Dissecting the Poster Creation Process

ML Tlachac

WPI REU 2022

Why am I Presenting About Posters?

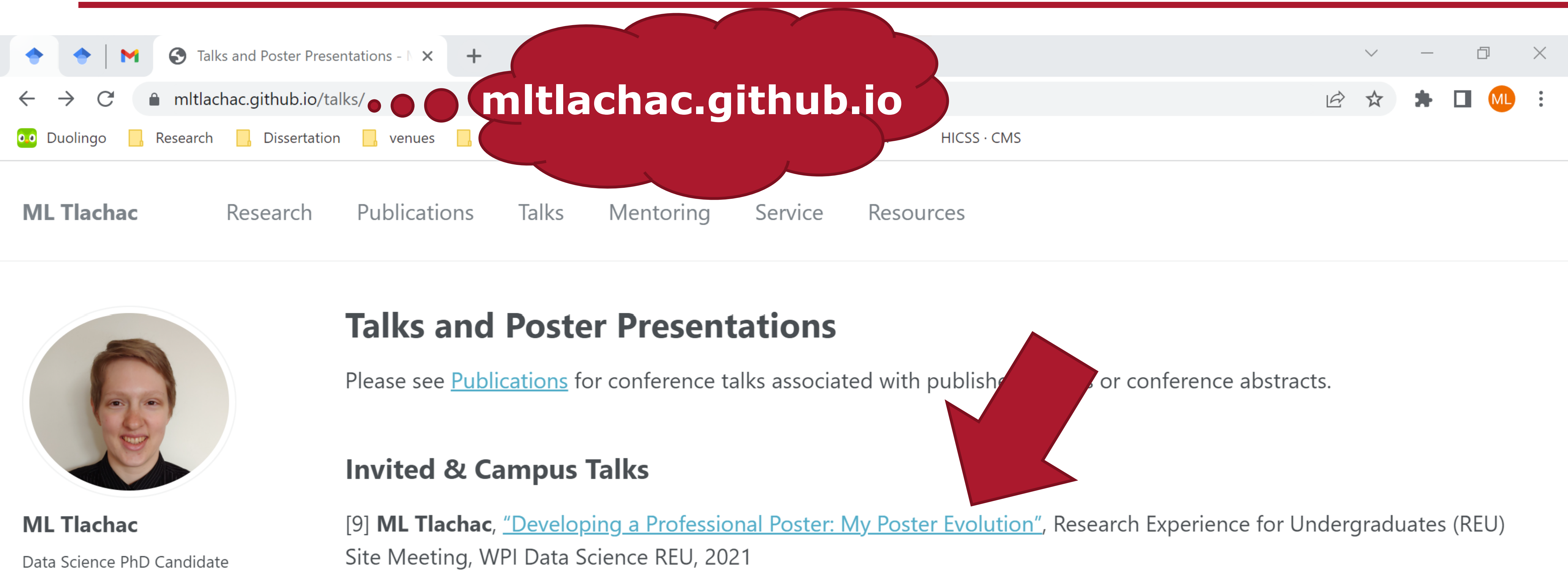
20 Posters Created

12 Presentations

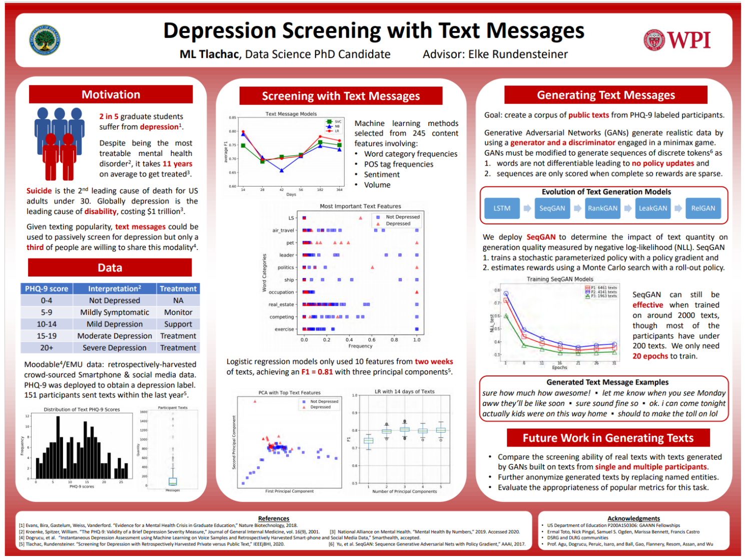
8 Venues

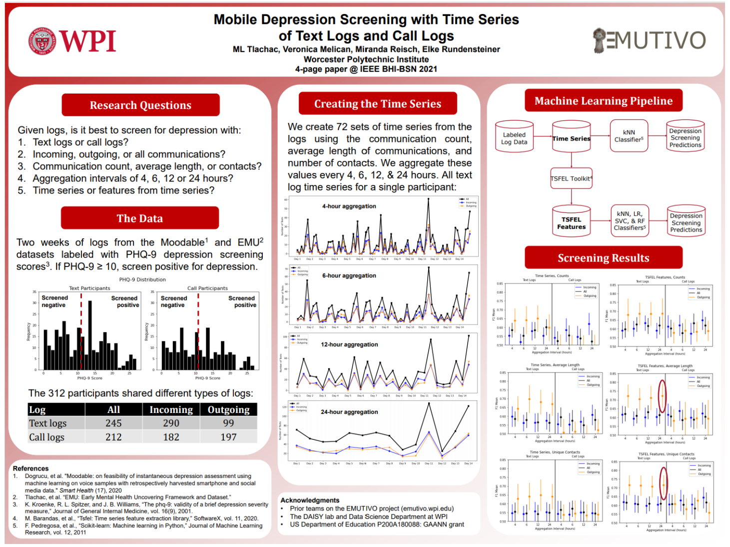
8 Projects

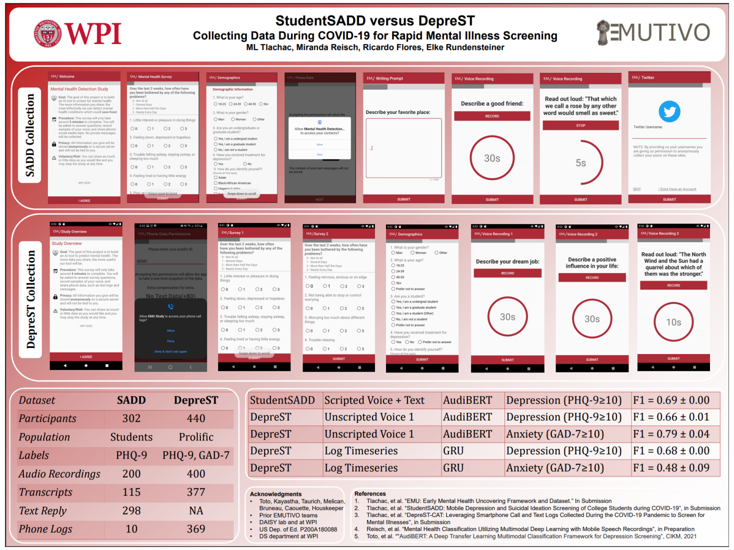
Creating Good Posters is a Journey

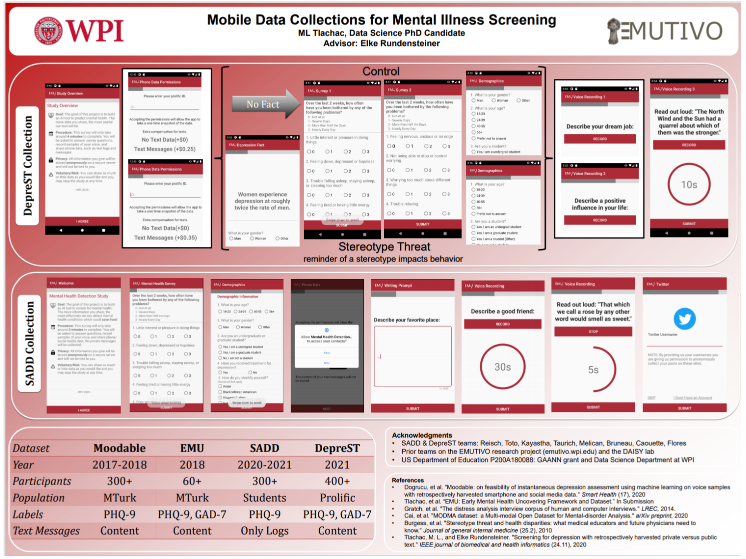


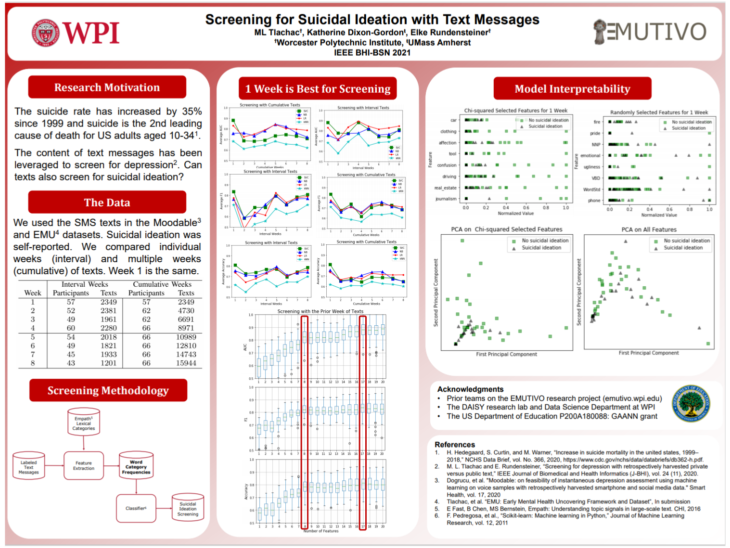
My Posters from 2020-2022











A Story Starts with a Title

(and a poster starts with a title block)

Examples of Poster Title Blocks

Depression Screening with Text Messages

ML Tlachac, Data Science PhD Candidate Advisor: Elke Rundensteiner

WPI

WPI

Mobile Data Collections for Mental Illness Screening

ML Tlachac, Data Science PhD Candidate

Advisor: Elke Rundensteiner

EMUTIVO

WPI

Mobile Depression Screening with Time Series of Text Logs and Call Logs

ML Tlachac, Veronica Melican, Miranda Reisch, Elke Rundensteiner

Worcester Polytechnic Institute

4-page paper @ IEEE BHI-BSN 2021

EMUTIVO

WPI

Screening for Suicidal Ideation with Text Messages

ML Tlachac[†], Katherine Dixon-Gordon[‡], Elke Rundensteiner[†]

