Data-driven approaches to detect & intervene on suicidal ideation

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Objectives

- Provide a basic understanding of Artificial Intelligence (AI) concepts used in suicide prevention
- Review technology approaches and studies conducted in real-world programs for identification suicidal ideation

Ahmedani et al., 2019

THERE IS RISK IN NOT IDENTIFYING SUICIDAL IDEATION

Suicide Prevention Across Health Continuum

Getty images

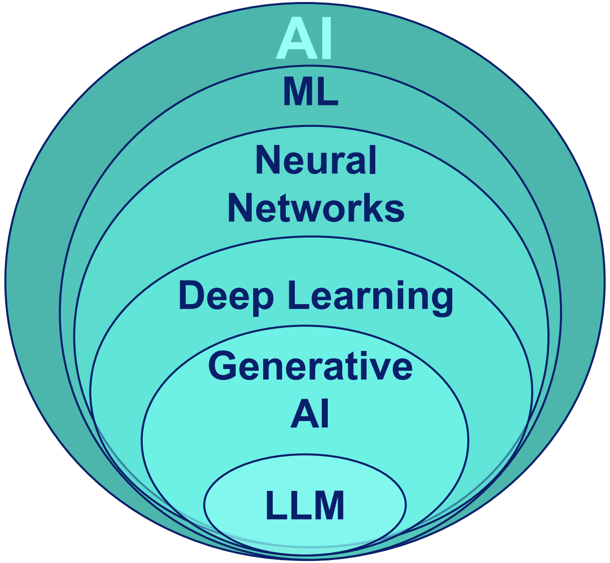
- **Up to 45%** of individuals who die by suicide had contact with their primary care provider in the month before death
- **Over 90%** of individuals who died by suicide had a healthcare visit in the year before death; **Nearly 30%** having a visit in the week before
- **About 50%** of those who died by suicide did not have a mental health diagnosis before death, limiting the reach of targeted interventions

Ahmedani et al., 2019

AI BASICS

Artificial Intelligence (AI) Levels and Complexity

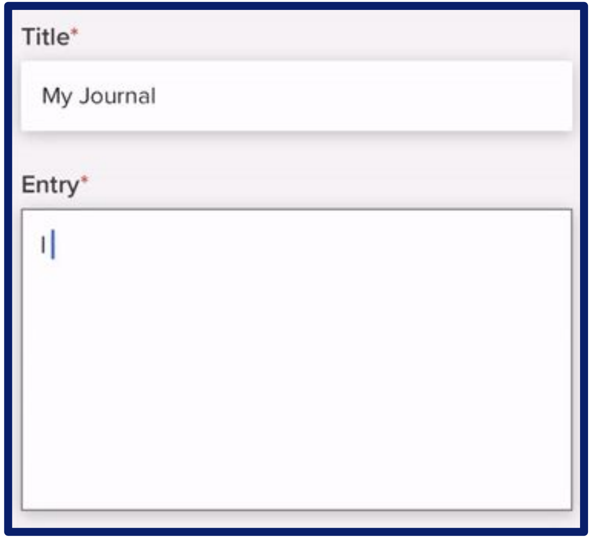
- **AI:** Umbrella term for tech aiming to mimic human intelligence
- **Machine Learning:** Subset of AI developing algorithms and models that enable computer systems to improve performance through data
- **Neural Networks:** Computational models inspired by the brain, processing information through interconnected nodes
- **Deep Learning:** Machine learning using multi-layered neural networks to learn complex patterns from large datasets
- **NLP:** AI techniques to understand and interpret human language
- **LLM:** AI models trained on vast text data to understand and generate human-like language



NATURAL LANGUAGE PROCESSING

NLP in Action

- NLP **analyzes free-text** entries
- NLP algorithm **identifies high-risk words** and phrases related to suicide
- System processes user inputs asynchronously, enabling **24/7 monitoring**



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STUDY 1

Using NLP to Detect Suicidal Ideation and Prompt Urgent Interventions

- Retrospective study on **425 unique people flagged for SI using NLP**
- **58%** of these individuals **did not screen positive for SI** or complete assigned PHQ-9 within 30 days of the alert
- **NLP is surfacing risk that traditional screening is missing**, while providing prompt high-touch intervention through alert systems, crisis outreach, and tailored referral paths

