Using New Technologies to Better Understand, Predict, and Prevent Suicidal Behavior

Matthew Nock, Ph.D.

Harvard University

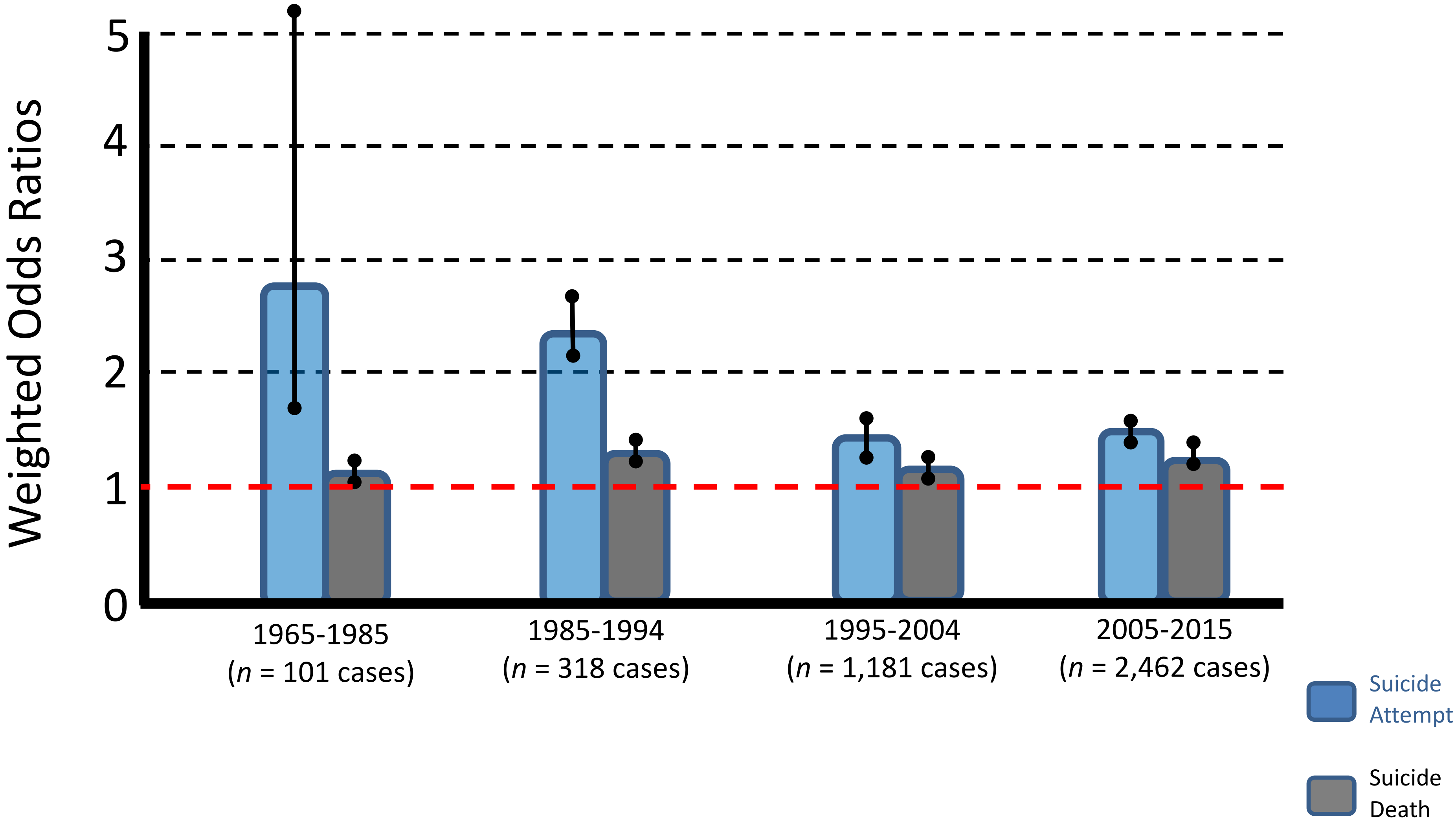
Suicide is a Complex Problem

- Human minds have been studying it for thousands of years
- 11th leading cause of death (no change in past 100 years)
- We have made some progress

  (e.g., identified risk factors, promising treatments)
- Progress is slow, stagnant

  "In God we trust. All others must bring data" –W. Edwards Deming

Prediction of Suicide Attempts and Death: 1965-2015



Franklin, Ribeiro, Fox, Bentley, Kleiman, Jaroszewski, Chang, & Nock (2017). Psychol Bulletin.

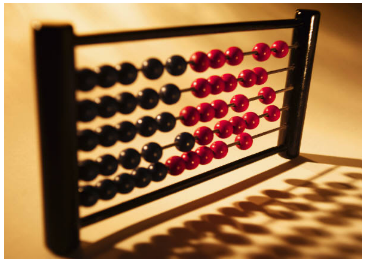
Top Five Predictor Categories across Decades

1965-1985	1985-1994	1995-2004	2005-2015
1. Demographics	1. Internalizing Symptoms	1. Internalizing Symptoms	1. Demographics
2. Internalizing Symptoms	2. Prior SITBs	2. Demographics	2. Internalizing Symptoms
3. Life Events	3. Life Events	3. Externalizing Symptoms	3. Externalizing Symptoms
4. Prior SITBs	4. Demographics	4. Prior SITBs	4. Prior SITBs
5. Externalizing Symptoms	5. Externalizing Symptoms	5. Life Events	5. Life Events
73.8% of all cases	73.2% of all cases	76.3% of all cases	80.3% of all cases

Same predictors + Same methods = Same Results

WE NEED NEW APPROACHES!