[†]Worcester Polytechnic Institute, [‡]UMass Amherst

IEEE BHI-BSN 2021

EMUTIVO

WPI

StudentSADD versus DepreST

Collecting Data During COVID-19 for Rapid Mental Illness Screening

ML Tlachac, Miranda Reisch, Ricardo Flores, Elke Rundensteiner

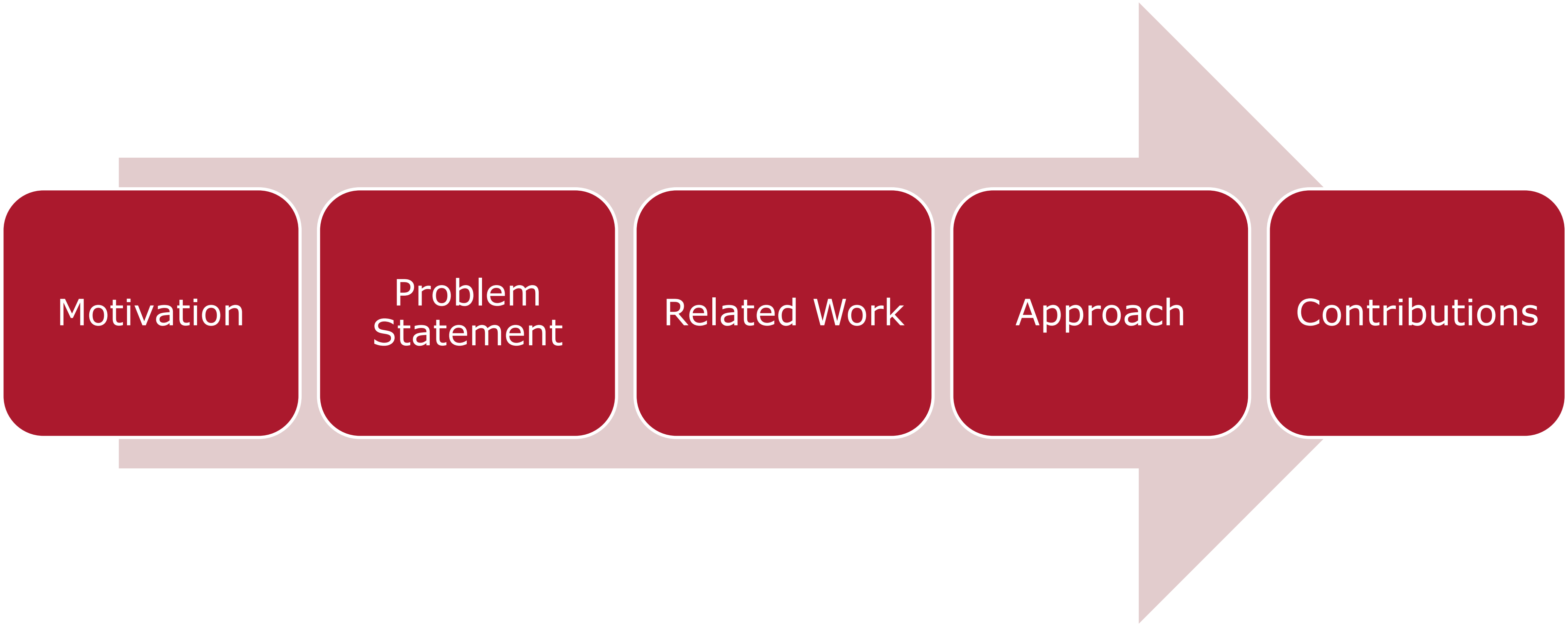
EMUTIVO

What is in a Story?

(and by extension a poster?)

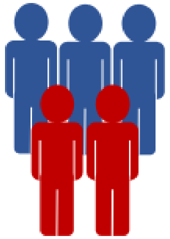
Story Sections

What is in an Introduction?



Examples of Poster Introductions

Motivation



2 in 5 graduate students suffer from **depression**[1].

Despite being the most treatable mental health disorder[2], it takes **11 years** on average to get treated[3].

Suicide is the 2nd leading cause of death for US adults under 30. Globally depression is the leading cause of **disability**, costing $1 trillion[3].

Given texting popularity, **text messages** could be used to passively screen for depression but only a **third** of people are willing to share this modality[4].

Research Questions

Given logs, is it best to screen for depression with:

1. Text logs or call logs?
2. Incoming, outgoing, or all communications?
3. Communication count, average length, or contacts?
4. Aggregation intervals of 4, 6, 12 or 24 hours?
5. Time series or features from time series?

Research Motivation

The suicide rate has increased by 35% since 1999 and suicide is the 2nd leading cause of death for US adults aged 10-34[1].

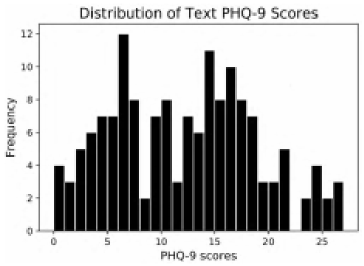
The content of text messages has been leveraged to screen for depression[2]. Can texts also screen for suicidal ideation?

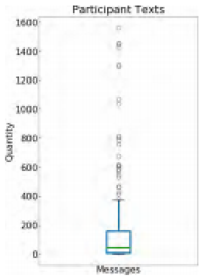
Examples of Poster Data Descriptions

Data

PHQ-9 score	Interpretation[2]	Treatment
0-4	Not Depressed	NA
5-9	Mildly Symptomatic	Monitor
10-14	Mild Depression	Support
15-19	Moderate Depression	Treatment
20+	Severe Depression	Treatment

Moodable[4]/EMU data: retrospectively-harvested crowd-sourced Smartphone & social media data. PHQ-9 was deployed to obtain a depression label. 151 participants sent texts within the last year[5].

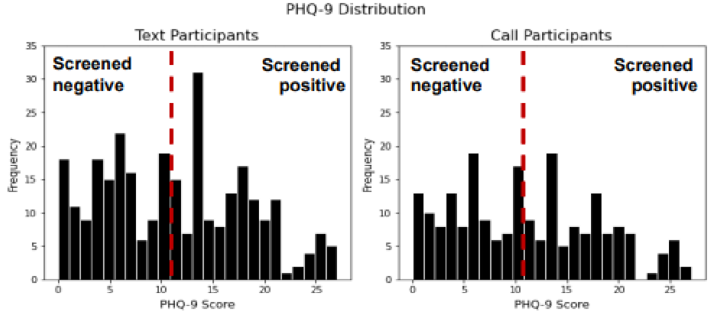




Dataset	**Moodable**	**EMU**	**SADD**	**DepreST**
Year	2017-2018	2018	2020-2021	2021
Participants	300+	60+	300+	400+
Population	MTurk	MTurk	Students	Prolific
Labels	PHQ-9	PHQ-9, GAD-7	PHQ-9	PHQ-9, GAD-7
Text Messages	Content	Content	Only Logs	Content

The Data

Two weeks of logs from the Moodable[1] and EMU[2] datasets labeled with PHQ-9 depression screening scores[3]. If PHQ-9 ≥ 10, screen positive for depression.



The 312 participants shared different types of logs:

Log	All	Incoming	Outgoing
Text logs	245	290	99
Call logs	212	182	197

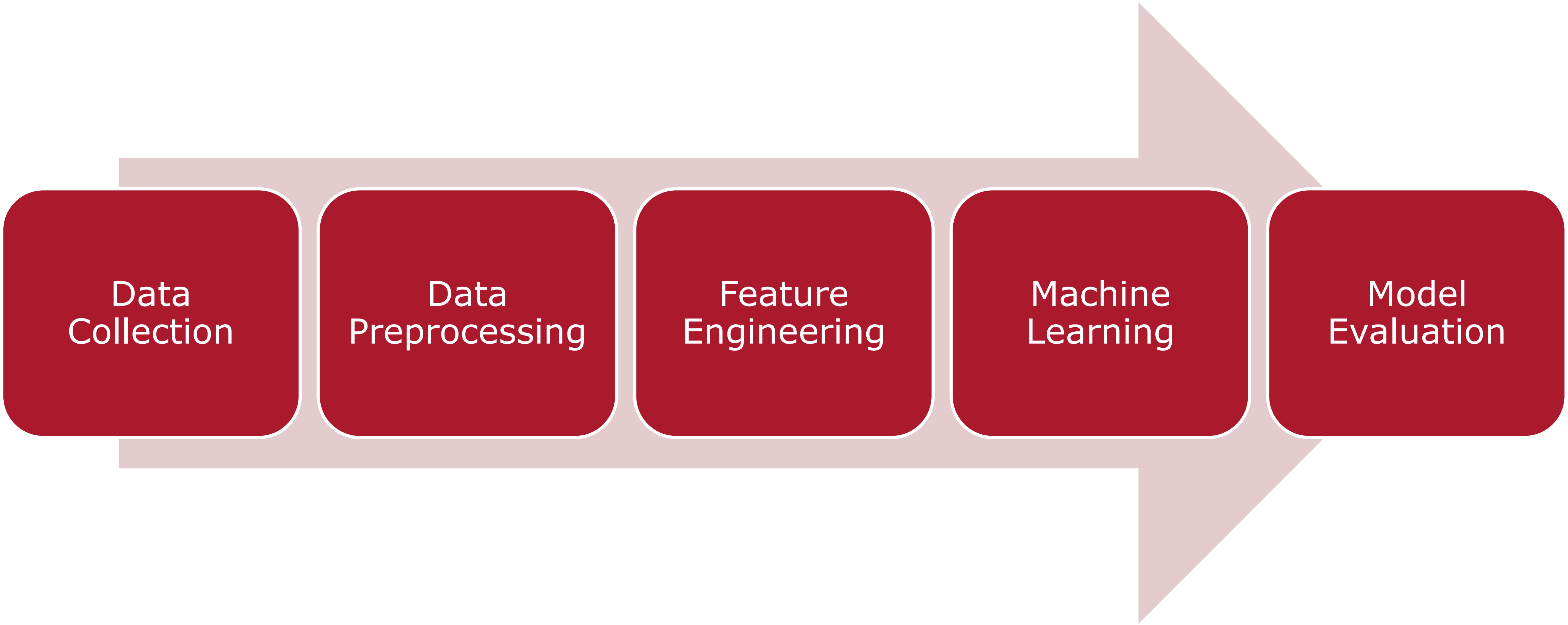
The Data

We used the SMS texts in the Moodable[3] and EMU[4] datasets. Suicidal ideation was self-reported. We compared individual weeks (interval) and multiple weeks (cumulative) of texts. Week 1 is the same.