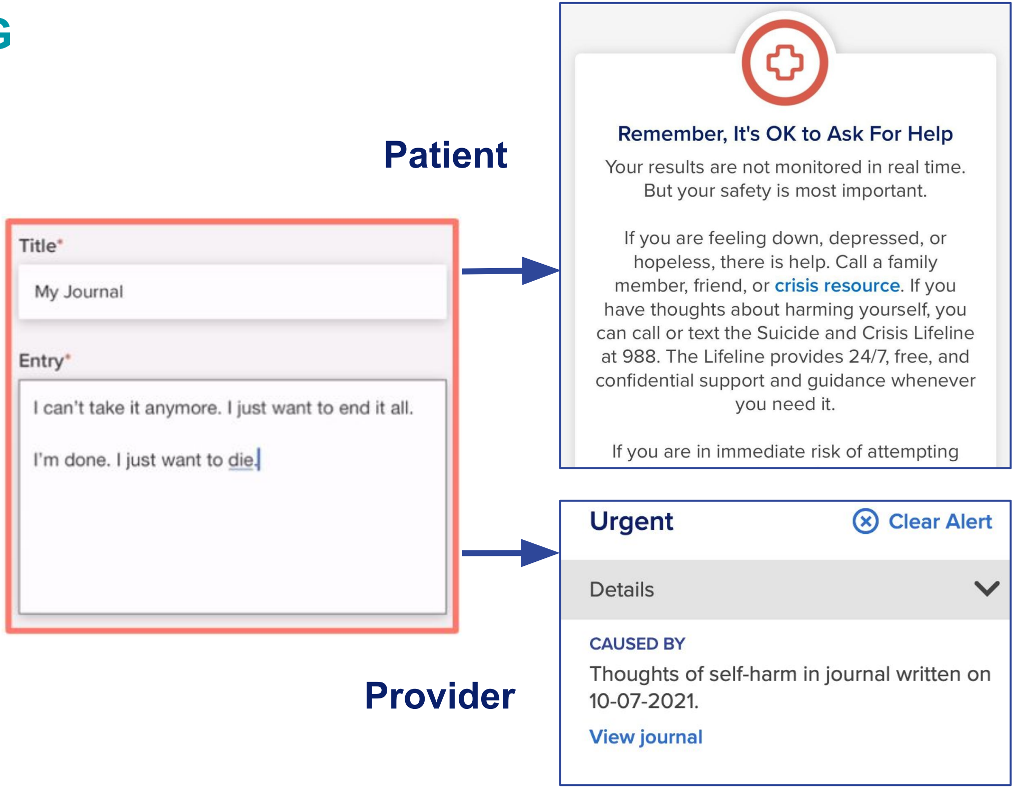
Read the full study:

Hartz et al., 2024

NATURAL LANGUAGE PROCESSING

NLP in Action

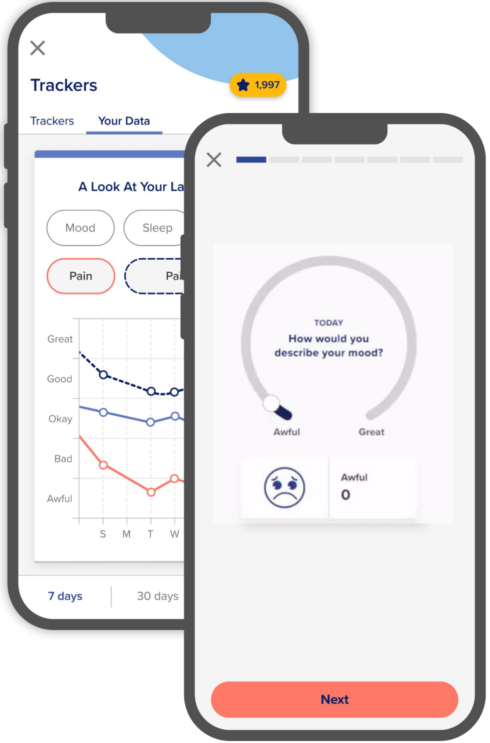
- **Real-time crisis resources delivered**; Alerts sent to care teams when detected
- Facilitates early intervention between scheduled appointments or assessments



STUDY 2

Leveraging EMA Data to Predict SI Risk

- We collected **> 44,000 EMA self-reports** on mood, sleep, stress, and pain using mHealth trackers (pictured).
- Tracker-to-PHQ9 ratio is **18-to-1**, allowing for monitoring between validated assessment delivery
- We analyzed EMA alongside responses to self-harm questions to develop a **predictive model of monthly SI risk**.

