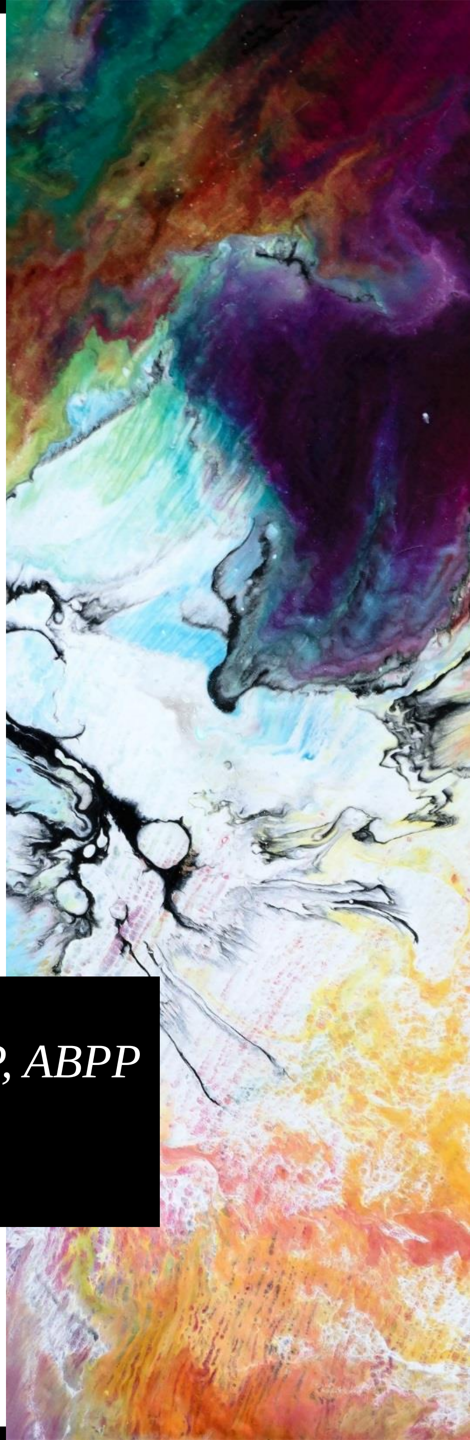
PREDICTING SUICIDE MORTALITY

Collin Davidson, PhD, LP, ABPP

Hennepin Healthcare



OVERVIEW

Suicide rates

Predicting suicide

The clinical viewpoint

Suicide risk factors

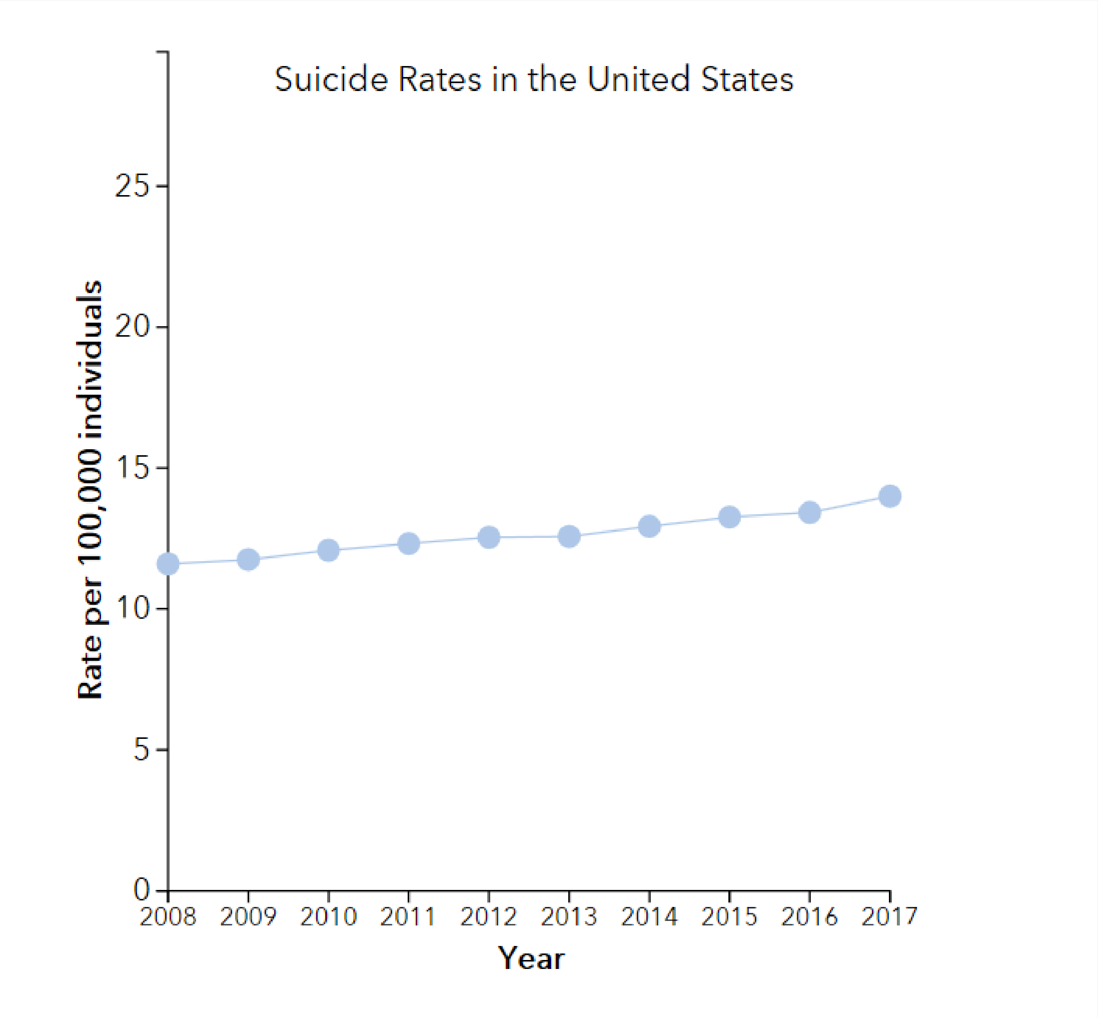
Machine learning and suicide prediction models

