ASR call. Contact patient to complete all PHQ questions. | [redacted] | [redacted] | 10/11/2011 |
| | ☐ | Overdue | 231 | Call patient to complete PHQ | PA - PHQ incomplete in DCAT ASR call. Contact patient to complete all PHQ questions. | [redacted] | [redacted] | 10/11/2011 |
| | ☐ | Overdue | 189 | Depression issue unresolved | SW - Address depression concerns. | [redacted] | [redacted] | 11/22/2011 |
| | ☐ | Overdue | 147 | High PHQ score | SW - Contact patient to discuss concerns relating to depression. | [redacted] | [redacted] | 1/3/2012 |

# Study 1*: A Comparative Effectiveness Trial to Test DCAT

*Led by Dr. Shinyi Wu (PI). I contributed to data analyses and manuscript preparations.

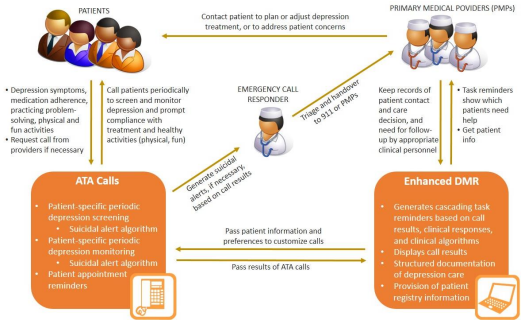
# Comparative Effectiveness Trial

- A three-arm quasi-experimental comparative trial in order to test DCAT[8]
  - 1,406 patients with type 2 diabetes from 8 primary care clinics of the LA County Dept. of Health Services (LAC-DHS) followed by 18 months
  - The majority were women (65%) and Hispanics (89%)
  - Patients assigned to 3 study arms based on clinics
    - UC (N=484): Usual Care in LAC-DHS primary care clinics
    - SC (N=480): Supported Care with LAC-DHS Disease Management Program (DMP) that implements collaborative depression care
    - TC (TC=442): Technology-facilitated Care with DCAT+DMP

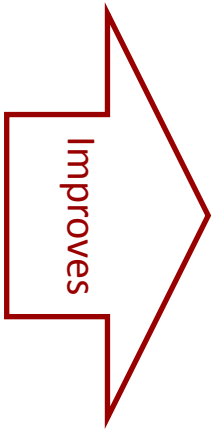
# Generalized Propensity Score

- In order to compare the three arms, I used the Generalized Propensity Score (GPS) method[9]
  - GPS is the conditional probability of receiving a particular intervention given the patient's baseline characteristics
  - GPS is used to adjust the inherent bias in non-randomized trial
  - In DCAT, 26 clinically important baseline characteristics were used to estimate GPS
  - Using GPS in analyzing 1) depression outcomes; 2) diabetes outcomes; 3) cost-effectiveness

# 6-Month Results (TC vs. UC)




DCAT




***Depression outcomes***:

1. PHQ-9 (Mean diff.=-1.19, p=0.02)
2. Depression remission (OR=2.98, p=0.04)
3. Satisfaction of emotional care (Mean diff.=0.21, p=0.07)

***Diabetes outcomes***:

1. Cholesterol level (Mean diff.=-15.94, p=0.01)
2. Sheehan disability scale (Mean diff.=-0.62, p=0.03)
3. Satisfaction in diabetes care (Mean diff.=0.19, p=0.05)

***Costs***

1. Total medical costs (Mean diff.=-$776, p<0.01)

# 6-Month Results (TC vs. SC)

- For providers
  - TC significantly saves provider resources (the average cost of a complete and positive PHQ-9 depression screening by human at $35 vs. by technology at $1)
- For patients
  - TC has slightly better depression and diabetes outcomes, the differences are insignificant as hypothesized
  - TC is likely to save patient medical costs (-$105 per patient), although the difference is insignificant
  - TC has greater than a 50% probability of being cost effective for patients as long as the willingness to pay for QALYs is greater than $40,000 (ref.=$150,000/per QALY)