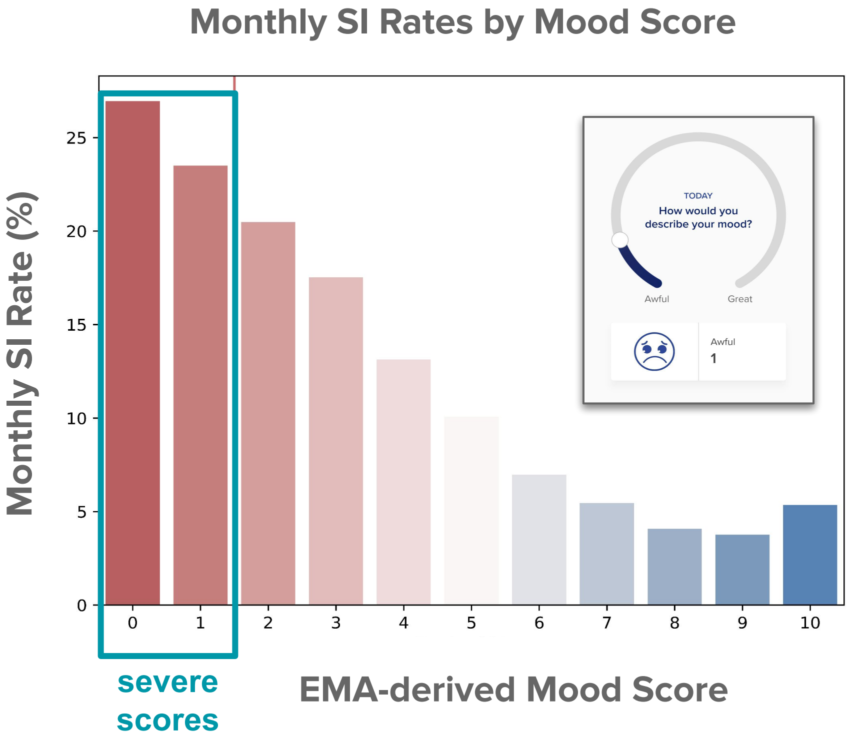


Kampa et al., 2024 (in press)

LEVERAGING EMA to PREDICT SI RISK

Basic Statistics to Advanced Modeling

- Binomial tests revealed significant relationships between EMA data (**severe** vs. **non-severe**) and SI risk
- Statistically & clinically significant (p<.001); Severe mood (25%), vs Non-severe (10%)
- Significant for Mood, Sleep, and Stress

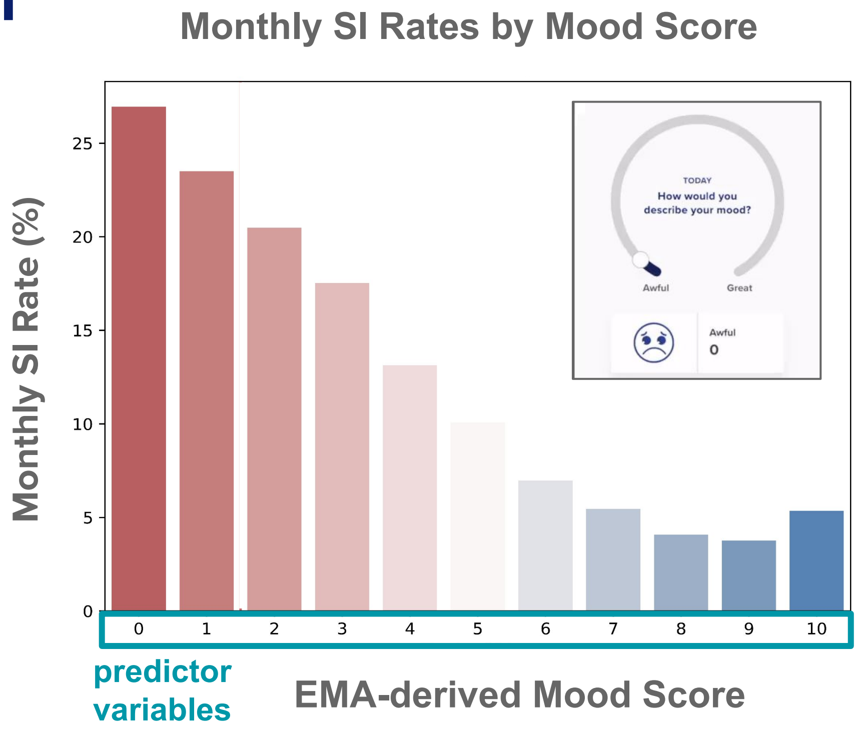


Kampa et al., 2024 (in press)