Summary

SUICIDE RATES

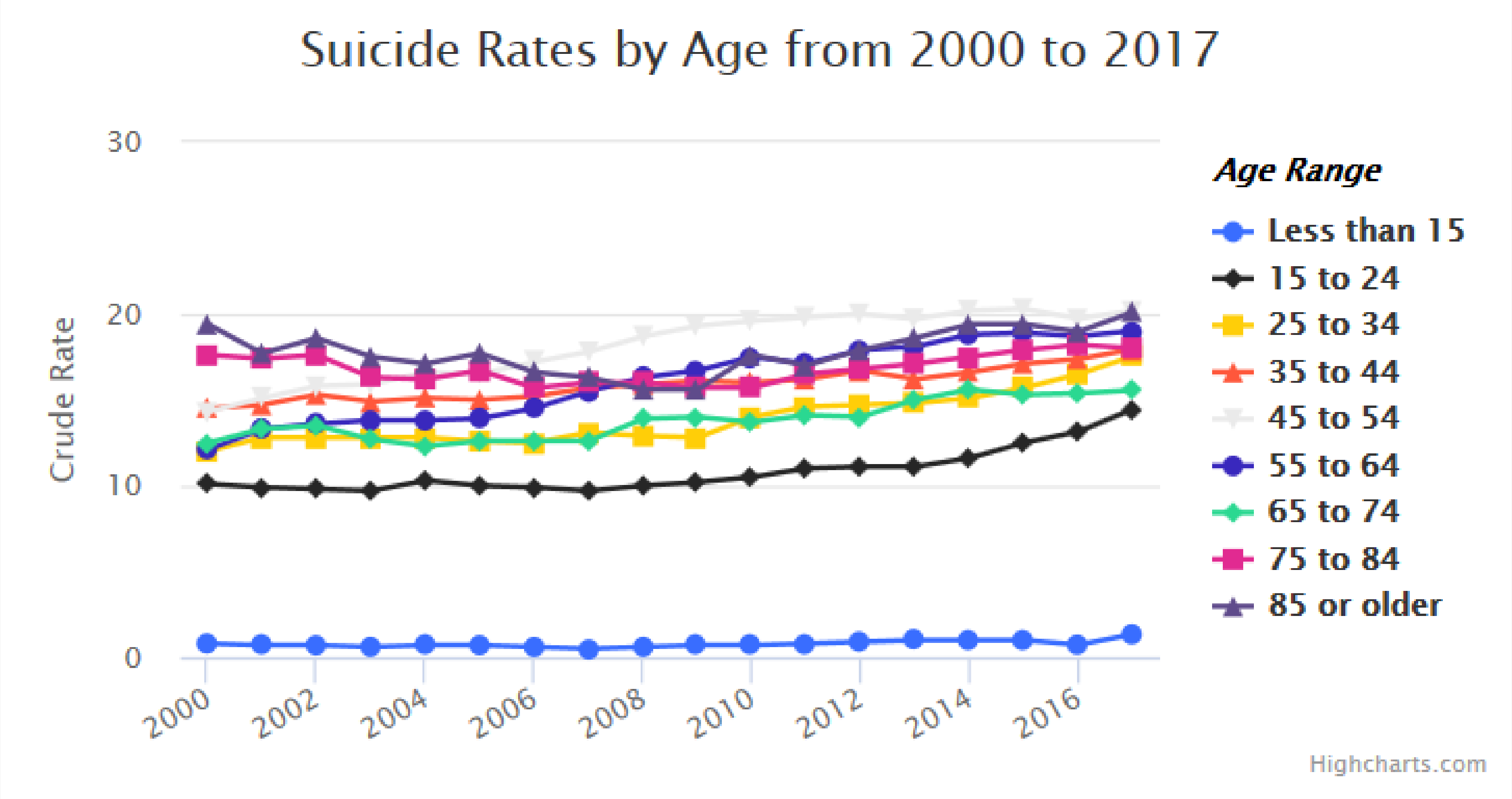
DEATHS BY SUICIDE

(American Foundation for Suicide Prevention, 2018)