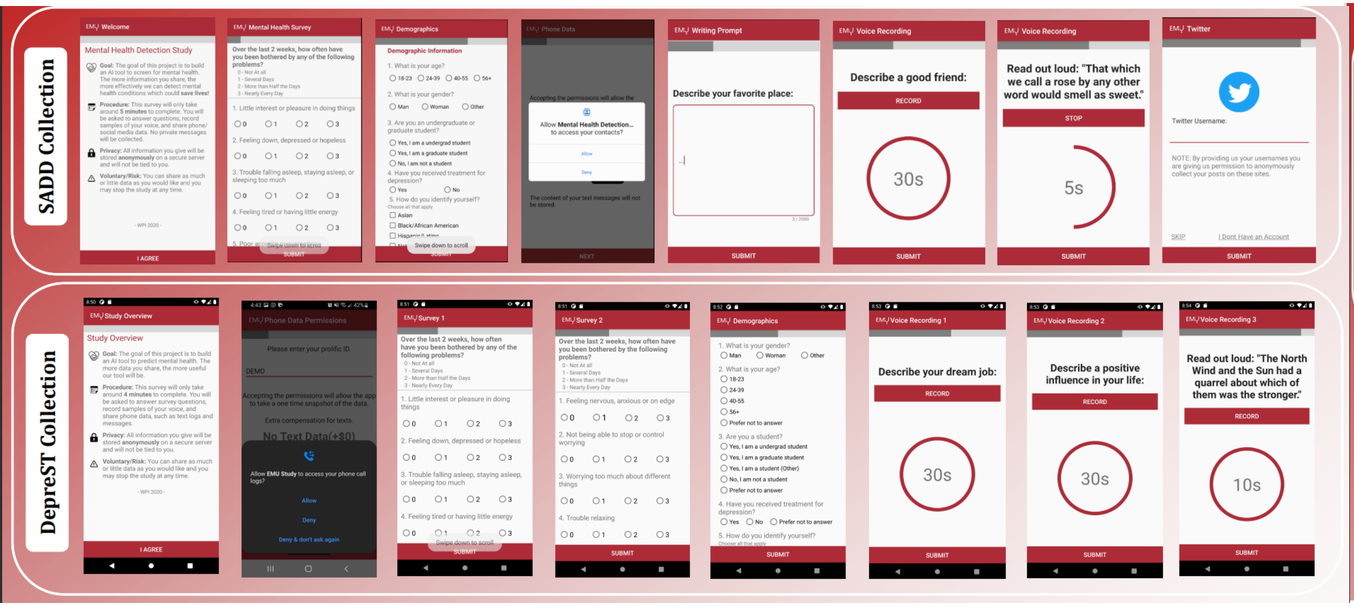
	Interval Weeks		Cumulative Weeks	
Week	Participants	Texts	Participants	Texts
1	57	2349	57	2349
2	52	2381	62	4730
3	49	1961	62	6691
4	60	2280	66	8971
5	54	2018	66	10989
6	49	1821	66	12810
7	45	1933	66	14743
8	43	1201	66	15944

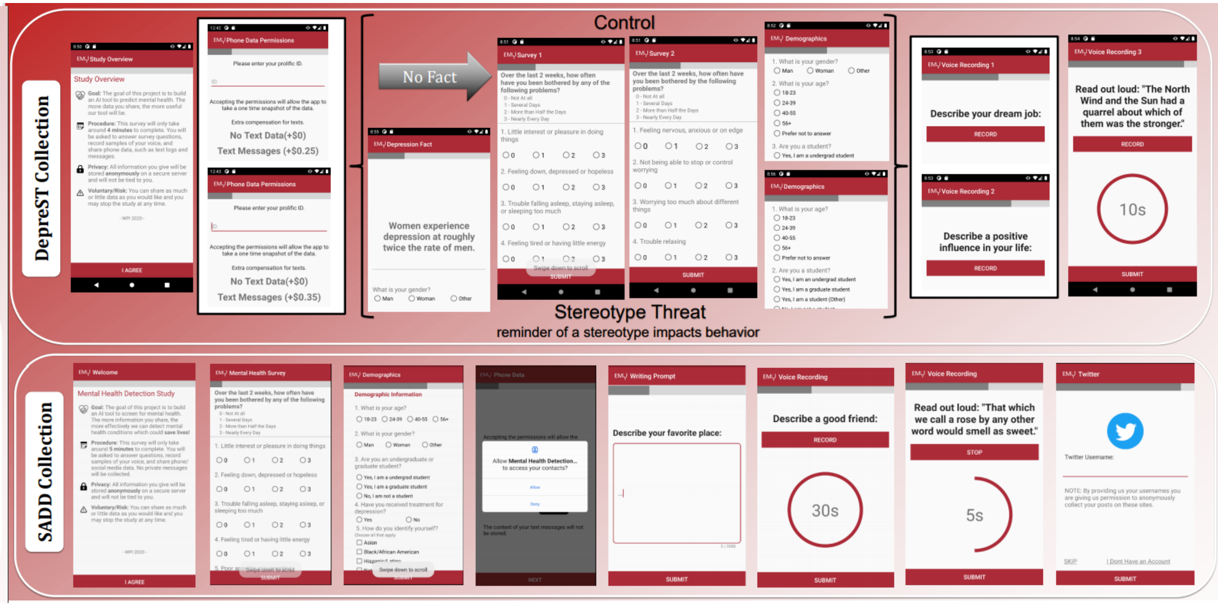
Dataset	**SADD**	**DepreST**
Participants	302	440
Population	Students	Prolific
Labels	PHQ-9	PHQ-9, GAD-7
Audio Recordings	200	400
Transcripts	115	377
Text Reply	298	NA
Phone Logs	10	369

What is in the Methodology?



Example of Poster Methodology: Data Collection

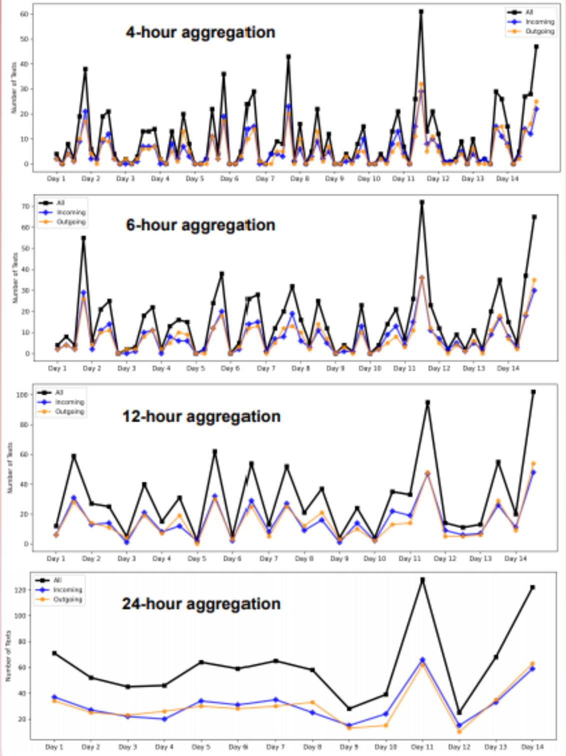




Example of Poster Methods: Data Preprocessing

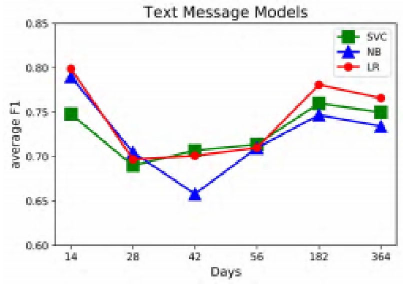
Creating the Time Series

We create 72 sets of time series from the logs using the communication count, average length of communications, and number of contacts. We aggregate these values every 4, 6, 12, & 24 hours. All text log time series for a single participant:



Example of Poster Methods: FE & ML

Screening with Text Messages



Machine learning methods selected from 245 content features involving:

- Word category frequencies
- POS tag frequencies
- Sentiment
- Volume

Generating Text Messages

Goal: create a corpus of **public texts** from PHQ-9 labeled participants.

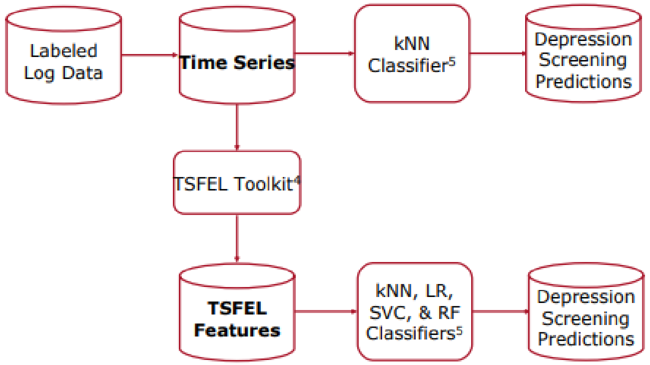
Generative Adversarial Networks (GANs) generate realistic data by using a **generator and a discriminator** engaged in a minimax game. GANs must be modified to generate sequences of discrete tokens[6] as

1. words are not differentiable leading to **no policy updates** and
2. sequences are only scored when complete so rewards are sparse.