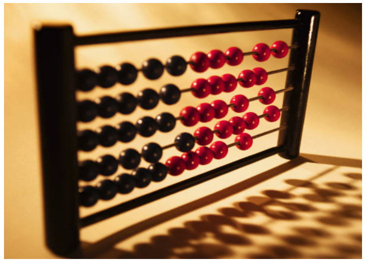
Franklin, Ribeiro, Fox, Bentley, Kleiman, Jaroszewski, Chang, & Nock (2017). Psychol Bulletin.








Time is right for convergence between the study of our complex problems and new technologies and computing approaches to help study and treat them.



?

Time is right for convergence between the study of our complex problems and new technologies and computing approaches to help study and treat them.

Gaps in Understanding

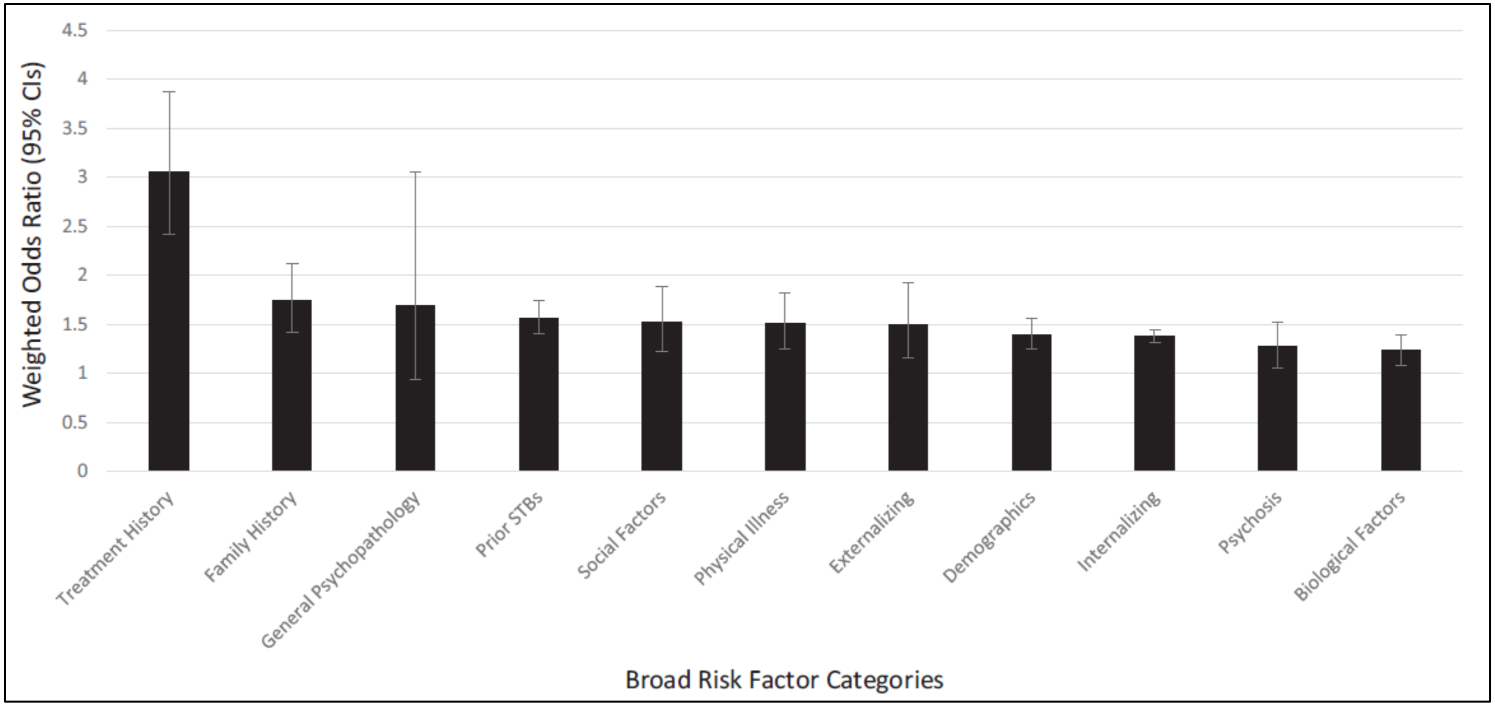
1. Need methods for ***combining*** known risk factors

2. Need ***objective*** data on suicidal thoughts

3. Need data on ***imminent*** risk

1. Need method of *combining* risk factor data

- Risk factors have been identified



- ~99% of studies examine bivariate RFs; few efforts to develop and test methods of combining risk factors

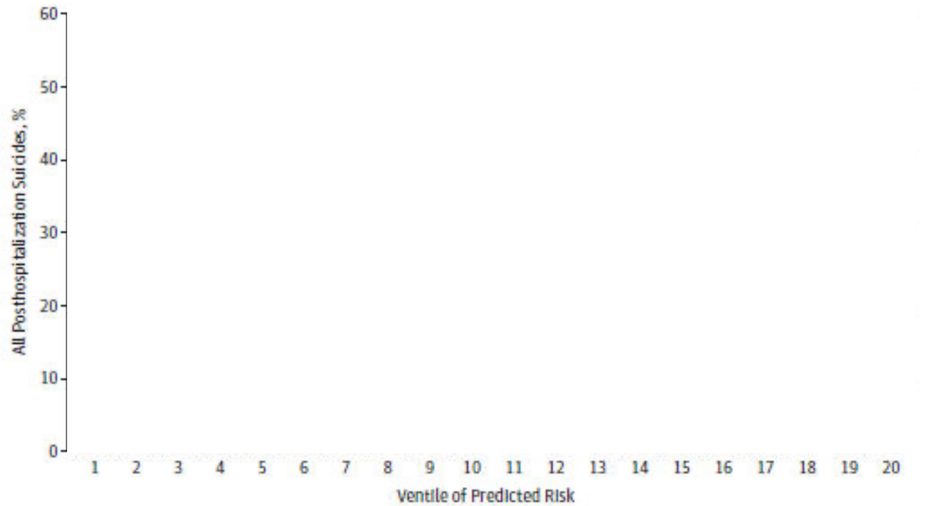
- **NEEDED**: Methods of combining risk/protective factors to more accurately predict suicidal behavior

Franklin, Ribeiro, Fox, Bentley, Kleiman, Jaroszewski, Chang, & Nock (2017). Psychol Bull.