# Summary of Findings in Study 1

- Compared to usual primary care
  - DCAT + Disease Management Program (DMP) improved depression & diabetes outcomes, increased patient satisfaction of care, and was cost-saving.
- Compared to only DMP
  - DCAT+DMP saved provider's time to target patients in need of depression care and care coordination, and thus helped overcome barriers to implement collaborative care
  - DCAT+DMP had the same level of health outcomes and are more likely to be cost-effective for patients

# Publications, Manuscripts and Awards

PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY

Wu, B, **Jin, H**, Vidyanti, I, Lee, PJ, Ell, K, & Wu, S. (2014). Collaborative depression care among Latino patients in diabetes disease management, Los Angeles, 2011-2013. *Prev Chronic Dis, 11*, E148. doi: 10.5888/pcd11.140081

- **Honorable Mention Award** (among 62 submissions), 2014 Annual Student Research Paper Contest, CDC's *Preventing Chronic Disease* journal
- MEDSCAPE CME Credit

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Ramirez M, Wu S, **Jin H**. (2015). Acceptance of remote depression monitoring using automated telephonic assessment among low income Latino patients in diabetes disease management. Journal of Medical Internet Research, manuscript in submission.

Wu S, **Jin H**, Vidyanti I, Chou C, Ell K, Lee P, Guterman J, Katon W. (2015). Comparative effectiveness of interventions to accelerate adoption of depression care management for diabetes patients: 6-month outcomes. Target: JAMA Psychiatry, manuscript in preparation.

# Study 2*: Predicting Depression among Patients with Diabetes

*I initiated this study and led proposal preparation, analysis, and paper writing

# Towards a More Patient-Centered Care

- DMP/DCAT screen and monitor all patients → waste of resources on 70% non-depressed patients
  - unnecessary depression screening/monitoring may be viewed as offensive[10]
- Under diagnosis and treatment of depression for safety-net patients in usual care

- Solution: using predictive analytics to develop a model-based approach

# Conceptual Framework

## Current

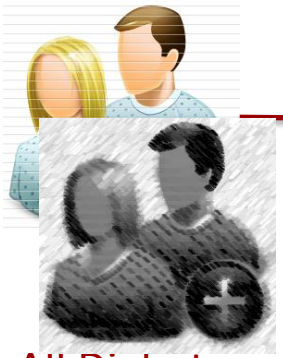
Engaged Diabetes Patients

Universal Depression Screening

Non-engaged Diabetes Patients

No Screening and thus Undiagnosed

## Proposed Model-Based Policy



All Diabetes Patients

Predicted as likely Depressed?

Yes

Depression Screening

No

No Screening

# Research Questions

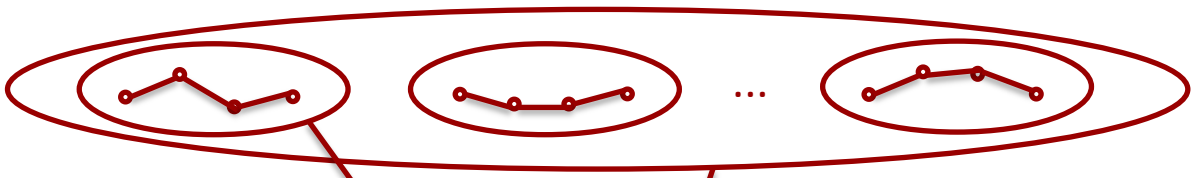
1) How to predict occurrence of depression among diabetes patients? (Study 2)
2) Does the prediction model based policy help providers better prioritize resources and time and increase the efficiency of depression screening? (Study 3)

# Study Design

- Secondary data analysis
  - 4 waves of DCAT data (baseline, 6, 12, 18 months)
- Predicted outcome
  - PHQ-9 score (0~27, PHQ-9≥10 indicates major depression)[11]
- Prediction model
  - multilevel Poisson regression (a.k.a. Poisson mixed-effects model)
- Candidate predictors
  - 9 time-invariant factors (e.g. gender, race, etc.) + 20 time-varying factors (e.g. employment, pain, etc.), all evidence-based
- Predictor selection
  - p-value based (conditional t-test), univariate + backward selection
- Model development
  - training set (80% samples, N=2728); test set (20% samples, N=684)