LEVERAGING EMA to PREDICT SI RISK

Quantifying Relationships with OLS and Logistic Regression

- OLS regression showed **strong linear relationships** with Mood ($r^2 = .92$), Sleep ($r^2 = .87$), Stress ($r^2 = .94$); all $p<.001$
- Sequential logistic regression: Significant **risk increases with 1-point differences**: Mood: 37.7% Sleep: 17.7% Stress: 17.3%



Kampa et al., 2024 (in press)

LEVERAGING EMA to PREDICT SI RISK

Multi-level Modeling & Symptom Severity Prediction

- Developed multi-level models to predict PHQ-9 categories: **Probability of depression severity based on mood score**
- Model accounts for nested data structure (multiple reports per user)

For every mood tracker score ***input*** *by a user, we can* ***output*** *the likelihood that they fall within a given PHQ-9 severity category:*

Mood Tracker Score	0	1	2	3	4
None-Minimal (1)	0.033	0.047	0.068	0.097	0.137
Mild (2)	0.086	0.118	0.158	0.203	0.251
Moderate (3)	0.172	0.210	0.244	**0.265**	**0.270**
Moderately Severe (4)	0.306	0.309	**0.292**	0.259	0.217
Severe (5)	**0.403**	**0.315**	0.238	0.175	0.126

Kampa et al., 2024 (in press)

LEVERAGING EMA to PREDICT SI RISK

Symptom Severity Prediction

For a user who tracks a zero for mood,

~ 88% chance of experiencing current clinical depression symptoms

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LEVERAGING EMA to PREDICT SI RISK

From Analysis to Action

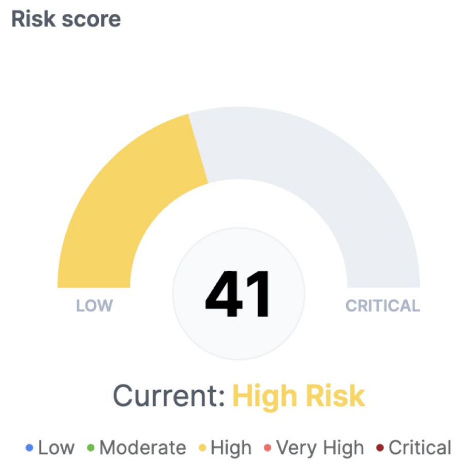
- EMA data is integrated into risk prediction models, as **part of a larger risk or causal complexity score**
- EMA is unique, in that it **enables detection of rapid changes in well-being**
- Facilitates **timely interventions** based on real-time patient data

Kampa et al., 2024 (in press)

COMBINING DATA SOURCES

Risk and Complexity Modeling

- **ML models outperform** traditional clinical assessment (AUC 0.67 vs 0.77) *
- Combining **multiple data sources** offers comprehensive risk assessment and detects subtle changes:
  - **EHR and Claims**: Provide historical context through structured and unstructured data
  - **Self-reports**: Capture real-time experiences and subjective states
  - **Passive data collection**: Offers objective measures, such as digital phenotyping (e.g., smartphone use patterns, etc.)



* Nock et al., 2022

STUDY 3

Risk Modeling

- **ML** Developed using data from **> 3,000 individuals**
- Incorporates **multiple data sources**: Validated assessments, EMA, app use patterns, treatment engagement
- ML algorithm weighs variables based on their predictive power for mental health condition or suicide risk
- Generates a score from 1-5, with 5 indicating highest risk
- Strong correlation with both PHQ-9 (r=0.74) and GAD-7 (r=0.80)
- Outperforms traditional assessments in detecting "hidden" risk

ML Risk Score used for:

1. Population monitoring
2. Compare patients across the population
3. Establish personal baselines for alerting

RISK MODELING FOR CARE COORDINATION

Access to the *Right* Level of Care

Population Data

- Assessment
- Journals
- EMA
- SDOH
- Physical Activity
- Other Data Inputs

Triage Engine

Clinical Decision Support

- Validated Assessments
- AI-powered RIsk Score
- Natural Language Processing (NLP)
- Alerts