1. Need method of *combining* risk factor data

- Predict which patients die by suicide in year after hospitalization (high risk period)
- Machine learning applied to medical/administrative data to create risk scores
- Data: 53,769 hospitalizations over 6 years (Army soldiers)

Figure 2. Concentration of Risk of Posthospitalization Suicides by Ventile of Predicted Risk Based on the Discrete-Time Penalized Survival Model With a Mixing Parameter Penalty of 1.0

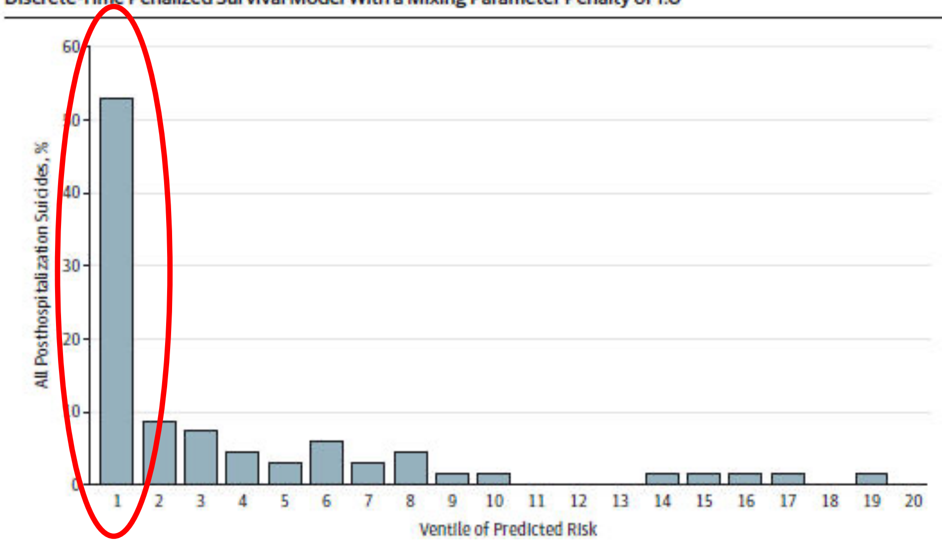


Kessler et al. (2015). *JAMA Psychiatry.*

1. Need method of <u>*combining*</u> risk factor data

- Predict which patients die by suicide in year after hospitalization (high risk period)
- Machine learning applied to medical/administrative data to create risk scores
- Data: 53,769 hospitalizations over 6 years (Army soldiers)

Figure 2. Concentration of Risk of Posthospitalization Suicides by Ventile of Predicted Risk Based on the Discrete-Time Penalized Survival Model With a Mixing Parameter Penalty of 1.0



*First ventile: 52.9% of suicides, rate=3,824/100,000 (vs. 18.5 in Army)

*46.3% of this group had either: suicide death, accidental death, attempt, or re-hospitalization

*All done with data lying dormant in medical & administrative records

*Follow-up project replicates this approach in 5 civilian healthcare systems

Kessler et al. (2015). JAMA Psychiatry. /Barak-Corren et al. (2017). Am J Psychiatry. /Barak-Corren et al. (2020). JAMA-Net Op.

1. Need method of *combining* risk factor data

- Can prediction be improved by combining sources of data?

- 2,000 patients presenting to ED with psychiatric complaint, 1-month f-up
  - ML applied to EHR
  - Patient iPad survey
  - Clinician prediction

- Clinicians not much better than chance (AUC=.67)
- ML on EHR improved prediction (AUC=.71)
- ML + Self-report best prediction (AUC=.77)

- ~30% of those determined to be at high-risk made a suicide attempt in next month

- Brief (20-item; ~4 min) scale performs as well as full model

- Beginning RCT testing benefit of giving risk information to clincians

Nock et al. (2022). JAMA Network Open

2. Need *objective* markers of suicide risk

- Current assessment methods are limited by reliance on explicit report
- Problematic because:
  - Motivation to conceal suicidal thoughts
  - Suicidal thoughts are often transient in nature
  - May lack conscious awareness of current risk or ability to report on it
- 78% of patients who die by suicide in hospital deny thoughts/intent
  (Busch, Fawcett & Jacobs, 2003)
- **NEEDED**: Methods of assessing risk not reliant on self-report