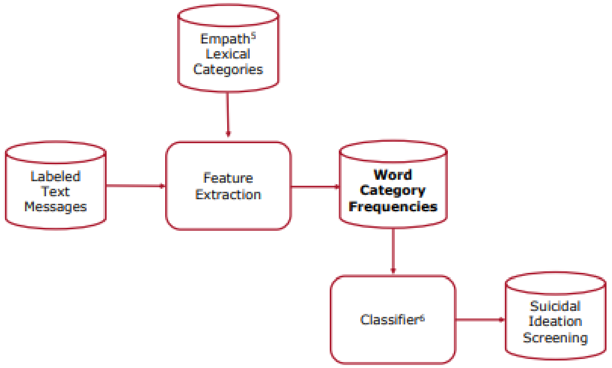
Evolution of Text Generation Models

LSTM → SeqGAN → RankGAN → LeakGAN → RelGAN

Machine Learning Pipeline

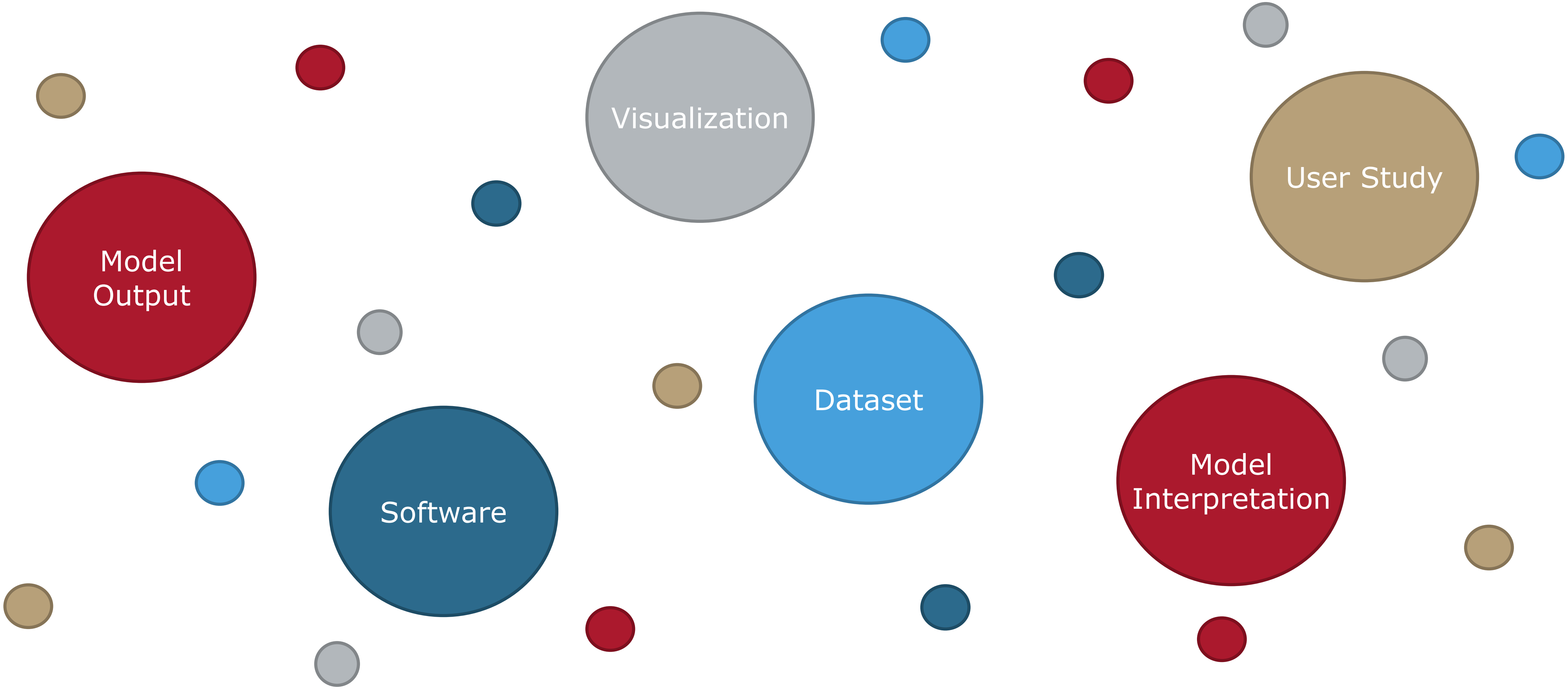


Screening Methodology

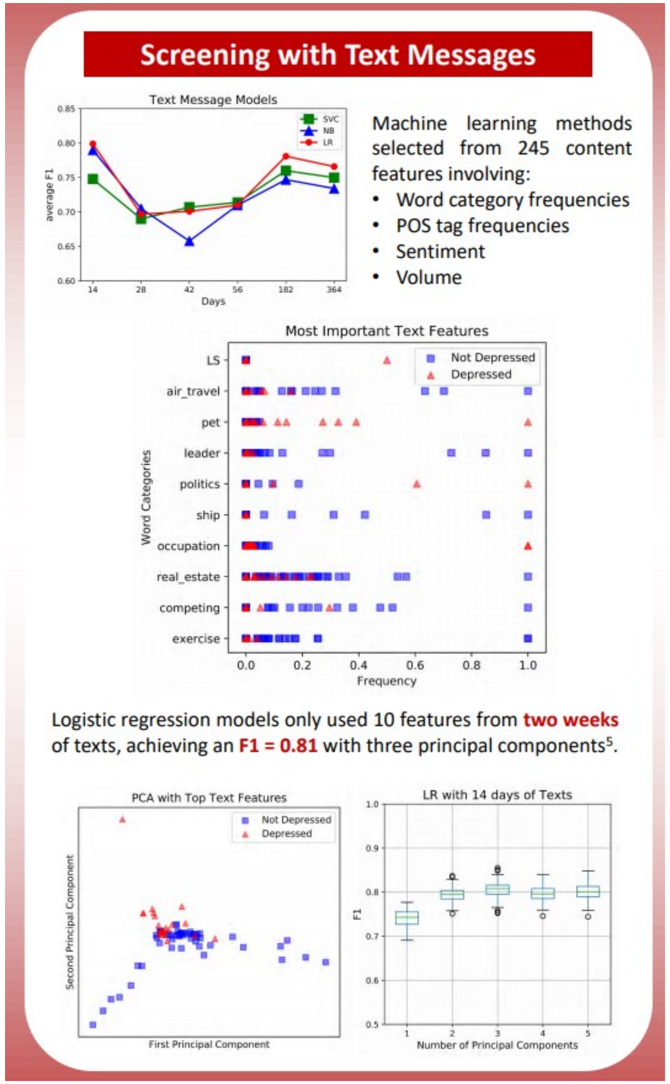


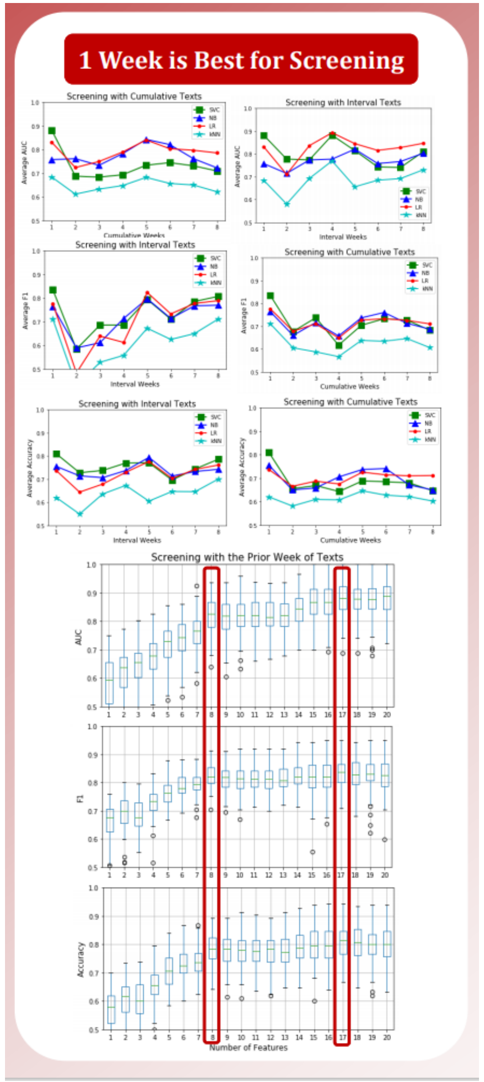
StudentSADD	Scripted Voice + Text	AudiBERT	Depression (PHQ-9≥10)
DepreST	Unscripted Voice 1	AudiBERT	Depression (PHQ-9≥10)
DepreST	Unscripted Voice 1	AudiBERT	Anxiety (GAD-7≥10)
DepreST	Log Timeseries	GRU	Depression (PHQ-9≥10)
DepreST	Log Timeseries	GRU	Anxiety (GAD-7≥10)

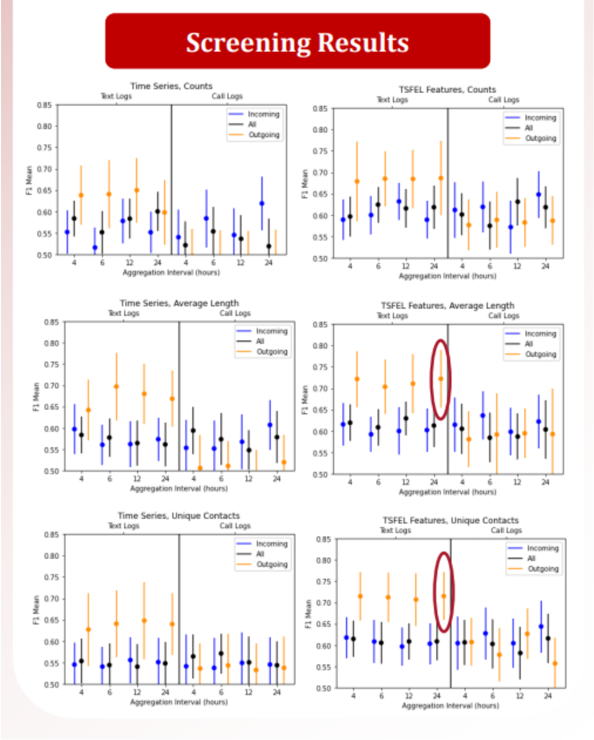
What are Results?