# Multilevel Poisson Regression

- Clustered nature of longitudinal data



- Level-1 model

$$\ln(\mathrm{PHQ9}_{i,t}) \sim \pi_{0,i} + \pi_{1,i}t + \pi_{tvp_1}x_{tvp_1,t} + \cdots + \pi_{tvp_l}x_{tvp_l,t}$$

- Level-2 model

$$\pi_{0,i} = \gamma_{0,0} + \gamma_{0,1}x_{tip_{0,1}} + \cdots + \gamma_{0,m}x_{tip_{0,m}} + \zeta_{0,i}$$

$$\pi_{1,i} = \gamma_{1,0} + \gamma_{1,1}x_{tip_{1,1}} + \cdots + \gamma_{1,n}x_{tip_{1,n}} + \zeta_{1,i}$$

- Mixed-effects form

$$\ln(\mathrm{PHQ9}_{i,t}) \sim \underbrace{(\gamma_{0,0} + \gamma_{0,1}x_{tip_{0,1}} + \cdots + \gamma_{0,m}x_{tip_{0,m}} + \pi_{tvp_1}x_{tvp_1,t} + \cdots + \pi_{tvp_l}x_{tvp_l,t}) + (\gamma_{1,0} + \gamma_{1,1}x_{tip_{1,1}} + \cdots + \gamma_{1,n}x_{tip_{1,n}})t}_{\text{fixed effect}} + \underbrace{(\zeta_{0,i} + \zeta_{1,i}t)}_{\text{random effect}}$$

# Using the Model for Prediction

- Population-average prediction
  - only fixed effects
- Subject-specific prediction
  - fixed + random effects
- At least one wave of data for estimating random effects
  - Study baseline: only population-average prediction available
  - 6, 12, 18 months: both population-average and subject-specific predictions available

# Model Validation

- Predicted PHQ-9 vs. Real PHQ-9
  - Root Mean Squared Error (RMSE)

| Prediction Type | Baseline | 6-Month Follow-up | 12-Month Follow-up | 18-Month Follow-up |
|---|---|---|---|---|
| Population-Average | 5.45 | 4.75 | 4.79 | 5.16 |
| Subject-Specific | NA | 4.12 | 3.51 | 4.08 |

*Patient historical records improve predictive accuracy

# Model Validation

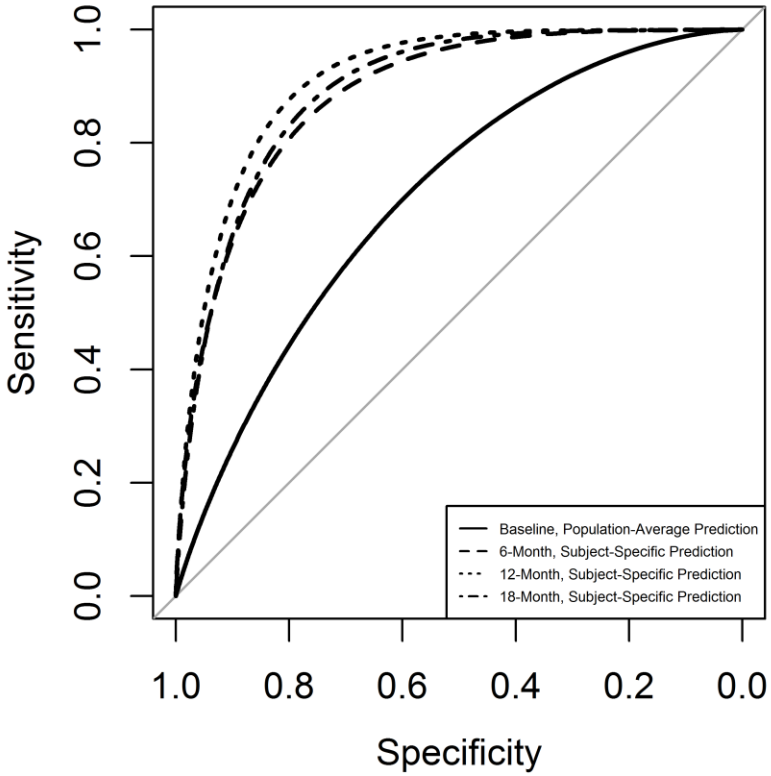
- Predicted PHQ-9 to classify real PHQ-9≥10 (i.e. major depression)
  - Area Under Receiver-Operating Curve (AUROC)

| Prediction Type | Baseline | 6-Month Follow-up | 12-Month Follow-up | 18-Month Follow-up |
|---|---|---|---|---|
| Population-Average | 0.70 | 0.84 | 0.82 | 0.84 |
| Subject-Specific | NA | 0.88 | 0.91 | 0.89 |