Measuring Implicit Suicidal Cognition

Death	Life
Me	Not Me

Death	Life
Me	Not Me

Death

Me

Life

Not Me

suicide

Death	Life
Me	Not Me

Death

Me

my

Life

Not Me

Death	Life
Me	Not Me

Death

Me

Life

Not Me

living

Death	Life
Me	Not Me

Death

Me

Life

Not Me

them

Death	Life
Me	Not Me

Death

Me

Life

Not Me

survive

Death	Life
Me	Not Me

Death

Me

Life

Not Me

dead

Death	Life
Me	Not Me

Death

Me

Life

Not Me

I

Death	Life
Me	Not Me

Death

Me

Life

Not Me

suicide

Death	Life
Me	Not Me

Life	Death
Me	Not Me

Life

Me

Death

Not Me

survive

Life	Death
Me	Not Me

Life	Death
Me	Not Me

mine

Life	Death
Me	Not Me

Life

Me

Death

Not Me

dead

Life	Death
Me	Not Me

Life	Death
Me	Not Me

their

Life	Death
Me	Not Me

Life

Me

Death

Not Me

I

Life	Death
Me	Not Me

Life

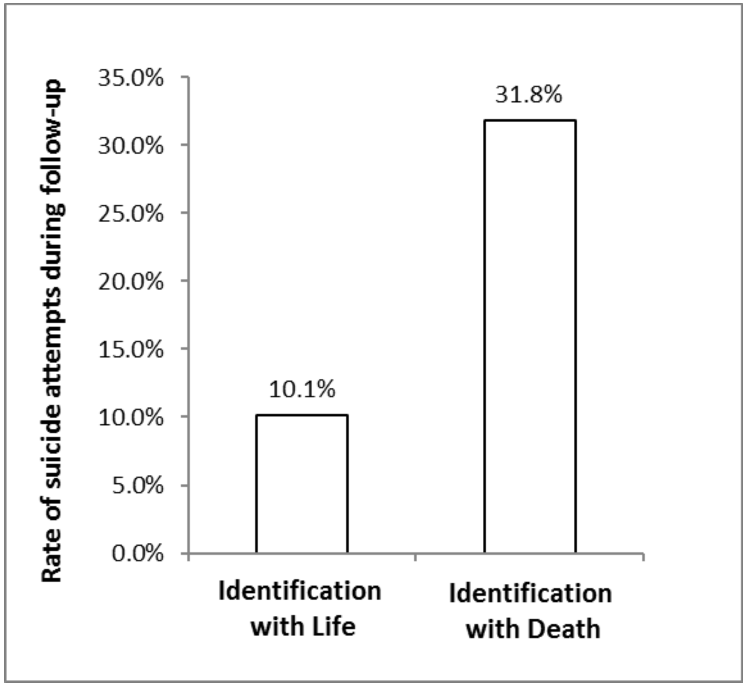
Death

Me

Not Me

living

2. Need *objective* markers of suicide risk



*Those with death ID were more likely to make an attempt after discharge

*IAT added incrementally to prediction of SA beyond diagnosis, clinician, patient, and SSI (OR=5.9, p<.05)

*Sensitivity= .50; Specificity= .81

Nock et al (2010). *Psychological Science*.

*Replication in ED in Alberta, Canada

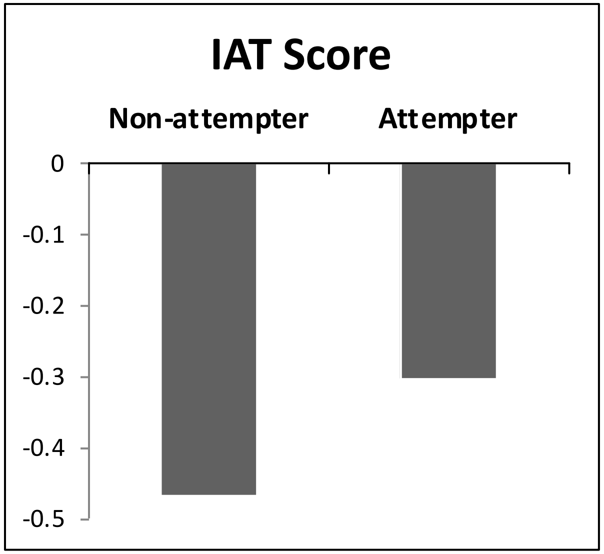
*IAT added incrementally to the prediction of self-harm at 3-month follow-up (OR=5.1, p<.05)

*Sensitivity= .43; Specificity= .79

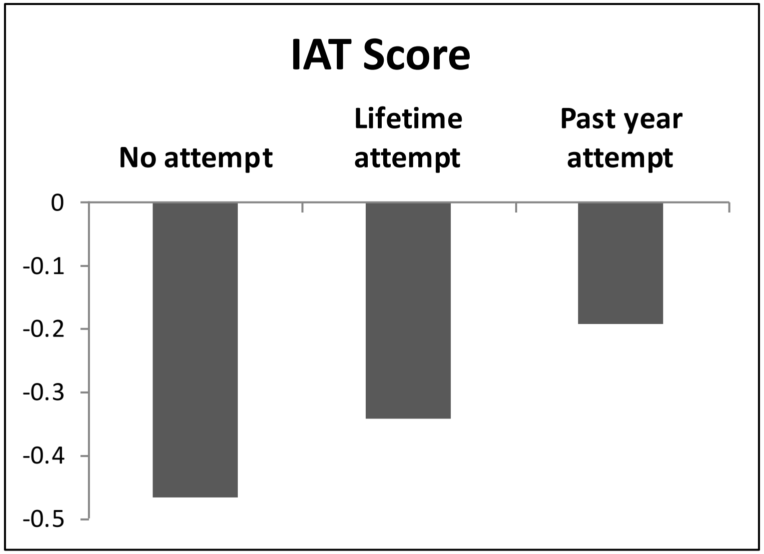
Randall et al (2013). *Psychological Assessment*.