Examples of Results: Machine Learning Results



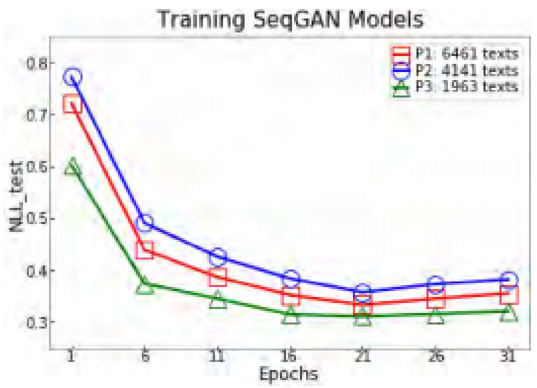




StudentSADD	Scripted Voice + Text	AudiBERT	Depression (PHQ-9≥10)	F1 = 0.69 ± 0.00
DepreST	Unscripted Voice 1	AudiBERT	Depression (PHQ-9≥10)	F1 = 0.66 ± 0.01
DepreST	Unscripted Voice 1	AudiBERT	Anxiety (GAD-7≥10)	F1 = 0.79 ± 0.04
DepreST	Log Timeseries	GRU	Depression (PHQ-9≥10)	F1 = 0.68 ± 0.00
DepreST	Log Timeseries	GRU	Anxiety (GAD-7≥10)	F1 = 0.48 ± 0.09

Example of Results: Additional

Other Model Output

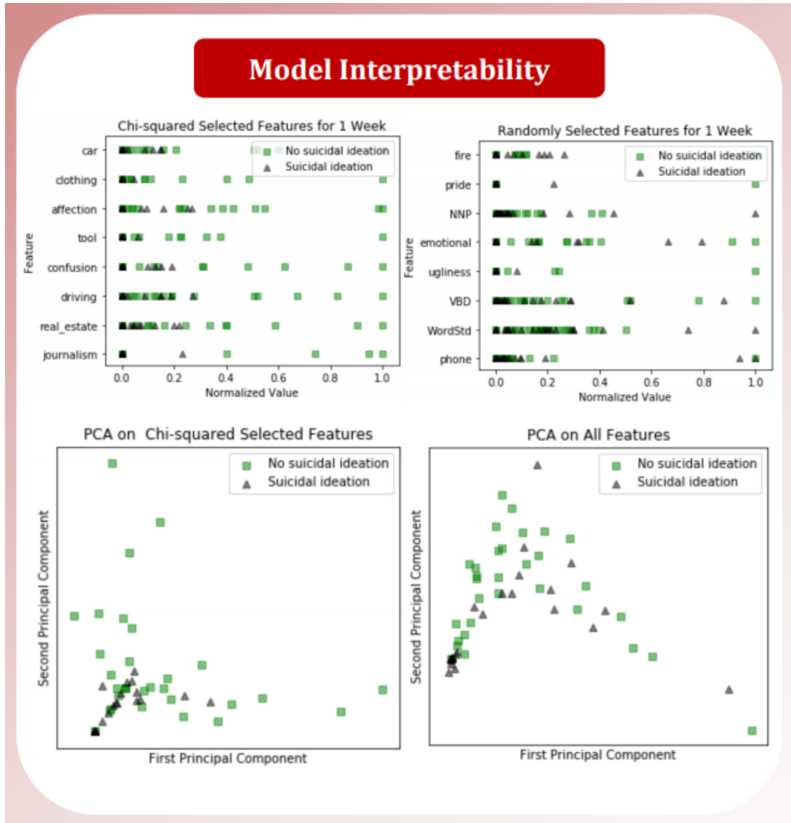


SeqGAN can still be **effective** when trained on around 2000 texts, though most of the participants have under 200 texts. We only need **20 epochs** to train.

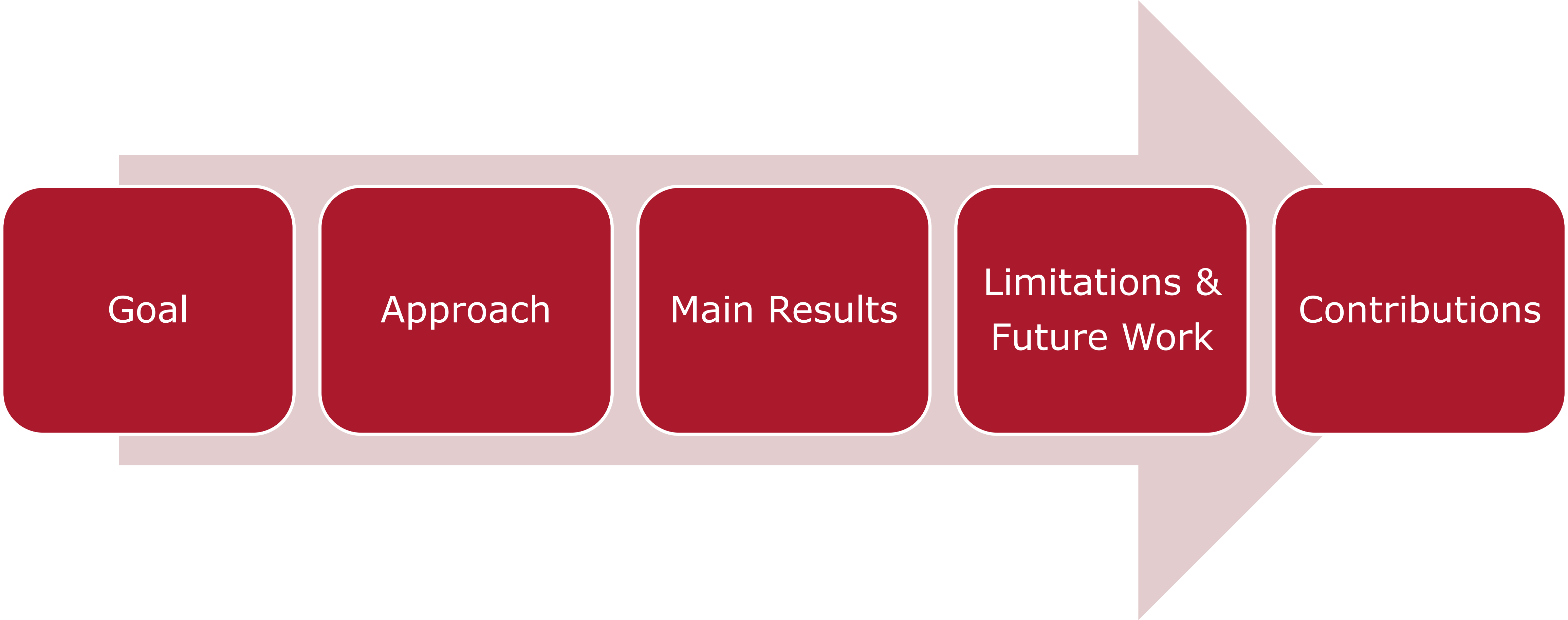
Generated Text Message Examples

sure how much how awesome! ▪ *let me know when you see Monday*
aww they'll be like soon ▪ *sure sound fine so* ▪ *ok. i can come tonight*
actually kids were on this way home ▪ *should to make the toll on lol*

Model Interpretation



What is in a Conclusion?



~~Examples of~~ Conclusions are Optional

Future Work in Generating Texts

- Compare the screening ability of real texts with texts generated by GANs built on texts from **single and multiple participants**.
- Further anonymize generated texts by replacing named entities.
- Evaluate the appropriateness of popular metrics for this task.

I DO NOT RECCOMEND

A Story Ends with Acknowledgments

(and references if a poster)

Examples of Acknowledgments & References

References

[1] Evans, Bira, Gastelum, Weiss, Vanderford. "Evidence for a Mental Health Crisis in Graduate Education," Nature Biotechnology, 2018.
[2] Kroenke, Spitzer, William. "The PHQ-9: Validity of a Brief Depression Severity Measure," Journal of General Internal Medicine, vol. 16(9), 2001.
[3] National Alliance on Mental Health. "Mental Health By Numbers," 2019. Accessed 2020.
[4] Dogrucu, et al. "Instantaneous Depression Assessment using Machine Learning on Voice Samples and Retrospectively Harvested Smart-phone and Social Media Data," Smarthealth, accepted.
[5] Tlachac, Rundensteiner. "Screening for Depression with Retrospectively Harvested Private versus Public Text," IEEEjBHI, 2020.
[6] Yu, et al. SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient," AAAI, 2017.

Acknowledgments

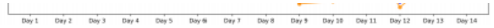
- US Department of Education P200A150306: GAANN Fellowships
- Ermal Toto, Nick Pingal, Samuel S. Ogden, Marissa Bennett, Francis Castro
- DSRG and DLRG communities
- Prof. Agu, Dogrucu, Peruic, Isaro, and Ball, Gao, Flannery, Resom, Assan, and Wu

Acknowledgments

- SADD & DepreST teams: Reisch, Toto, Kayastha, Taurich, Melican, Bruneau, Caouette, Flores
- Prior teams on the EMUTIVO research project (emutivo.wpi.edu) and the DAISY lab
- US Department of Education P200A180088: GAANN grant and Data Science Department at WPI

References

- Dogrucu, et al. "Moodable: on feasibility of instantaneous depression assessment using machine learning on voice samples with retrospectively harvested smartphone and social media data." *Smart Health* (17), 2020
- Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset." In Submission
- Gratch, et al. "The distress analysis interview corpus of human and computer interviews." *LREC*, 2014.
- Cai, et al. "MODMA dataset: a Multi-modal Open Dataset for Mental-disorder Analysis." *arXiv preprint*, 2020
- Burgess, et al. "Stereotype threat and health disparities: what medical educators and future physicians need to know." *Journal of general internal medicine* (25.2), 2010
- Tlachac, M. L., and Elke Rundensteiner. "Screening for depression with retrospectively harvested private versus public text." *IEEE journal of biomedical and health informatics* (24.11), 2020



References

1. Dogrucu, et al. "Moodable: on feasibility of instantaneous depression assessment using machine learning on voice samples with retrospectively harvested smartphone and social media data." *Smart Health* (17), 2020
2. Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset."
3. K. Kroenke, R. L. Spitzer, and J. B. Williams, "The phq-9: validity of a brief depression severity measure," Journal of General Internal Medicine, vol. 16(9), 2001.
4. M. Barandas, et al., "Tsfel: Time series feature extraction library," SoftwareX, vol. 11, 2020.
5. F. Pedregosa, et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, 2011

Acknowledgments

- Prior teams on the EMUTIVO project (emutivo.wpi.edu)
- The DAISY lab and Data Science Department at WPI
- US Department of Education P200A180088: GAANN grant

Acknowledgments

- Prior teams on the EMUTIVO research project (emutivo.wpi.edu)
- The DAISY research lab and Data Science Department at WPI
- The US Department of Education P200A180088: GAANN grant