*Subject-specific predictions achieve excellent classification (AUROC≈ 0.9)

# Model Validation

- Predicted PHQ-9 to classify real PHQ-9≥10 (i.e. major depression)
  - Receiver-Operating Curves
    - high sensitivity and moderate specificity is often required
    - subject-specific predictions can achieve sensitivity about 0.9 and specificity about 0.8




| | |
|---|---|
| ——— | Baseline, Population-average |
| – – – – | 6-Month, Subject-specific |
| ------- | 12-Month, Subject-specific |
| – · – · – | 18-Month, Subject-specific |

# Summary of Study 2

- A multilevel Poisson regression model to predict depression using longitudinal data
- Historical records can significantly improve prediction
  - Excellent classification of major depressed patients
- For those without historical records, prediction performance is not good
  - AUROC=0.70, at least 0.80 would be clinically useful

# Publications, Manuscripts and Awards

AIR-B AUTISM INTERVENTION RESEARCH NETWORK ON BEHAVIORAL HEALTH

Winner (among 32 proposals) of the Clinical Forecasting Pilot Grant Competition in 2013

2nd International Conference on Big Data and Analytics in Healthcare
Singapore • 22nd - 24th July 2014

**Jin H**, Wu S. Developing depression symptoms prediction models to improve depression care outcomes: Preliminary results. Proceedings of the 2nd International Conference on Big Data and Analytics in Healthcare. 2014

- **Best Poster Paper Award,** 2nd International Conference on Big Data and Analytics in Healthcare

METHODS of Information in Medicine

**Jin H**, Di Capua P, Wu B, Vidyanti I, Wu S. A generalized multilevel regression model using longitudinal data to predict depression among patients with diabetes. Invitation paper in minor revision for publication on *Methods of Information in Medicine*. 2015.

# Study 3*: Prediction Model Based Depression Screening Policy

*I initiated this study and led proposal preparation, analysis, and paper writing

# Improving Baseline Prediction

- Current AUROC=0.71, target >0.8
- Combine DCAT with another trial, Multifaceted Diabetes and Depression Program (MDDP)
  - N=1793, PHQ-9≥10, 43.84%; PHQ-9<10, 56.16%
  - both are depression-diabetes trials
- Refine candidate predictors
  - social & behavioral factors, common demographics, diabetes symptoms and other comorbidities
- Improve predictor selection
  - a correlation-based method[12]
  - search predictor space by hill-climbing algorithm

# Method

- Predict PHQ-9≥10
- Compare four prediction models
  - 2 linear models: Ridge logistic regression, multilayer perceptron
  - 2 nonlinear models: Support Vector Machine (SVM), random forest
- Select the ultimate model with largest AUROC

# Ultimate Prediction Model

- Seven predictors were selected
  1) gender
  2) Toobert diabetes self-care
  3) total number of diabetes complications
  4) previous diagnosis of major depressive disorder (Y/N)
  5) number of ICD-9 diagnoses in past 6 months
  6) chronic pain (Y/N)
  7) self-rated health status
- Ultimate prediction model
  - Ridge logistic regression (AUROC=0.81)

# Model-Based Policy

## Current

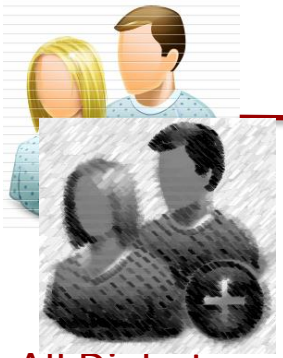
Engaged Diabetes Patients

Universal Depression Screening

Non-engaged Diabetes Patients

No Screening and thus Undiagnosed

## Proposed Model-Based Policy



All Diabetes Patients

Predicted as likely Depressed?