2. Need *objective* markers of suicide risk

- Effects also observed in more general population
- www.ProjectImplicitHealth.com



N = 6,229; (3,115 + 3,114)

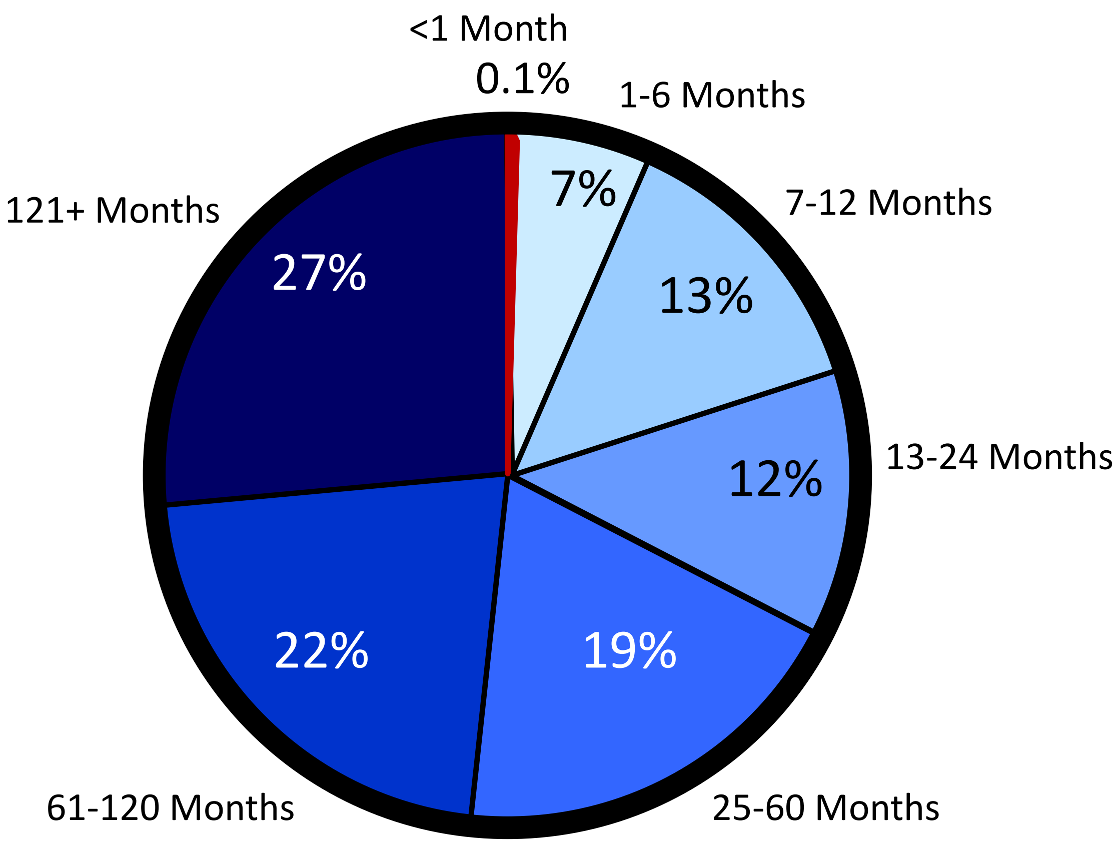


J. Glenn et al. (2017). J Abnormal Psychology.

3. Need data on *imminent risk*

- Clinicians want to know who is at risk for suicide NOW.
- What time period do existing studies cover?

Follow-Up Lengths for All Longitudinal SITB Studies 1965-2015



NEEDED: Studies on natural unfolding of suicidal thoughts/behaviors!

Franklin, Ribeiro, Fox, Bentley, Kleiman, Jaroszewski, Chang, & Nock (2017). Psychol Bull.