References

1. H. Hedegaard, S. Curtin, and M. Warner, "Increase in suicide mortality in the united states, 1999–2018," NCHS Data Brief, vol. No. 366, 2020, https://www.cdc.gov/nchs/data/databriefs/db362-h.pdf.
2. M. L. Tlachac and E. Rundensteiner, "Screening for depression with retrospectively harvested private versus public text," IEEE Journal of Biomedical and Health Informatics (J-BHI), vol. 24 (11), 2020.
3. Dogrucu, et al. "Moodable: on feasibility of instantaneous depression assessment using machine learning on voice samples with retrospectively harvested smartphone and social media data." Smart Health, vol. 17, 2020
4. Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset", In submission
5. E Fast, B Chen, MS Bernstein, Empath: Understanding topic signals in large-scale text. CHI, 2016
6. F. Pedregosa, et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, 2011

Acknowledgments

- Toto, Kayastha, Taurich, Melican, Bruneau, Caouette, Houskeeper
- Prior EMUTIVO teams
- DAISY lab and at WPI
- US Dep. of Ed. P200A180088
- DS department at WPI

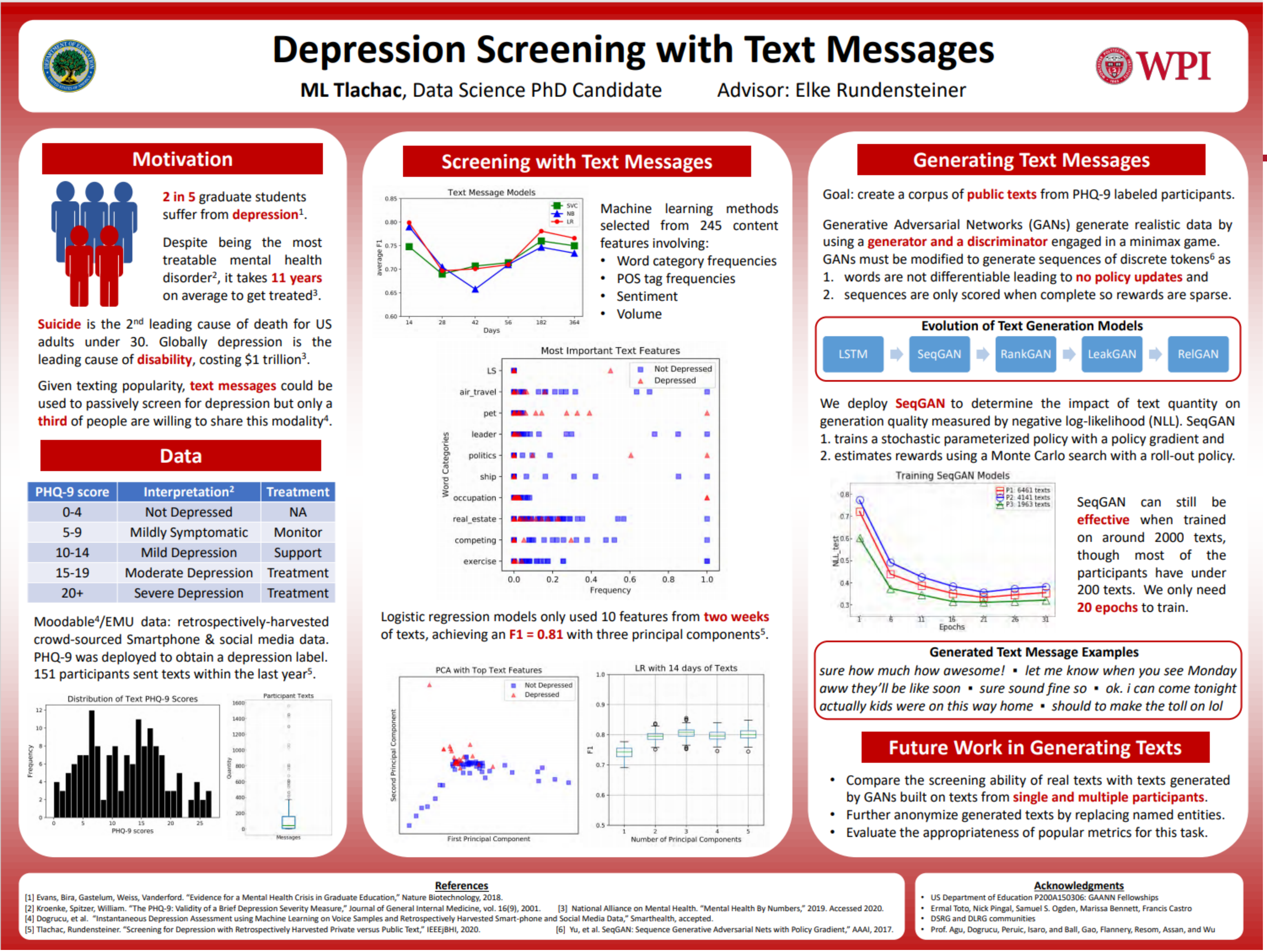
References

1. Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset." In Submission
2. Tlachac, et al. "StudentSADD: Mobile Depression and Suicidal Ideation Screening of College Students during COVID-19", in Submission
3. Tlachac, et al. "DepreST-CAT: Leveraging Smartphone Call and Text Logs Collected During the COVID-19 Pandemic to Screen for Mental Illnesses", in Submission
4. Reisch, et al. "Mental Health Classification Utilizing Multimodal Deep Learning with Mobile Speech Recordings", in Preparation
5. Toto, et al. ""AudiBERT: A Deep Transfer Learning Multimodal Classification Framework for Depression Screening", CIKM, 2021

Critiques of My Posters

with examples

Year: 2020
Format: In Person



Depression Screening with Text Messages

ML Tlachac, Data Science PhD Candidate   Advisor: Elke Rundensteiner

WPI

Motivation

2 in 5 graduate students suffer from depression[1].

Despite being the most treatable mental health disorder[2], it takes 11 years on average to get treated[3].

Suicide is the 2nd leading cause of death for US adults under 30. Globally depression is the leading cause of disability, costing $1 trillion[3].

Given texting popularity, text messages could be used to passively screen for depression but only a third of people are willing to share this modality[4].

Data

PHQ-9 score	Interpretation[2]	Treatment
0-4	Not Depressed	NA
5-9	Mildly Symptomatic	Monitor
10-14	Mild Depression	Support
15-19	Moderate Depression	Treatment
20+	Severe Depression	Treatment

Moodable[4]/EMU data: retrospectively-harvested crowd-sourced Smartphone & social media data. PHQ-9 was deployed to obtain a depression label. 151 participants sent texts within the last year[5].

Distribution of Text PHQ-9 Scores

Participant Texts

Screening with Text Messages

Text Message Models

Machine learning methods selected from 245 content features involving:

- Word category frequencies
- POS tag frequencies
- Sentiment
- Volume

Most Important Text Features

Logistic regression models only used 10 features from two weeks of texts, achieving an F1 = 0.81 with three principal components[5].

PCA with Top Text Features

LR with 14 days of Texts

Generating Text Messages

Goal: create a corpus of public texts from PHQ-9 labeled participants.

Generative Adversarial Networks (GANs) generate realistic data by using a generator and a discriminator engaged in a minimax game. GANs must be modified to generate sequences of discrete tokens[6] as

1. words are not differentiable leading to no policy updates and
2. sequences are only scored when complete so rewards are sparse.

Evolution of Text Generation Models

LSTM → SeqGAN → RankGAN → LeakGAN → RelGAN

We deploy SeqGAN to determine the impact of text quantity on generation quality measured by negative log-likelihood (NLL). SeqGAN

1. trains a stochastic parameterized policy with a policy gradient and
2. estimates rewards using a Monte Carlo search with a roll-out policy.

Training SeqGAN Models

SeqGAN can still be effective when trained on around 2000 texts, though most of the participants have under 200 texts. We only need 20 epochs to train.

Generated Text Message Examples

sure how much how awesome! ▪ *let me know when you see Monday*
aww they'll be like soon ▪ *sure sound fine so* ▪ *ok. i can come tonight*
actually kids were on this way home ▪ *should to make the toll on lol*

Future Work in Generating Texts

- Compare the screening ability of real texts with texts generated by GANs built on texts from single and multiple participants.
- Further anonymize generated texts by replacing named entities.
- Evaluate the appropriateness of popular metrics for this task.

References

[1] Evans, Bira, Gastelum, Weiss, Vanderford. "Evidence for a Mental Health Crisis in Graduate Education," Nature Biotechnology, 2018.
[2] Kroenke, Spitzer, William. "The PHQ-9: Validity of a Brief Depression Severity Measure," Journal of General Internal Medicine, vol. 16(9), 2001.
[3] National Alliance on Mental Health. "Mental Health By Numbers," 2019. Accessed 2020.
[4] Dogrucu, et al. "Instantaneous Depression Assessment using Machine Learning on Voice Samples and Retrospectively Harvested Smart-phone and Social Media Data," Smarthealth, accepted.
[5] Tlachac, Rundensteiner. "Screening for Depression with Retrospectively Harvested Private versus Public Text," IEEEjBHI, 2020.
[6] Yu, et al. SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient," AAAI, 2017.