Configurable Logic

- Logic-based triggers
- Business logic

Behavioral Health Care

- Suicide Prevention
- Internal or External:
  - Virtual Providers
  - Network Resources
- Integrated Care Program
- Digital CBT & Self-guided

Ongoing monitoring keeps individuals supported at the right level as needs change

INCREASING DEMAND

Increased Identification

2023

19,595 Urgent Alerts

248 unique individuals with NLP generated urgent alerts

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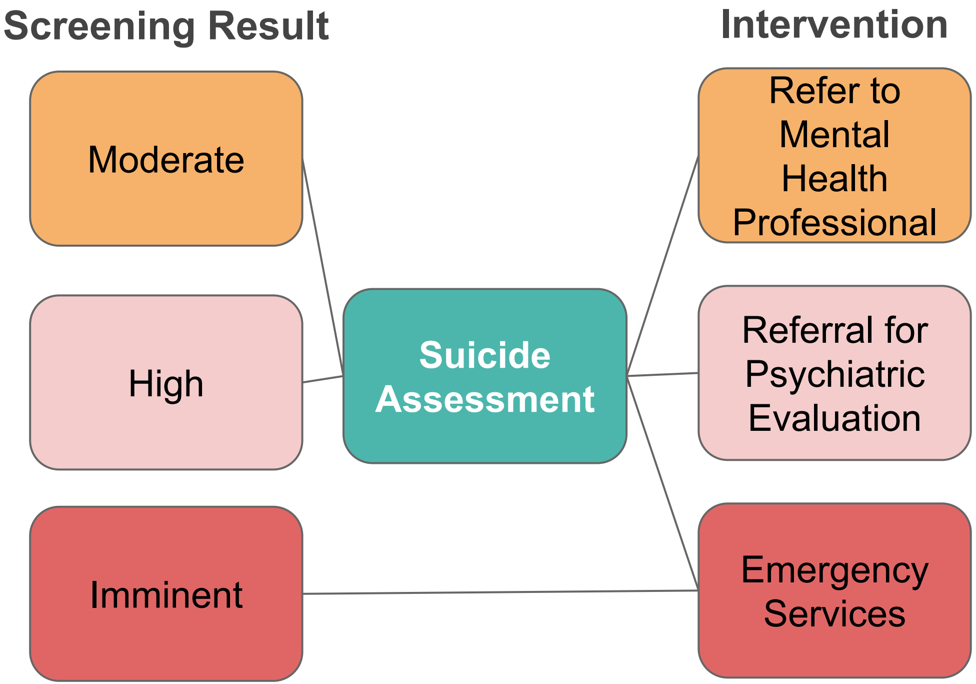
Increased Need for Screening & Assessment



STUDY 4

Remote Asynchronous Suicide Screening

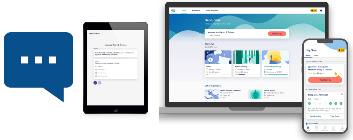
- **~ 16,000 remote suicide screenings** (ASQ, C-SSRS), conducted by behaioral health professionals
- **Reviewing protocols, procedures, and workflows** selected by behavioral health programs that opted-in for remote screening and alert management
- **First review** of utilizing remote, async suicide screening measures delivered by technology

asQ
Ask Suicide-Screening Questions

THE COLUMBIA
LIGHTHOUSE
PROJECT
IDENTIFY RISK. PREVENT SUICIDE.

Interoperability & Integrations are Necessary

Patient



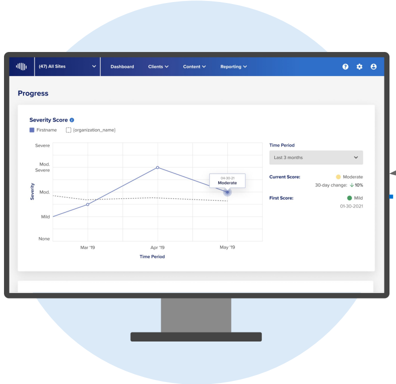
Validated or PRO Measures: Remote & In Person

Passive Data: Digital Phenotyping, Wearables, etc

Health Information Exchange & Payer Data

Public Datasets (Social Vulnerability, etc)

Behavioral Health Providers



Mental Health Registry

Data insights from patient activity inform care team actions

Medical Provider

EHR

Key data points flow to and from EHR

References

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* NeuroFlow publications available in full print at www.neuroflow.com/research

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