3. Need data on ***imminent risk***

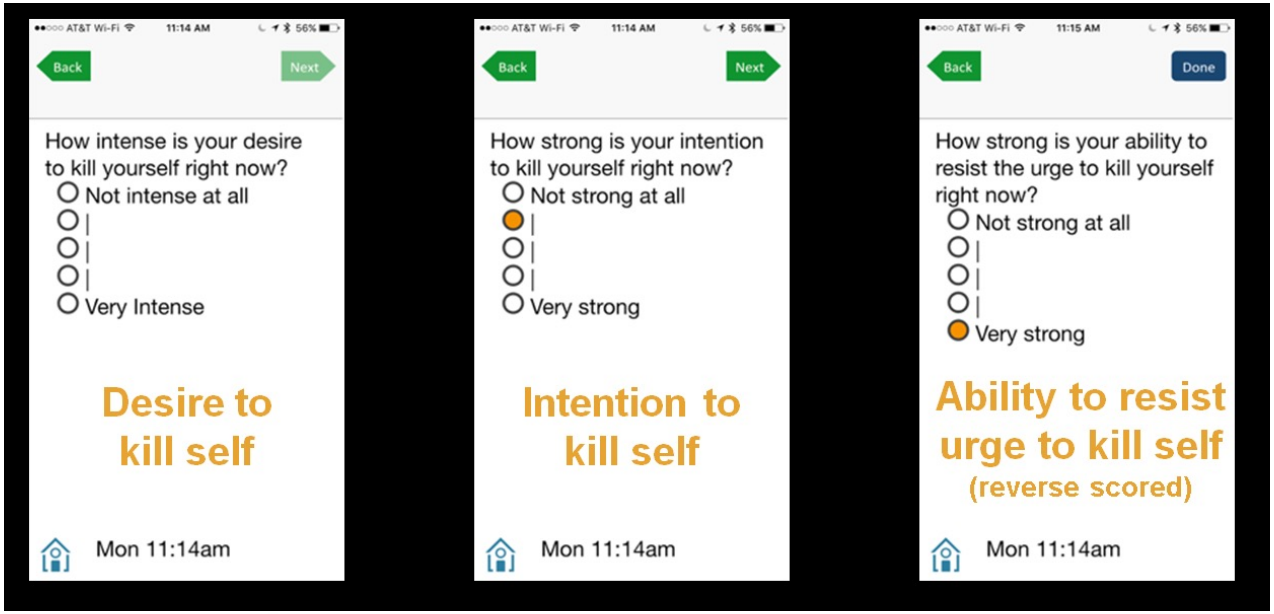




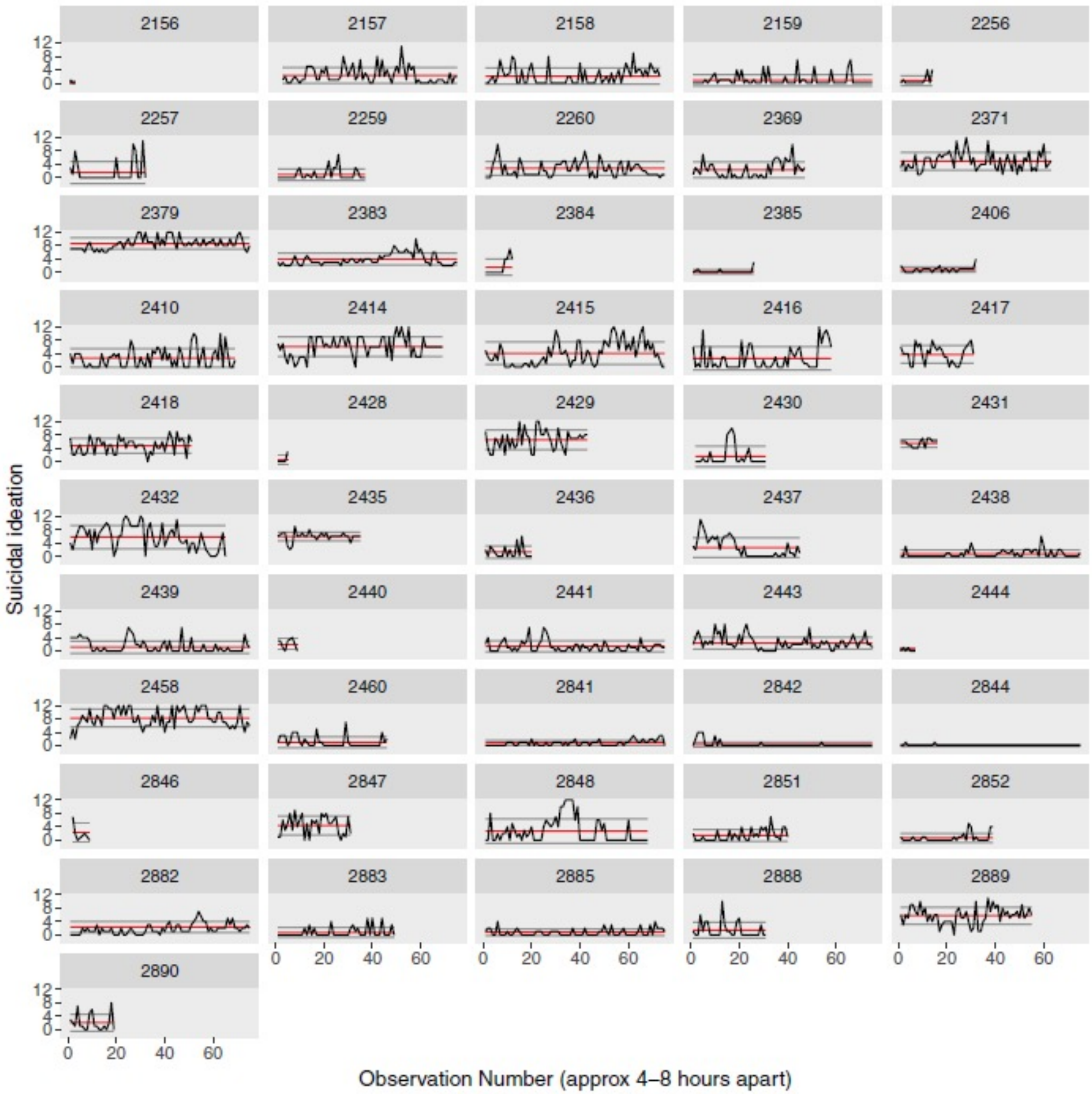

- *Digital phenotyping*: "moment-by-moment quantification of the individual-level phenotype *in situ* using data from personal digital devices" (JP Onnela)
  - Capture fine-grained, dynamic changes/fluctuations in phenomenon (e.g., how do thoughts, feelings, behaviors change during suicidal episode?)
  - Decrease influence of recall bias
  - Observe processes predicting behavior in context (vs. laboratory/interview room)
- Test existing theories using ecologically valid data, collect never-before available data to develop new theories
- Provide novel opportunities for intervention BEFORE problem occurs