Yes

Depression Screening

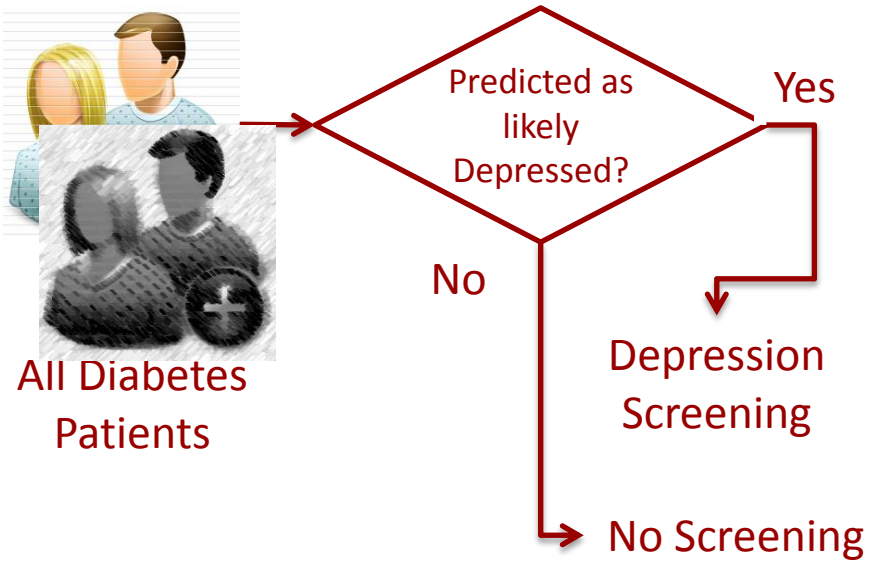
No

No Screening

# Model-Based Policy

- Possible benefits
  1) avoid providing unnecessary, possibly annoying, and resource-wasting depression screening/monitoring for non-depressed patients
  2) improves efficiency of depression screening
  3) identify non-engaged patients that at high risk to depression

**Proposed Model-Based Policy**



# Comparing Depression Screening Policies

## 1) Model-based Policy

Patients with Diabetes

Predicted as likely Depressed?

Yes → Depression Screening

No → No Screening

# Comparing Depression Screening Policies

## 2) Universal Screening

Patients with Diabetes

PATIENT HEALTH QUESTIONNAIRE-9 (PHQ-9)

| Over the last 2 weeks, how often have you been bothered by any of the following problems? (Use "✓" to indicate your answer) | Not at all | Several days | More than half the days | Nearly every day |
|---|---|---|---|---|
| 1. Little interest or pleasure in doing things | 0 | 1 | 2 | 3 |
| 2. Feeling down, depressed, or hopeless | 0 | 1 | 2 | 3 |
| 3. Trouble falling or staying asleep, or sleeping too much | 0 | 1 | 2 | 3 |
| 4. Feeling tired or having little energy | 0 | 1 | 2 | 3 |
| 5. Poor appetite or overeating | 0 | 1 | 2 | 3 |
| 6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down | 0 | 1 | 2 | 3 |
| 7. Trouble concentrating on things, such as reading the newspaper or watching television | 0 | 1 | 2 | 3 |
| 8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual | 0 | 1 | 2 | 3 |
| 9. Thoughts that you would be better off dead or of hurting yourself in some way | 0 | 1 | 2 | 3 |

For office coding: 0 ___ + ___ + ___ + ___

=Total Score: ___

If you checked off any problems, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?