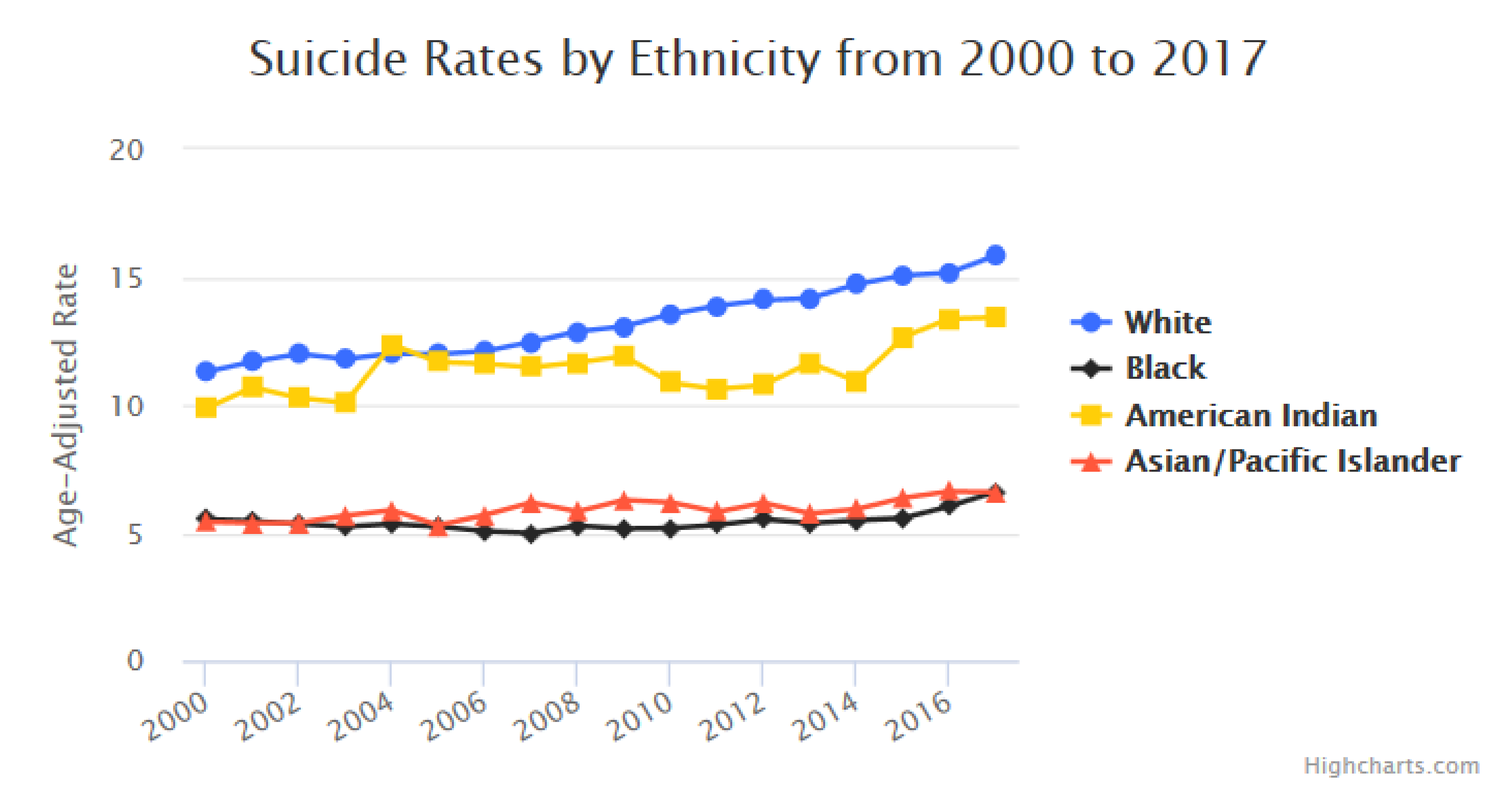
AGE-BASED SUICIDE RATES

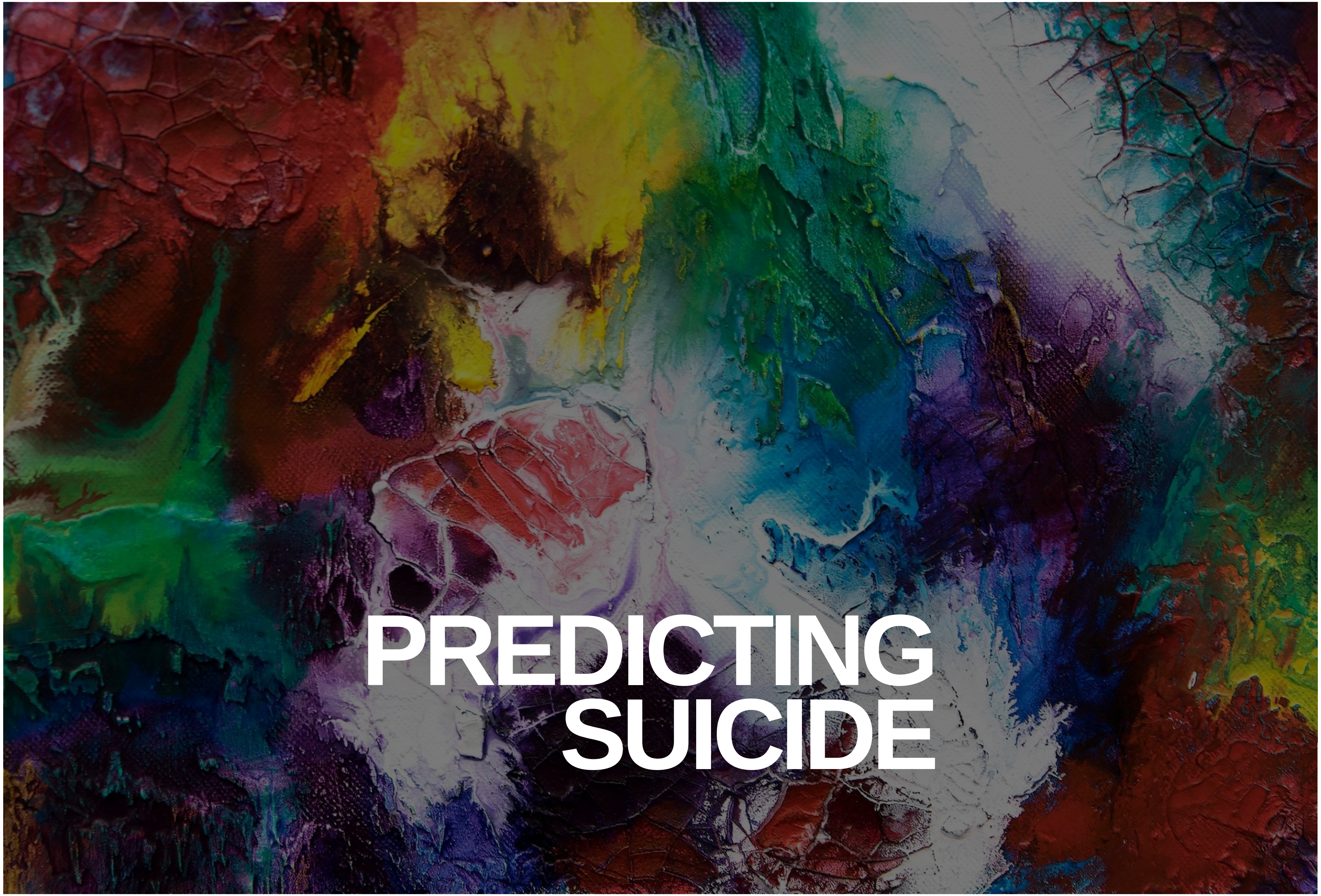
(American Foundation for Suicide Prevention, 2018)