Acknowledgments

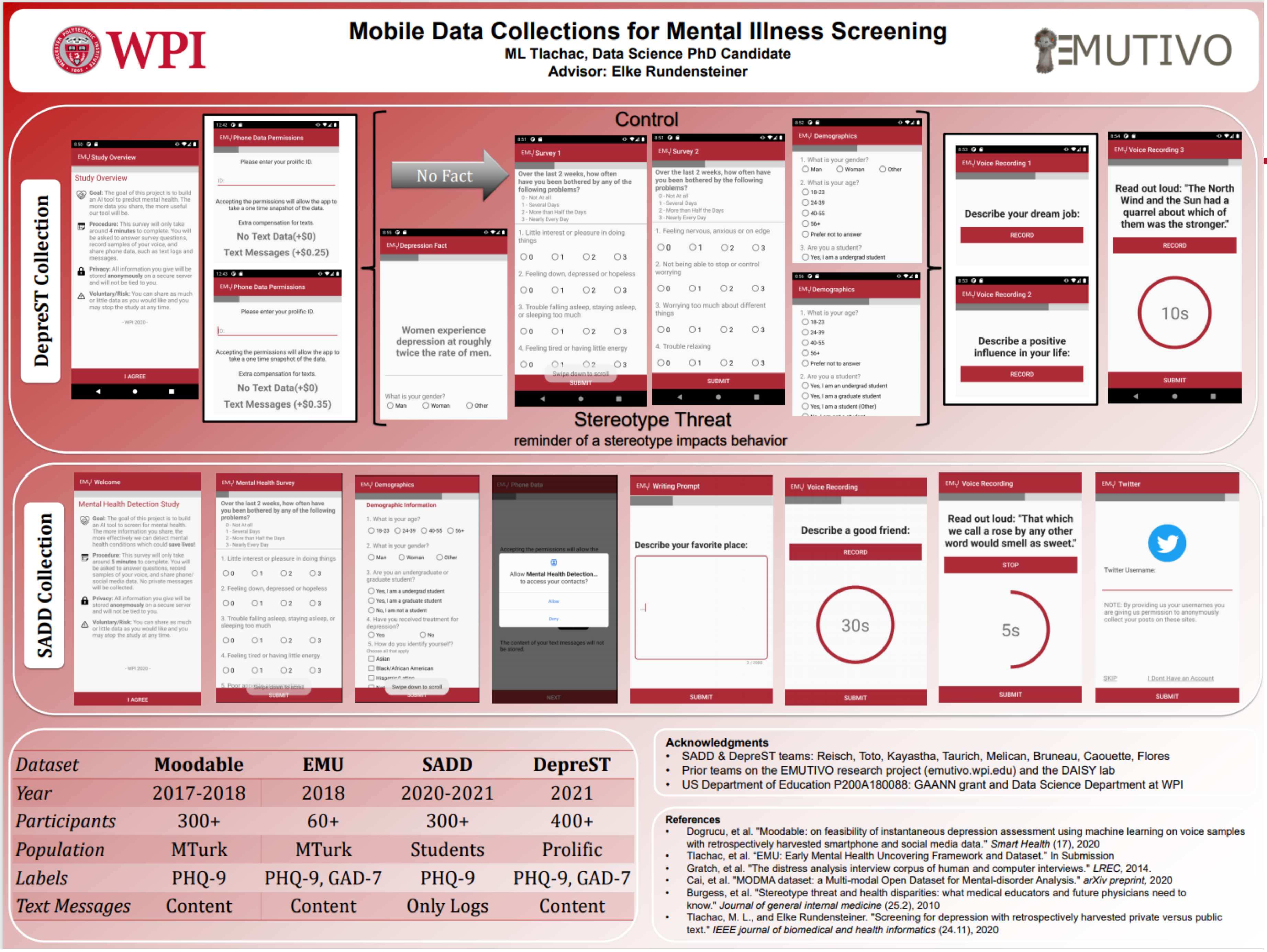
- US Department of Education P200A150306: GAANN Fellowships
- Ermal Toto, Nick Pingal, Samuel S. Ogden, Marissa Bennett, Francis Castro
- DSRG and DLRG communities
- Prof. Agu, Dogrucu, Peruic, Isaro, and Ball, Gao, Flannery, Resom, Assan, and Wu

The Bad

- Story too big for a poster
- Why mention future work?

The Good

- Important words in red
- Generated text examples are fun for readers



Mobile Data Collections for Mental Illness Screening

ML Tlachac, Data Science PhD Candidate
Advisor: Elke Rundensteiner

Dataset	Moodable	EMU	SADD	DepreST
Year	2017-2018	2018	2020-2021	2021
Participants	300+	60+	300+	400+
Population	MTurk	MTurk	Students	Prolific
Labels	PHQ-9	PHQ-9, GAD-7	PHQ-9	PHQ-9, GAD-7
Text Messages	Content	Content	Only Logs	Content

Acknowledgments
- SADD & DepreST teams: Reisch, Toto, Kayastha, Taurich, Melican, Bruneau, Caouette, Flores
- Prior teams on the EMUTIVO research project (emutivo.wpi.edu) and the DAISY lab
- US Department of Education P200A180088: GAANN grant and Data Science Department at WPI

References
- Dogrucu, et al. "Moodable: on feasibility of instantaneous depression assessment using machine learning on voice samples with retrospectively harvested smartphone and social media data." *Smart Health* (17), 2020
- Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset." In Submission
- Gratch, et al. "The distress analysis interview corpus of human and computer interviews." *LREC*, 2014.
- Cai, et al. "MODMA dataset: a Multi-modal Open Dataset for Mental-disorder Analysis." *arXiv preprint*, 2020
- Burgess, et al. "Stereotype threat and health disparities: what medical educators and future physicians need to know." *Journal of general internal medicine* (25.2), 2010
- Tlachac, M. L., and Elke Rundensteiner. "Screening for depression with retrospectively harvested private versus public text." *IEEE journal of biomedical and health informatics* (24.11), 2020

Year: 2021
Format: Virtual

The Bad
- Can't read text in screenshots
- Can't match references

The Good
- No unnecessary words on poster
- Visually interesting

Mobile Depression Screening with Time Series of Text Logs and Call Logs

ML Tlachac, Veronica Melican, Miranda Reisch, Elke Rundensteiner
Worcester Polytechnic Institute
4-page paper @ IEEE BHI-BSN 2021

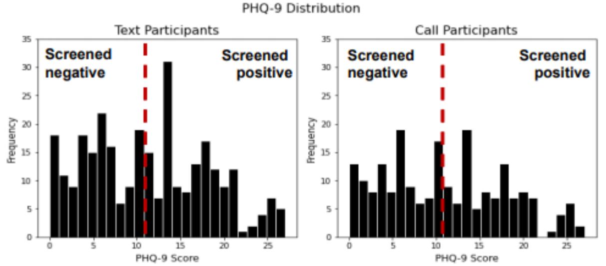
Research Questions

Given logs, is it best to screen for depression with:

1. Text logs or call logs?
2. Incoming, outgoing, or all communications?
3. Communication count, average length, or contacts?
4. Aggregation intervals of 4, 6, 12 or 24 hours?
5. Time series or features from time series?

The Data

Two weeks of logs from the Moodable[1] and EMU[2] datasets labeled with PHQ-9 depression screening scores[3]. If PHQ-9 ≥ 10, screen positive for depression.

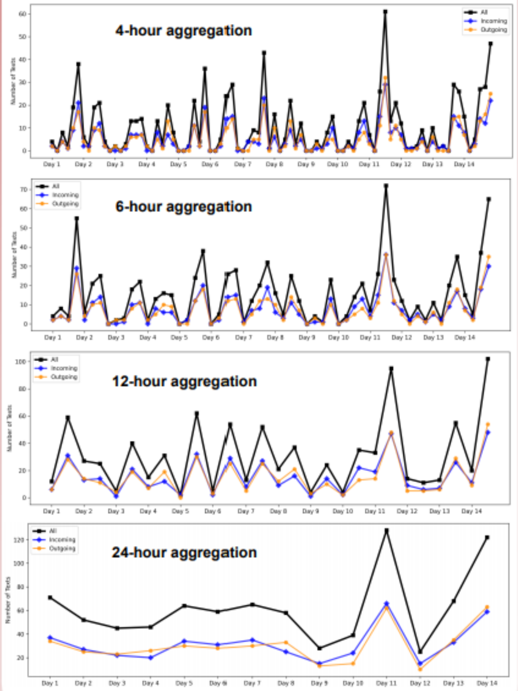


The 312 participants shared different types of logs:

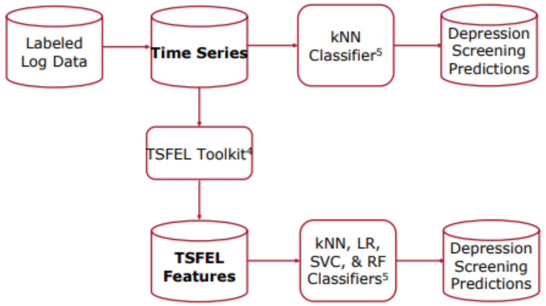
Log	All	Incoming	Outgoing
Text logs	245	290	99
Call logs	212	182	197

Creating the Time Series

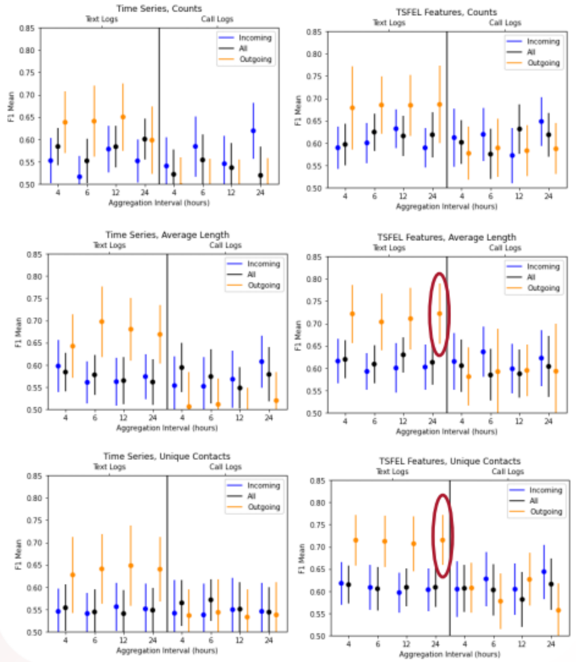
We create 72 sets of time series from the logs using the communication count, average length of communications, and number of contacts. We aggregate these values every 4, 6, 12, & 24 hours. All text log time series for a single participant:



Machine Learning Pipeline



Screening Results



References

1. Dogrucu, et al. "Moodable: on feasibility of instantaneous depression assessment using machine learning on voice samples with retrospectively harvested smartphone and social media data." *Smart Health* (17), 2020
2. Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset."
3. K. Kroenke, R. L. Spitzer, and J. B. Williams, "The phq-9: validity of a brief depression severity measure," Journal of General Internal Medicine, vol. 16(9), 2001.
4. M. Barandas, et al., "Tsfel: Time series feature extraction library," SoftwareX, vol. 11, 2020.
5. F. Pedregosa, et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, 2011

Acknowledgments

- Prior teams on the EMUTIVO project (emutivo.wpi.edu)
- The DAISY lab and Data Science Department at WPI
- US Department of Education P200A180088: GAANN grant