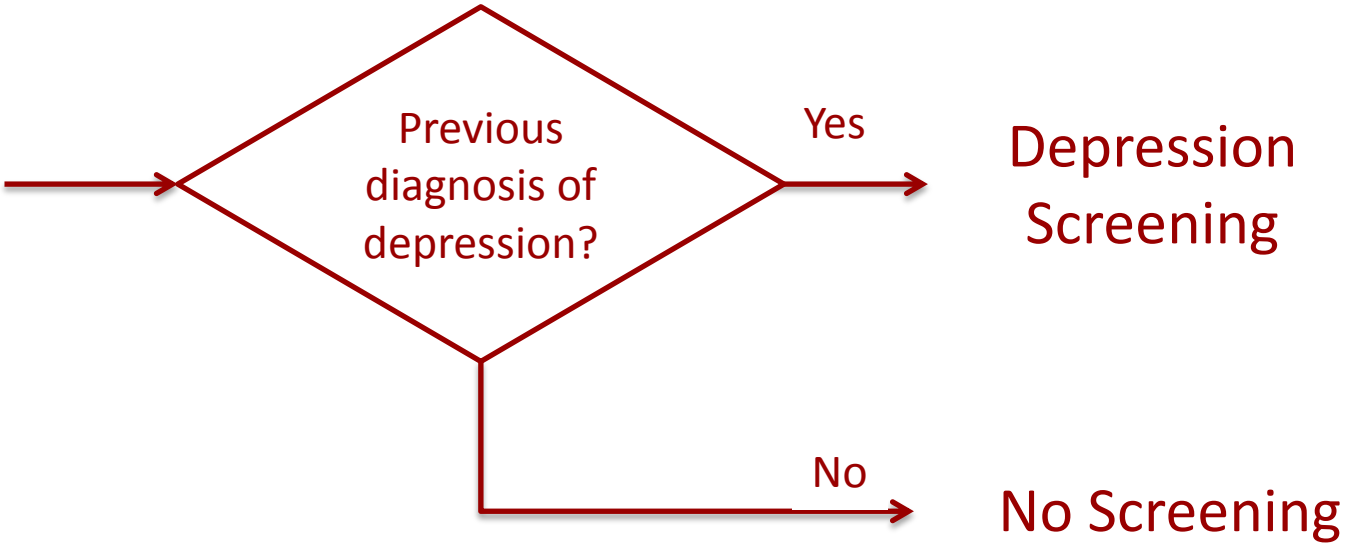
| Not difficult at all | Somewhat difficult | Very difficult | Extremely difficult |
|---|---|---|---|
| ☐ | ☐ | ☐ | ☐ |