RACE-BASED SUICIDE RATES

(American Foundation for Suicide Prevention, 2018)




PREDICTING
SUICIDE

PREDICTING SUICIDE

Suicide attempts and deaths have very low base rates (14 per 100,000 in 2017)

Low base rate events are statistically difficult to predict unless risk factors have an exceedingly large effect

Suicidologists have focused on identifying risk factors and warning signs for suicidal behaviors

PREDICTING SUICIDE

(Franklin et al., 2017)

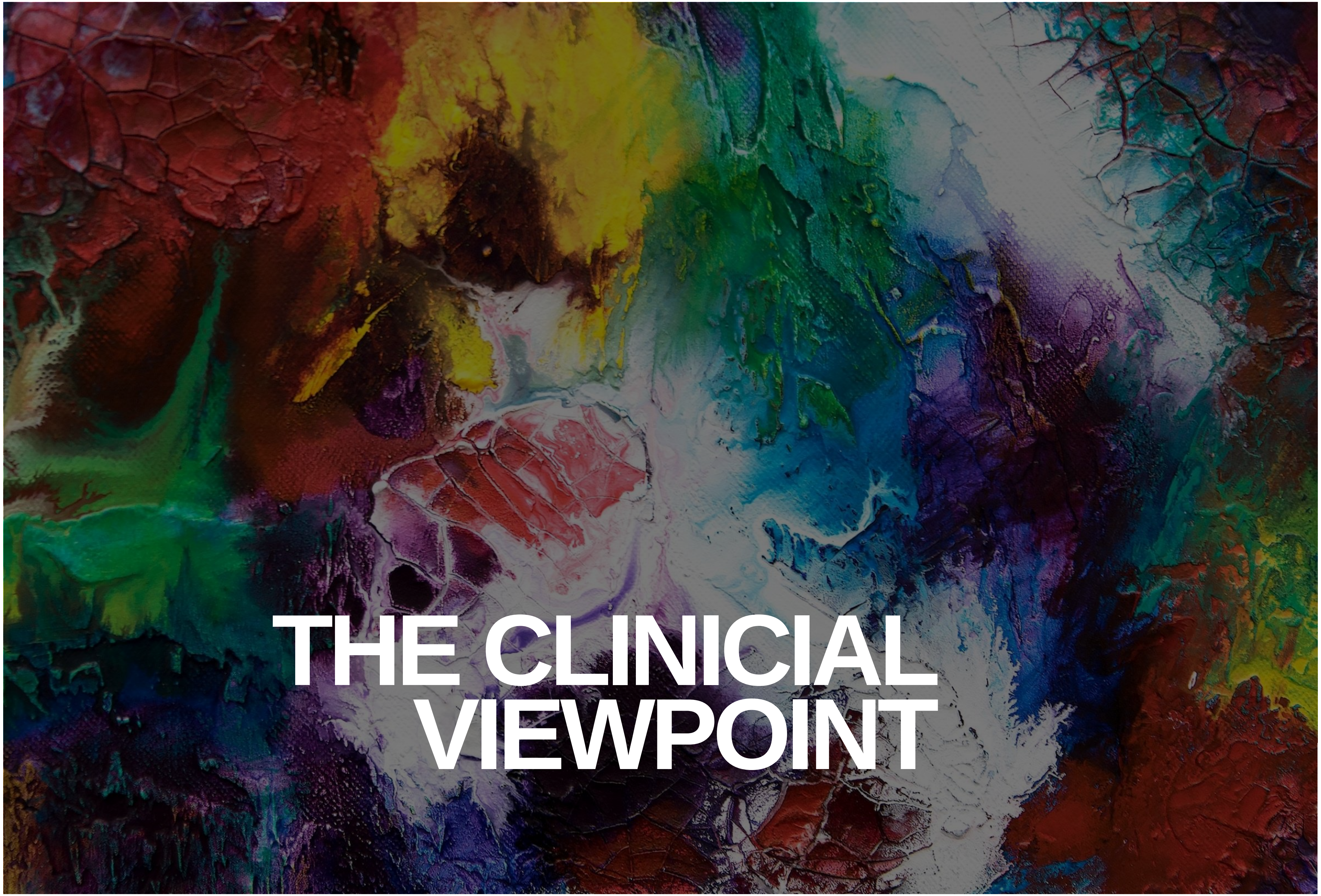
The lifetime rate of death by suicide in the general population is 1.6%

The lifetime rate of death by suicide among outpatients with mood disorders is 2%

The lifetime rate of death by suicide inpatients with mood disorders is 4%

96 to 98% of mood disorder patients will *NOT* die by suicide

THE CLINICIAL VIEWPOINT



CLINICAL GUIDELINES REGARDING RISK FACTORS AND WARNING SIGNS

American Foundation for Suicide Prevention

American Association of Suicidology

World Health Organization

Centers for Disease Control and Prevention

NIH National Institute of Mental Health

COMPARING CLINICAL GUIDELINES

(Bernert, Hom, & Roberts, 2014)

Psychiatric Disorders

Medical disorders including pain

Traumatic brain injury

Previous attempts

Family history of suicide

Access to lethal means

Stressful life events

Traumatic exposure…etc.