Digital Monitoring of Suicidal Thinking

- Smartphone monitoring 4-6x/day of adults with suicide ideation for 1 month

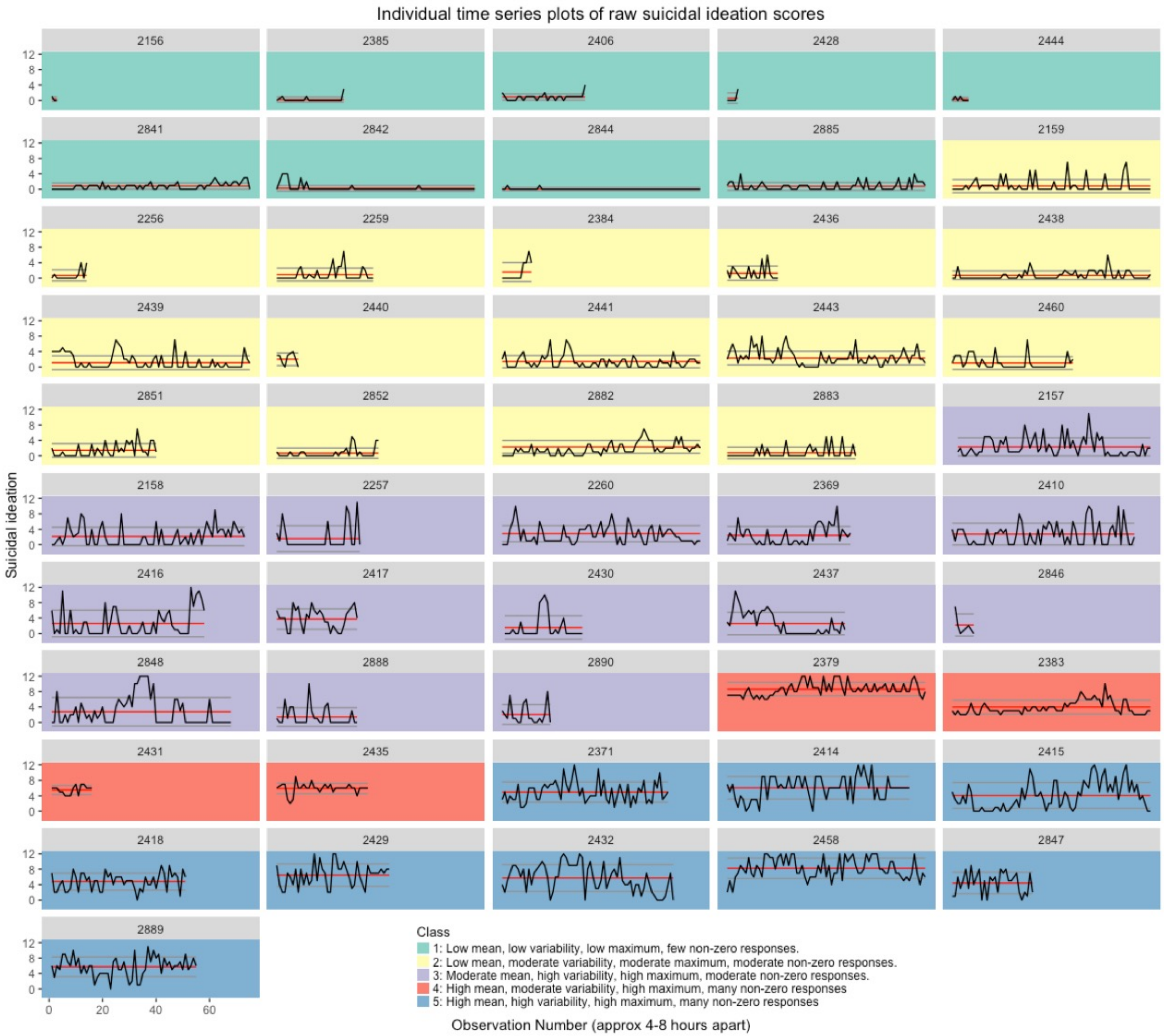


Variability of Suicidal Thoughts



Kleiman et al. (2017). Journal of Abnormal Psychology.

Subtypes of Suicidal Thoughts(?)



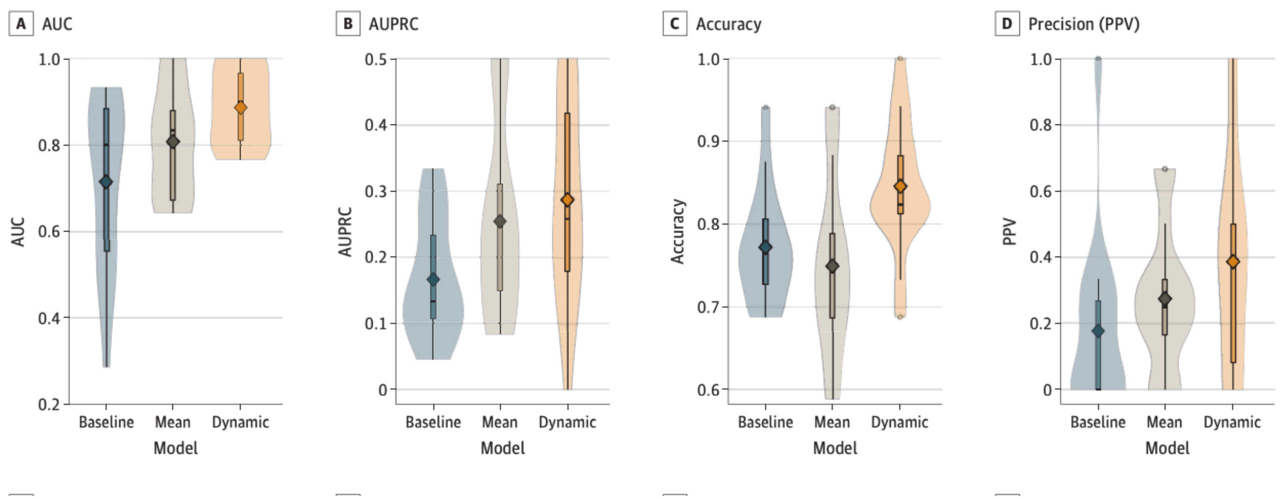
Kleiman et al. (2018). Depression & Anxiety.

Smartphone Data Improve Prediction of Suicide Attempt

- Can dynamic factors (variability in SI) during hospitalization better predict post-hospital SA?