Depression Screening

# Comparing Depression Screening Policies

## 3) Heuristic-based policy: #1

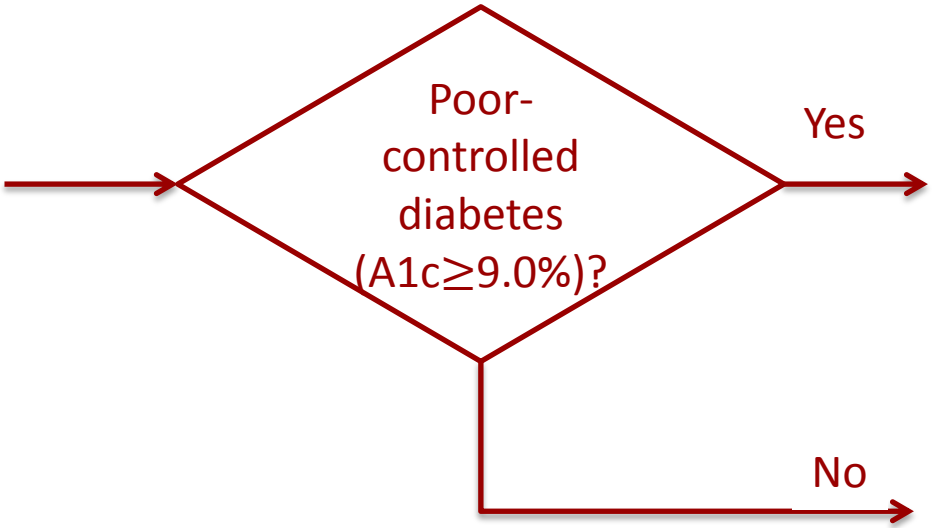
Patients with Diabetes



# Comparing Depression Screening Policies

## 4) Heuristic-based policy: #2

Patients with Diabetes



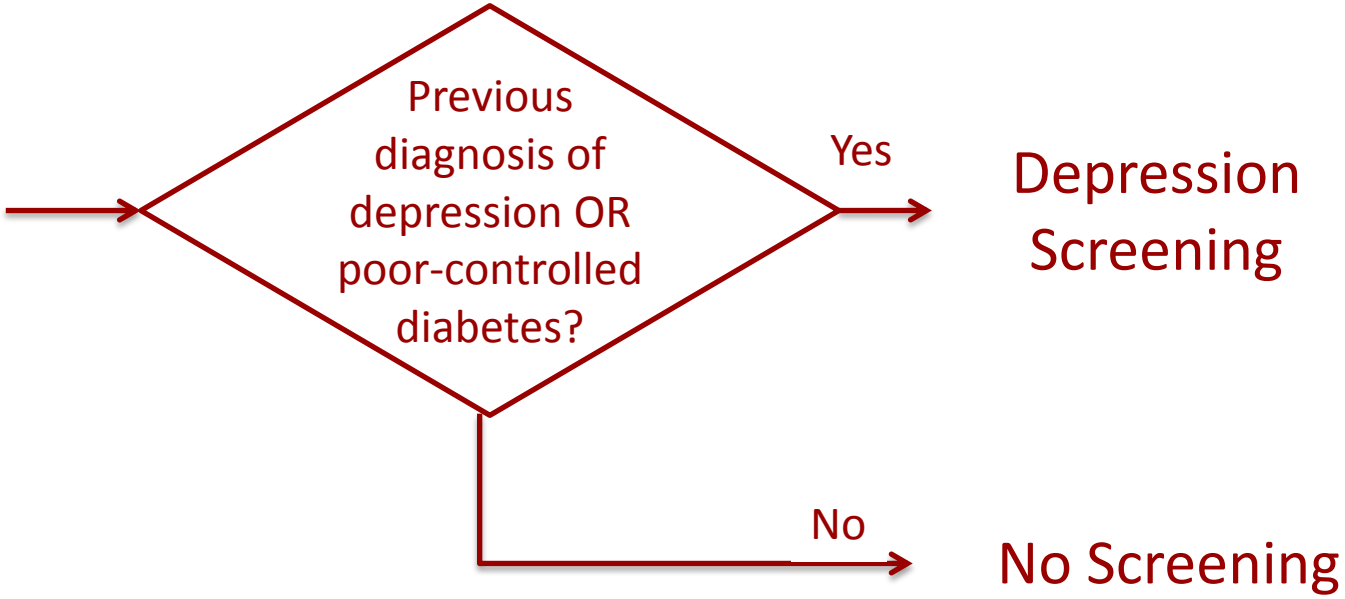

Depression Screening

No Screening

# Comparing Depression Screening Policies

## 5) Heuristic-based policy: #3

Patients with Diabetes



# Comparing Depression Screening Policies

- Comparing policies under two scenarios

## Scenario 1: two-step PHQ screening

Patients Meeting Policy Inclusion Criteria

PHQ-2≥3

Yes

PHQ-9

No

Not Depressed

## Scenario 2: full PHQ-9 screening

Patients Meeting Policy Inclusion Criteria

PHQ-9

# Comparing Depression Screening Policies

- Only present the results of using the improved prediction model for patients without historical data
- Evaluating and comparing
  - measures relevant to the use of provider resources and time
    1) proportion of patients receiving PHQ-2 screening
    2) proportion of patients receiving PHQ-9 screening
    3) average number of questions asked per patient
    4) rate of depression identification
- Evaluating only on DCAT baseline data
  - DCAT enrolled both depressed and non-depressed patients → a better representation of the real patient population

# Policy Comparison Result

- Scenario 1, i.e., two-step PHQ screening

(* significantly different to model-based policy)

| Measure | Model-Based Policy | Universal Screening |
|---|---|---|
| Proportion of patients receiving PHQ-2 screening | 32.3% | 100%* |
| Proportion of patients receiving PHQ-9 screening | 16.5% | 29.1%* |
| Number of screening questions asked per patient | 1.80 | 4.04* |
| Depression identification rate | 49.5% | 78.7%* |

# Policy Comparison Result

- 2-step PHQ screening (* significantly different to model-based policy)

| Measure | Model-Based Policy | Heuristic-Based Partial Screening Policy #1 (Depression History) |
|---|---|---|
| Proportion of patients receiving PHQ-2 screening | 32.3% | 8.6%* |
| Proportion of patients receiving PHQ-9 screening | 16.5% | 5.5%* |
| Number of screening questions asked per patient | 1.80 | 0.56* |
| Depression identification rate | 49.5% | 18.5%* |