COMPARING CLINICAL GUIDELINES

(Bernert, Hom, & Roberts, 2014)

10 clinical practice guidelines

12 additional resources

1,353 pages in total

Mostly rationally derived by experts in the field

COMPARING CLINICAL GUIDELINES

(Bernert, Hom, & Roberts, 2014)

Lack of clear consensus

"assessment of evidence-based suicide risk factors (100 %)
assessment of suicidal intent (80 %)
recommended treatments (80 %)
restricting access to means (80 %)
postvention practice recommendations (70 %)
suicide risk level categorizations (60 %)
recommended risk assessment measures (60 %)
tools for outpatient management (60 %)
confidentiality issues (60 %)
training recommendations (50 %)
legal issues (50 %)
safety planning (40 %)
ethical considerations (30 %)."

SUICIDE RISK FACTORS

RISK FACTORS FOR SUICIDAL BEHAVIOR

(Franklin et al., 2017)

Meta-analysis looking at longitudinal studies over the last 50 years

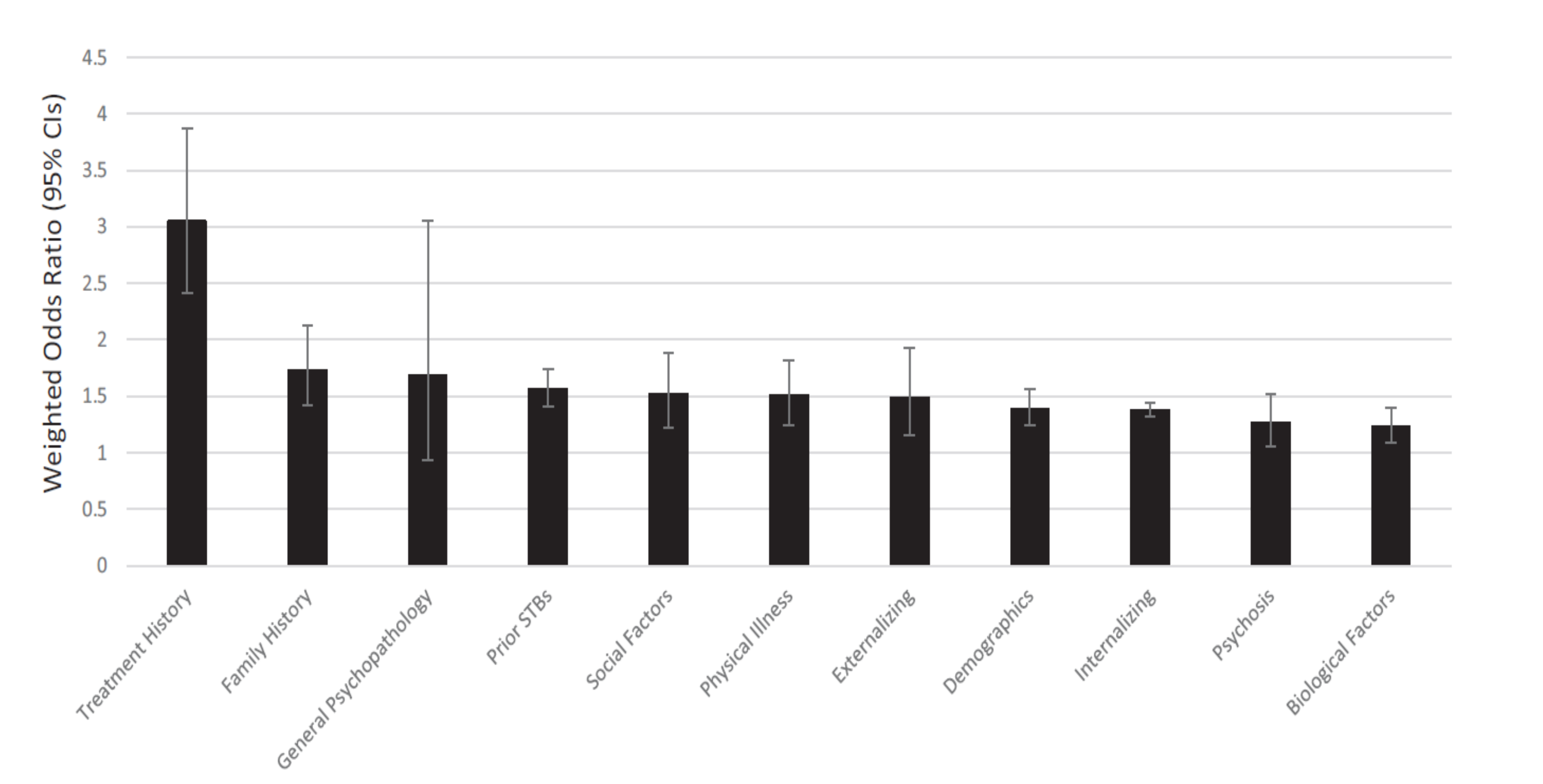
The study analyzed effects in 365 papers

Resulted in 3,923 cases of risk and protective factors

Aimed to identify risk and protective factors across a wide variety of categories
(i.e., biological, screening measures, cognition, demographics, externalizing and internalizing disorders, family history, general psychopathology, implicit processes, personality traits, physical illness, psychosis, previous suicidal behavior, exposure to suicidal behavior, social factors, and treatment history)

RISK FACTORS FOR DEATH BY SUICIDE

(Franklin et al., 2017)



RISK FACTORS FOR SUICIDAL BEHAVIOR

(Franklin et al., 2017)

Conclusions:

Risk factors are generally weak and inaccurate predictors of suicide attempts and deaths

Prediction has not improved over time

Longer time intervals did not demonstrate better prediction (many studies 5-10 years)

No risk factor category is meaningfully stronger than another

RISK FACTORS FOR SUICIDAL BEHAVIOR

(Franklin et al., 2017)

Conclusions (continued):