- 83 adult inpatients provided 4-6x/day reports of SI

Figure 1. Suicide Attempt Prediction Model Metrics



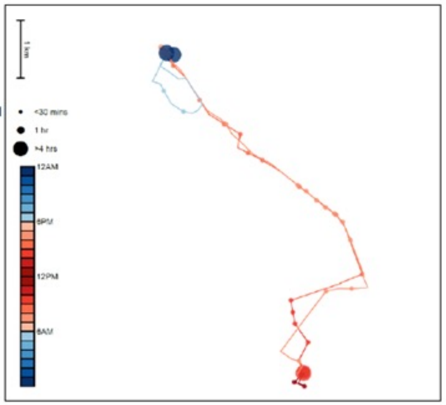
- Probability of acute change in SI is strongest predictor of SA

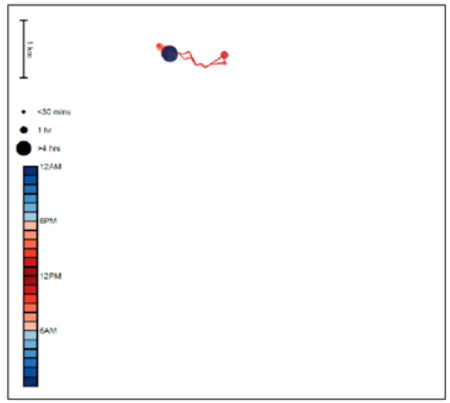
Wang et al. (2021). JAMA Network Open.

Passive monitoring via smartphones & wearables

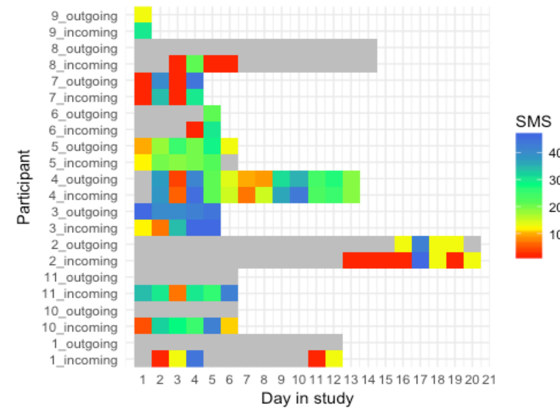
Passive

Phone: GPS, accelerometer, call/text data, Bluetooth





(JP Onnela, *Beiwe*)



* # texts inversely associated with SI (in prep)

Biosensor data: EDA, HRV, accelerometer, skin temp

EDA=.50

HRV=.67

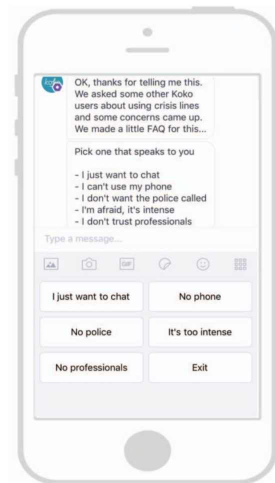
ACC=.75

(Fedor et al., in prep)

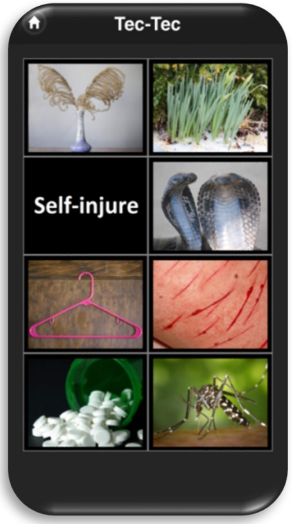
U01MH116928-01: 300 adults & 300 adolescents over 6 months post-hospital

Digital Interventions

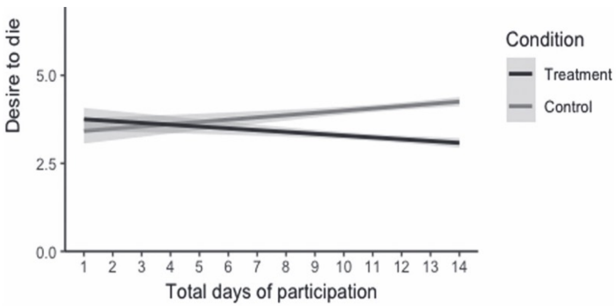
- ML-driven real-time intervention via chatbot
  (Jaroszewski et al., 2019)
  - 23% increase in use of crisis services in next few hours
  - 40,000 participants in 5 weeks



- Game-like conditioning ("matching") app
  (Franklin et al., 2016)
  - 20-60% reductions in suicidal and self-injurious behavior over 30 days
  - Via increased aversion to suicide and more positive self-image



- Digital bibliotherapy platform (TheMighty.com)
  (Franz et al., 2023)
  - Significant reductions in suicidal thinking over 2 weeks, via increased hope/connectedness



Conclusions

- Opportunities for advance:
  - Prediction using EHR and other data sources (social media, etc.)
  - Detection & prediction using objective measures
  - Scalable real-time interventions

- Key challenges for the future:
  - How to deliver risk scores to clinicians? Patients?
  - Which assessments/interventions with which patients (HTE)?
  - Ethics of monitoring and implicit assessments & interventions?

Funding & Collaborators

- National Institute of Mental Health
- Department of Defense; US Army; US Air Force
- American Foundation for Suicide Prevention
- Griswold Suicide Prevention Fund
- Fuss Family Research Fund
- For the Love of Travis Fund

<u>Nock Lab</u>

Alex Millner (Franciscan)
Kate Bentley (MGH)
Becky Fortgang
Evan Kleiman (Rutgers)
Kelly Zuromski
Shirley Wang
Daniel Coppersmith
Osiris Rankin
Franckie Castro-Ramirez
Grant Jones
Azure Reid-Russell
Taylore McGuire…& many others!

<u>Collaborators</u>

Ron Kessler (HMS)
Jordan Smoller (HMS/MGH)
Ben Reis (HMS/BCH)
JP Onnela (HMS)
Phil Wang (CHA)
Rob Morris (Koko)
Ben Cook (CHA)
Rosalind Picard (MIT)
Jeff Huffman (MGH)
Stu Beck (MGH)
Nick Carson (CHA)

Using New Technologies to Better Understand, Predict, and Prevent Suicidal Behavior

Matthew Nock, Ph.D.

Harvard University