# Policy Comparison Result

- 2-step PHQ screening (* significantly different to model-based policy)

| Measure | Model-Based Policy | Heuristic-Based Partial Screening Policy | |
|---|---|---|---|
| | | #2 (Severe Diabetes) | #3 (Depression History OR Severe Diabetes) |
| Proportion of patients receiving PHQ-2 screening | 32.3% | 52.4%* | 56.2%* |
| Proportion of patients receiving PHQ-9 screening | 16.5% | 16.9% | 19.2%* |
| Number of screening questions asked per patient | 1.80 | 2.23* | 2.47* |
| Depression identification rate | 49.5% | 46.4% | 53.8% |

# Policy Comparison Result

- Scenario 2, i.e., full PHQ-9 screening

(*significantly different to model-based policy)

| Measure | Model-Based Policy | Universal Screening | Heuristic-Based Partial Screening Policy | | |
|---|---|---|---|---|---|
| | | | #1 | #2 | #3 |
| Proportion of patients receiving PHQ-9 screening | 32.3% | 100%* | 8.6%* | 52.4%* | 56.2%* |
| Number of screening questions asked per patient | 2.91 | 9.00* | 0.77* | 4.72* | 5.06* |
| Depression identification rate | 62.9% | 100%* | 20.6%* | 58.6% | 67.3% |

# Policy Comparison Result

- Scenario 2, i.e., full PHQ-9 screening

(*significantly different to model-based policy)

| Measure | Model-Based Policy | Universal Screening | Heuristic-Based Partial Screening Policy | | |
|---|---|---|---|---|---|
| | | | #1 | #2 | #3 |
| Proportion of patients receiving PHQ-9 screening | 32.3% | 100%* | 8.6%* | 52.4%* | 56.2%* |
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# Summary of Findings in Study 3

- The model-based policy
  - saves resources and improves efficiency compared to universal screening
  - improves depression identification rate or saves resources and time compared to heuristic-based policies
  - reasonable to expect better results for patients with historical records (analysis ongoing)

# Future Applications of the Model-Based Policy

- A decision-support system based on available medical information to better prioritize the use of provider resources and time
- A preliminary screening step for primary care providers to routinely manage patient population
- A tool to help providers proactively reach out to at-risk patients

# Publications, Manuscripts and Awards

PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY

**Jin H**, Wu S, Di Capua P. A clinical forecasting model to predict comorbid depression among diabetes patients with application in depression screening policy making. Accepted for publication on *Preventing Chronic Disease*. 2015.

- **Honorable Mention Award** (among 59 submissions), 2015 Annual Student Research Paper Contest, CDC's *Preventing Chronic Disease* journal

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**Jin H**, Wu S, Di Capua P. Extending a clinical forecasting model to predict future occurrence of depression among diabetes patients with application in depression screening policy making. Target: Preventing Chronic Disease, manuscript in preparation. 2015.

# Wrap-Up

# Summary of Today's Talk

- We talked about
  1) the importance and barriers of evidence-based collaborative depression care
  2) using DCAT to facilitate the adoption of collaborative care
  3) developing depression prediction model
  4) towards a more patient-centered depression care using a prediction model based approach

# Implications for Clinical Practices

1) Using the prediction model to proactively identify patients at high risk for depression
   - ✓ Benefits: avoiding unnecessary, possibly annoying, and resource-wasting depression screening/monitoring for non-depressed patients
2) Using DCAT automated telephone to screen/monitor those high-risk patients
   - ✓ Benefits: safe, valid, and cost-saving technology
3) Integrating call results with patient registry and task prompting systems to facilitate evidence-based depression care
   - ✓ Benefits: improving clinical outcomes and patient satisfaction

# Future Research

- Expand DCAT to improve population health
  - in application for a PCORI grant, LA county wide, 32 clinics, 20,000 patients, which will include a testing of the model-based depression screening approach
  - Expanding the technology for other patients such as cancer patients and investigating innovative ideas
- Keep investigating the model-based approach
  - further improving predictive accuracy
  - extending to broader populations
  - embracing new challenges and opportunities (NIH: Precision Medicine Initiatives; NSF: Smart Health)

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# Thank you!

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