Protective factors are not commonly studied and are also weak predictors

Risk factor categories are homogeneous across the 50 years and have become more homogenized over time

No evidence of unique predictors of suicidal ideation vs. attempt vs. death

The combined risk factors only correctly identified 9% of suicide deaths

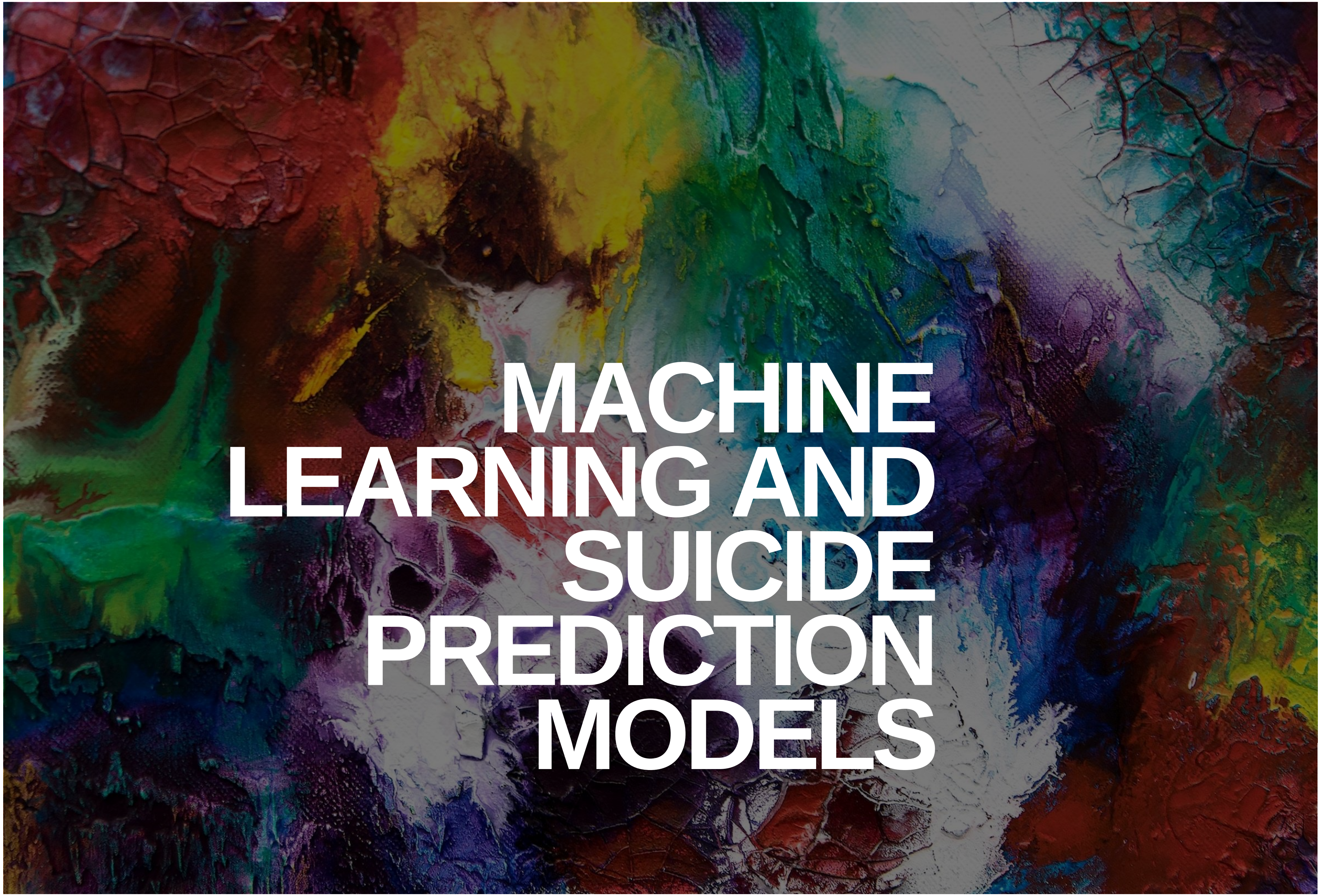
RISK FACTORS FOR SUICIDAL BEHAVIOR

(Franklin et al., 2017)

“In terms of clinical significance, assuming these weighted odds ratio figures would apply on a population level, these combined risk factor effects would increase the 1-year odds of:

Suicide death from 0.013 to 0.019 per 100 people
Suicide attempt from 0.33 to 0.49 per 100 people
And suicide ideation from 2 to 3 per 100 people.”

Suicide death from 13 to 19 per 100,000 people
Suicide attempt from 330 to 490 per 100,000 people
And suicide ideation from 2,000 to 3,000 per 100,000 people.



MACHINE LEARNING AND SUICIDE PREDICTION MODELS

USING MACHINE LEARNING (ML) TO PREDICT SUICIDE

(Kessler et al., 2015)

Examined suicide deaths following 53,869 hospitalizations of active duty Army soldiers

Developed an actuarial risk algorithm based on machine learning (penalized regression and regression trees)

68 soldiers died by suicide in the 12 month follow-up period

USING MACHINE LEARNING TO PREDICT SUICIDE

(Kessler et al., 2015)

The best predictors of death by suicide were:

- Male sex (OR 7.9)
- Older age at enlistment (OR 1.9)
- Verbal violence (OR 2.2)
- Weapons possession (OR 5.6)
- Prior suicidality (OR 2.9)
- Number of antidepressant prescriptions (OR 1.3)