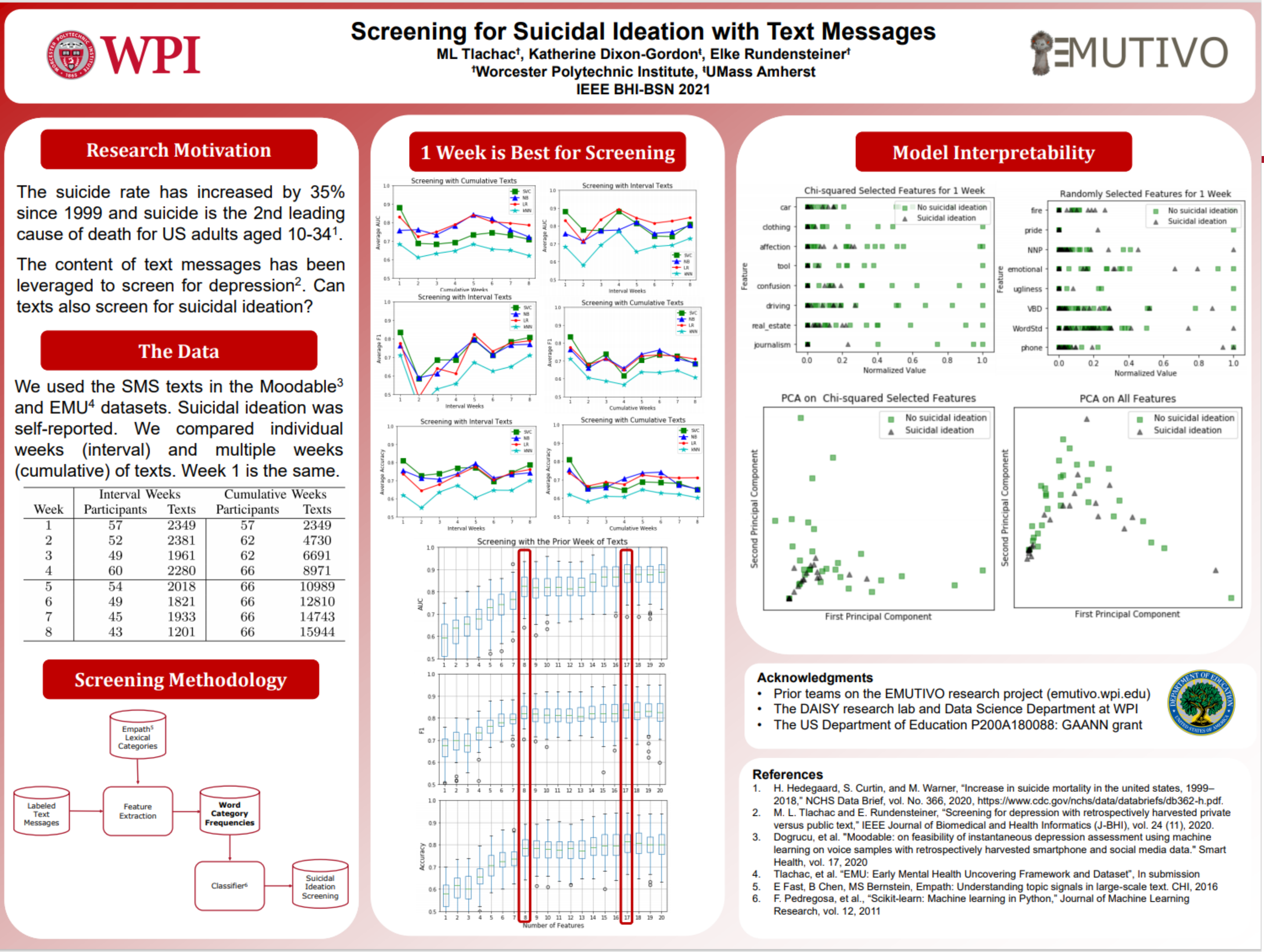
Year: 2021
Format: In Person

The Bad

- Colors are unbalanced
- Title of result plots are too small to read

The Good

- Large font
- Fun pipeline



Year: 2021
Format: In Person

The Bad

- Too many words at the start
- Plots in middle panel are small

The Good

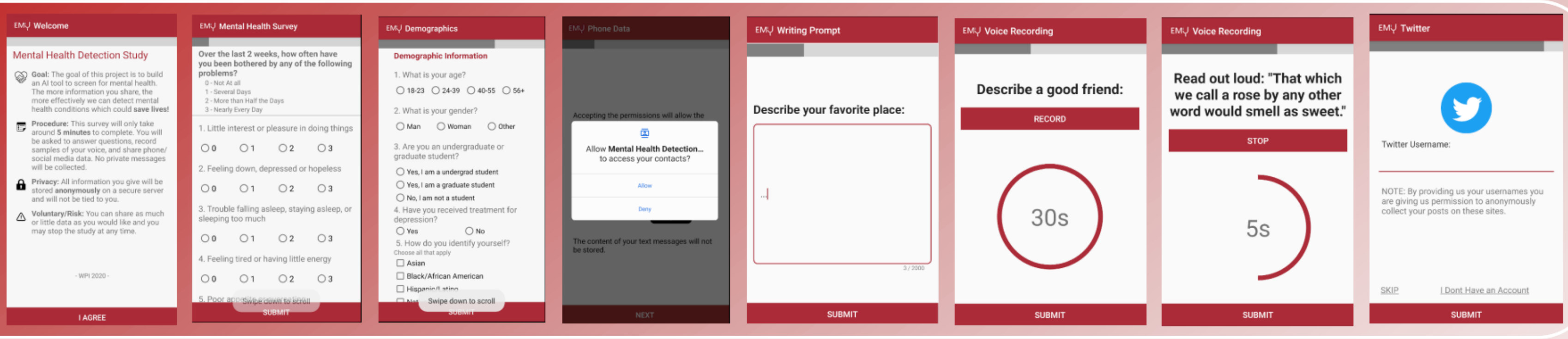
- Circled results
- Many visualizations

StudentSADD versus DepreST

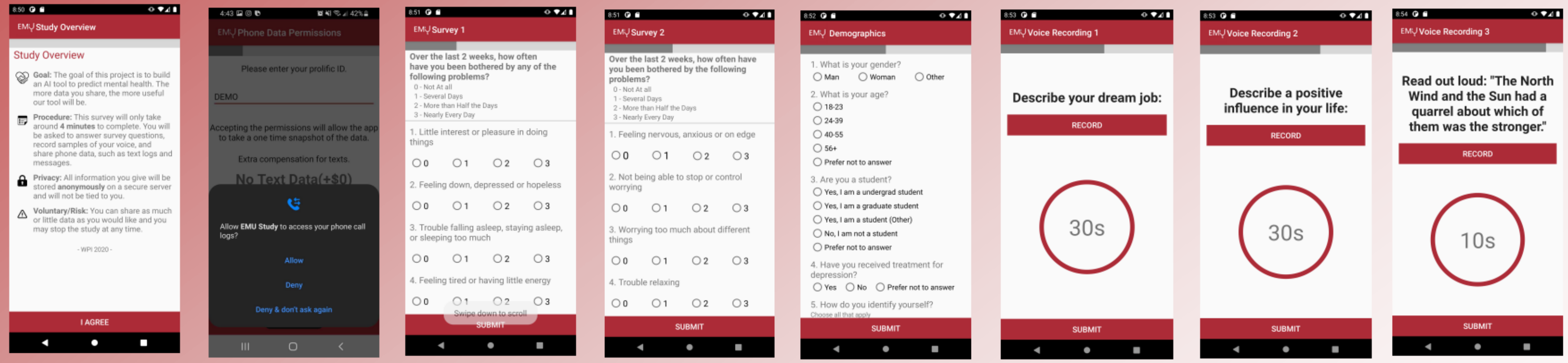
Collecting Data During COVID-19 for Rapid Mental Illness Screening

ML Tlachac, Miranda Reisch, Ricardo Flores, Elke Rundensteiner

SADD Collection



DepreST Collection



Dataset	SADD	DepreST
Participants	302	440
Population	Students	Prolific
Labels	PHQ-9	PHQ-9, GAD-7
Audio Recordings	200	400
Transcripts	115	377
Text Reply	298	NA
Phone Logs	10	369

StudentSADD	Scripted Voice + Text	AudiBERT	Depression (PHQ-9≥10)	F1 = 0.69 ± 0.00
DepreST	Unscripted Voice 1	AudiBERT	Depression (PHQ-9≥10)	F1 = 0.66 ± 0.01
DepreST	Unscripted Voice 1	AudiBERT	Anxiety (GAD-7≥10)	F1 = 0.79 ± 0.04
DepreST	Log Timeseries	GRU	Depression (PHQ-9≥10)	F1 = 0.68 ± 0.00
DepreST	Log Timeseries	GRU	Anxiety (GAD-7≥10)	F1 = 0.48 ± 0.09

Acknowledgments

- Toto, Kayastha, Taurich, Melican, Bruneau, Caouette, Houskeeper
- Prior EMUTIVO teams
- DAISY lab and at WPI
- US Dep. of Ed. P200A180088
- DS department at WPI

References

1. Tlachac, et al. "EMU: Early Mental Health Uncovering Framework and Dataset." In Submission
2. Tlachac, et al. "StudentSADD: Mobile Depression and Suicidal Ideation Screening of College Students during COVID-19", in Submission
3. Tlachac, et al. "DepreST-CAT: Leveraging Smartphone Call and Text Logs Collected During the COVID-19 Pandemic to Screen for Mental Illnesses", in Submission
4. Reisch, et al. "Mental Health Classification Utilizing Multimodal Deep Learning with Mobile Speech Recordings", in Preparation
5. Toto, et al. ""AudiBERT: A Deep Transfer Learning Multimodal Classification Framework for Depression Screening", CIKM, 2021

Year: 2022
Format: Virtual

The Bad

- Can't read text in screenshots
- Results table time consuming to read

The Good

- **Improvement of prior poster**
- Visually interesting

Extra Tips

For posters

Poster Design Tips

All Posters

- Know your audience
- Less is more
  - Minimize content and words
  - Text big enough to read
  - Readable text/background colors
  - Consistent accessible font
- Maximize visualizations/tables
  - High quality images
- Make reading order clear

Printed Posters for In-Person

- Use a column-based format
- Put while panels over colorful background to reduce ink
- Include a small (white) border in case printing misalignment

Presenting Tips

For Beforehand

- Have an elevator pitch ready
- Practice responding to questions
- Have notebook to write suggestions and/or contact info
- Plan what you're going to wear
  - Comfortable & clean
  - Don't forget to think about shoes

For During

- Invite people to your poster
  - Even if you are in a conversation
  - "Just a quick recap…"
- Do not turn your back on any audience member
- Engage in a conversation
- Ask questions and adapt
  - "Do you know about Catalan #s?"
- Have fun!