The full model included 73 variables to predict death by suicide

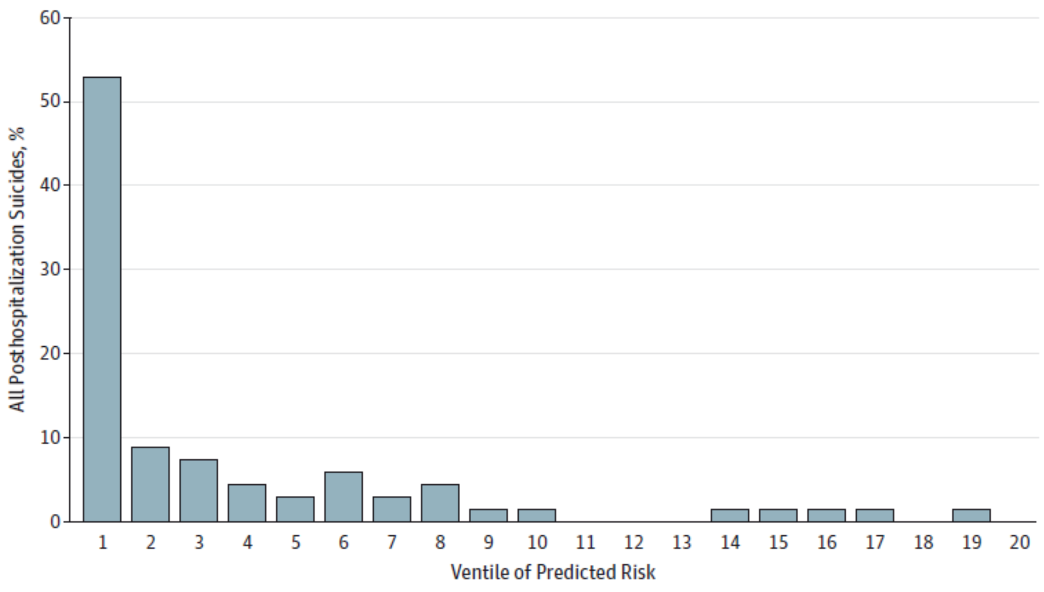
USING MACHINE LEARNING TO PREDICT SUICIDE

(Kessler et al., 2015)

Researchers divided the sample into risk ventiles (20 different levels of risk)

52% of suicides occurred among the 5% highest risk admissions per this algorithm

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



ML TO PREDICT SUICIDE

(Walsh, Ribeirio, & Franklin, 2017)

Examined non fatal suicide attempts identified in medical records (n = 3,250)

Compared to non-suicidal self injury patients (n = 1,917) and random hospital cases (n = 12,695)

Used random forest ML to attempt to accurately categorize patients

ML TO PREDICT SUICIDE

(Walsh, Ribeirio, & Franklin, 2017)

Area under the receiver operating characteristic curve statistic (AUC)

AUC scores can range from 0.5 (accuracy no better than chance) to 1.0 (perfect accuracy

AUC Values comparing patients with non-fatal attempt to those with non-suicidal self-injury

	No prior attempt	Prior attempt	Traditional methods
7 days prior	0.82	0.85	0.66
720 days prior	0.75	0.76	0.68

ML TO PREDICT SUICIDE

(Walsh, Ribeirio, & Franklin, 2017)

AUC Values comparing patients with non-fatal attempt to random patients

	AUC
7 days prior	0.92
720 days prior	0.86

ML TO PREDICT SUICIDE

(Walsh, Ribeirio, & Franklin, 2017)

Table 2. Discriminative and Calibration Performance of Models by Time Period Before Suicide Attempts

Prediction window	AUC [95% CI]	Precision[a]	Recall[b]	Brier score[c]
7 days	0.84 [0.83, 0.85]	0.79	0.95	0.14
14 days	0.83 [0.82, 0.84]	0.79	0.95	0.15
30 days	0.82 [0.82, 0.83]	0.78	0.95	0.15
60 days	0.82 [0.81, 0.82]	0.77	0.95	0.15
90 days	0.81 [0.81, 0.82]	0.77	0.95	0.15
180 days	0.81 [0.80, 0.82]	0.76	0.94	0.16
365 days	0.83 [0.82, 0.84]	0.75	0.96	0.15
720 days	0.80 [0.80, 0.81]	0.74	0.95	0.16

Note: AUC = area under the receiver operating curve; CI = confidence interval. Cases were 3,250 patients with an expert-determined nonfatal suicide attempt; controls were 1,917 patients with a self-injury ICD code who could not be confirmed as having made a nonfatal suicide attempt.

[a]Precision ~ positive predictive value = the ratio of true positives divided by the sum of true positives and false positives. [b]Recall ~ sensitivity = the number of true positives divided by the sum of true positives and false negatives. [c]Brier score indexes the discrepancy between the predicted probability of a nonfatal suicide attempt and the actual outcome of a nonfatal suicide attempt for each individual. The metric ranges between 0 and 1, with scores closer to 0 indicating less discrepancy between predicted probability and actual outcome.

EHR TO PREDICT SUICIDE

(Simon et al. 2018)

Used data available in electronic health records in 7 healthcare systems to predict suicide attempts and deaths over 90 day follow up

Primary Care and Speciality Mental Healthcare settings (only visits with a mental health diagnosis)

2,960,929 participants

313 demographic and clinical characteristics from EHR

EHR TO PREDICT SUICIDE

(Simon et al. 2018)

Suicide death following:
Mental health specialty visit (of 43 predictors selected)
Suicide attempt diagnosis in past year
Benzodiazepine prescription in past 3 months
Mental health emergency department visit in past 3 months
Second-generation antipsychotic prescription in past 5 years
Mental health inpatient stay in past 5 years
Mental health inpatient stay in past 3 months
Mental health inpatient stay in past year
Alcohol use disorder diagnosis in past 5 years
Antidepressant prescription in past 3 months
PHQ-9 item 9 score=3 with PHQ-8 score
PHQ-9 item 9 score=1 with age
Depression diagnosis in past 5 years with age
Suicide attempt diagnosis in past 5 years with Charlson score
PHQ-9 item 9 score=2 with age
Anxiety disorder diagnosis in past 5 years with age

EHR TO PREDICT SUICIDE

(Simon et al. 2018)

Strongest predictors were mental health and substance use diagnosis, mental health emergency care and inpatient, and history of self harm

EHR TO PREDICT SUICIDE

(Simon et al. 2018)

Suicide Attempts prediction

	C-statistic
Specialty mental health	0.85
Primary care	0.85

EHR TO PREDICT SUICIDE

(Simon et al. 2018)

Suicide Deaths prediction

	C-statistic
Specialty mental health	0.86
Primary care	0.83

SYSTEMATIC REVIEW OF PREDICTION MODELS

(Belsher et al. 2019)

Systematic review of 17 studies with 64 suicide prediction models

11 studies looked at deaths; 6 at attempts

Included military, VA, and civilian healthcare settings

Aimed to investigate the balance of true positives and false negatives by looking at positive predictive values and sensitivity

SYSTEMATIC REVIEW OF PREDICTION MODELS

(Belsher et al. 2019)

Results demonstrated generally good classification of suicide mortality versus non deaths

AUCs ranging from 0.59 to 0.86

Sensitivities varied dependent upon the risk level indicated from 0.10 to 0.94

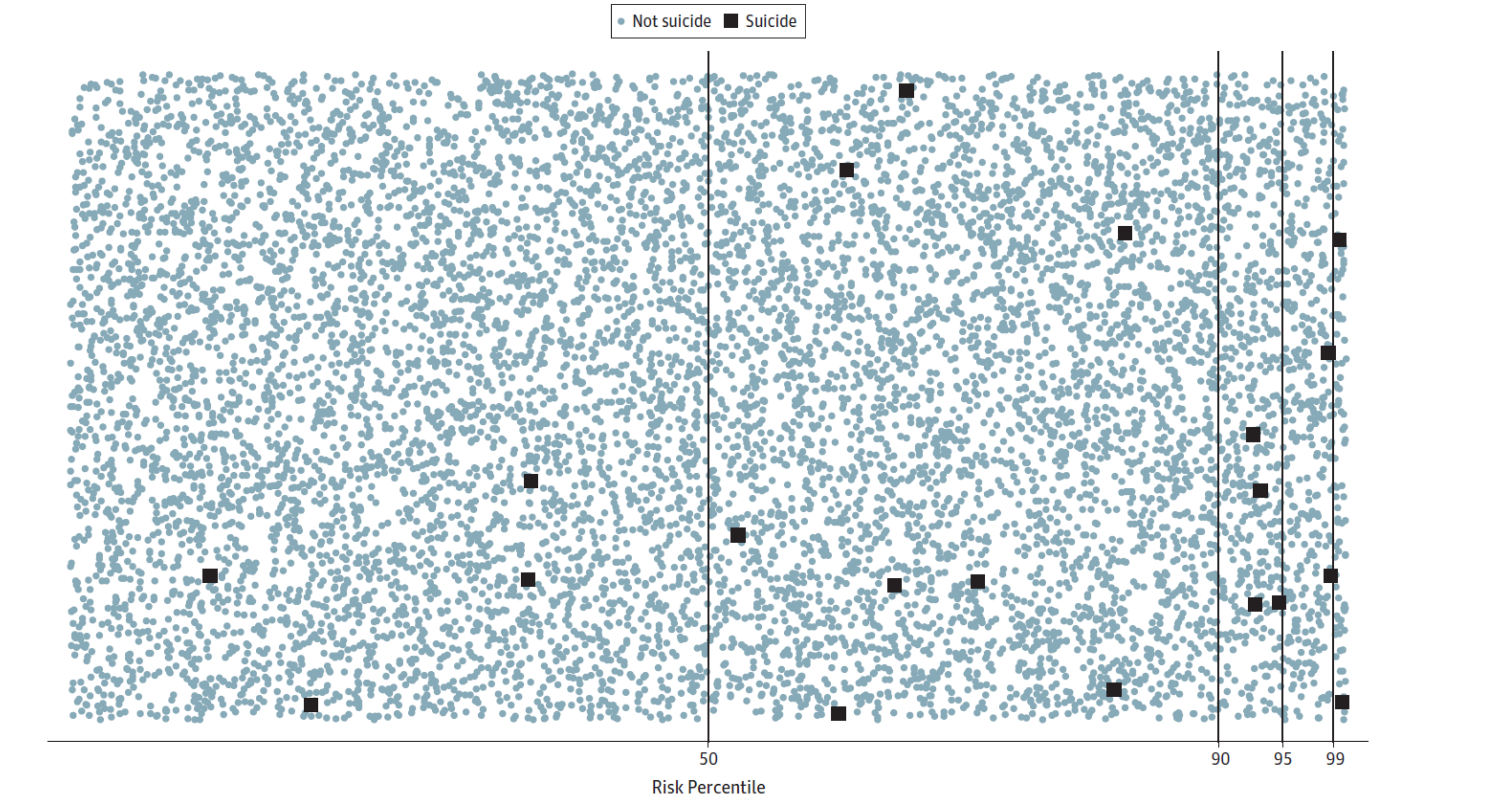
Positive predictive values were very poor mostly around 0.01

This statistic means 99 out of 100 people identified as at risk for death by suicide would not go on to die by suicide

The highest PPV was 0.19 in an Iranian sample with a very high rate of death by suicide (8,400 per 100,000)

SYSTEMATIC REVIEW OF PREDICTION MODELS

(Belsher et al. 2019)



SUMMARY

SUMMARY

Prediction of suicide mortality is inherently difficult due to very low base rates

Prediction must balance true positives and false negatives and there is no inherent "right" balance point

Suicide prediction models have begun to improve, especially those using ML algorithms

There is likely always going to be an upper limit on how useful prediction models will be

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THANK YOU

Collin Davidson, PhD, LP, ABPP

405-612-3428

davidsoncollin0@gmail.com