Understanding Client Support Strategies to Improve Clinical Outcomes in an Online Mental Health Intervention

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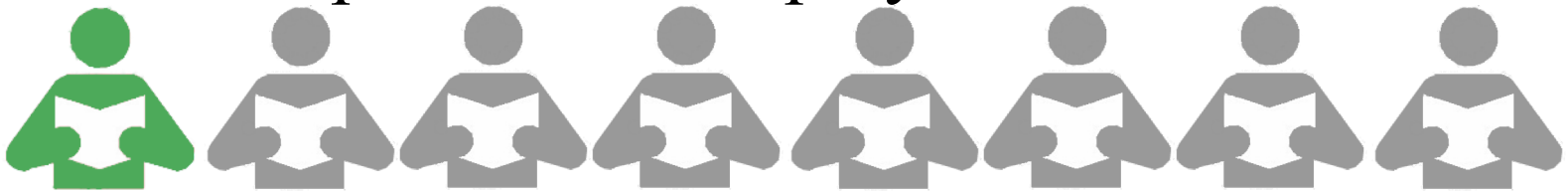
Outline

- Problem
- Solution
- Previous Work
- Research Goal
- Dataset
- Contributions
- Methods and Results
- Discussion

Mental Health Crisis – Widespread!

- Leading cause of suicide and disability.
- Lifetime occurrence

- Current: Depression in employees



- Current: Depression in college students

Mental Health Crisis – Huge Cost!

long-term sickness absence
in England **attributed to mental ill health**

In 2016,
42.7%
employment rate
for those who report mental illness as their main health problem (Mental illness, phobia, panics, nervous disorders (including depression, bad nerves or anxiety. **Compared to 74% of all population**

Total Socioeconomic Cost in England is estimated to be £105 billion.

Mental Health Crisis – Lack of access!

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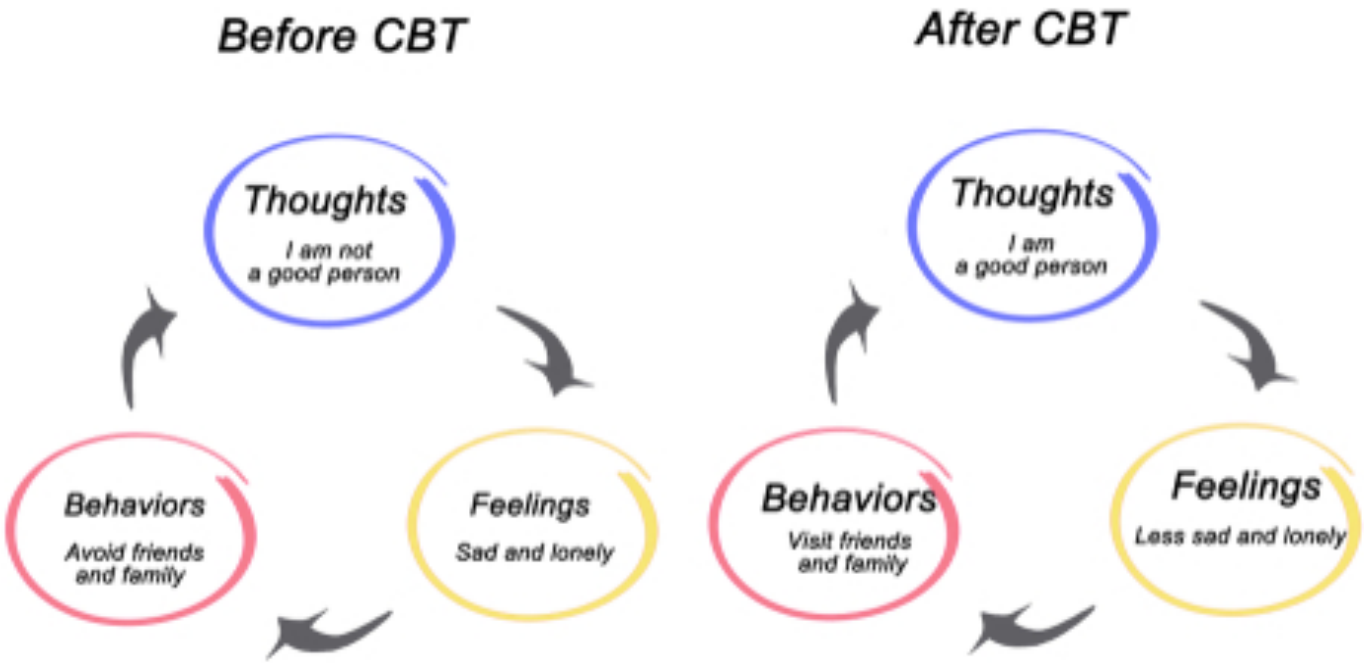
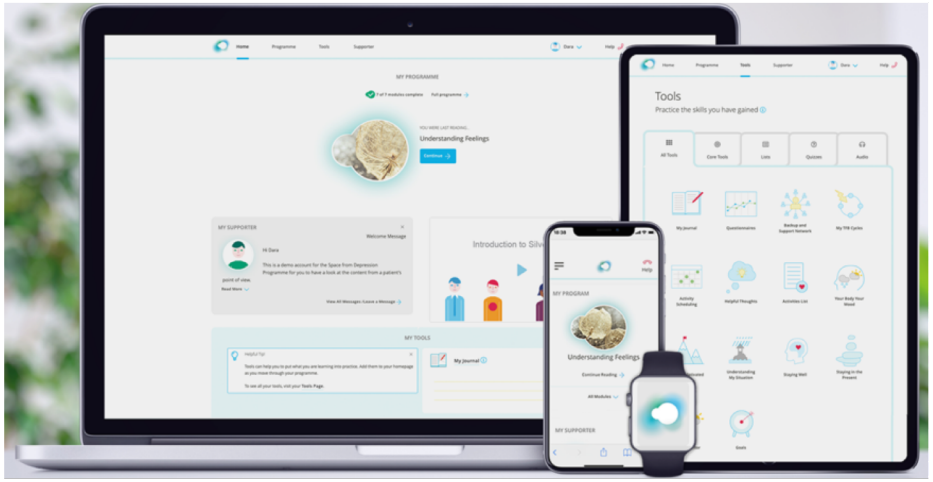
Mental Health Crisis – A Solution!

- Online Mental Health Services.
- CBT → Very structured --> Sofware!
- E.g.
  Internet-based Cognitive Behavioral Therapy (iCBT)



SilverCloud Health

SilverCloud



Space from **Anxiety**

Space from **Depression**

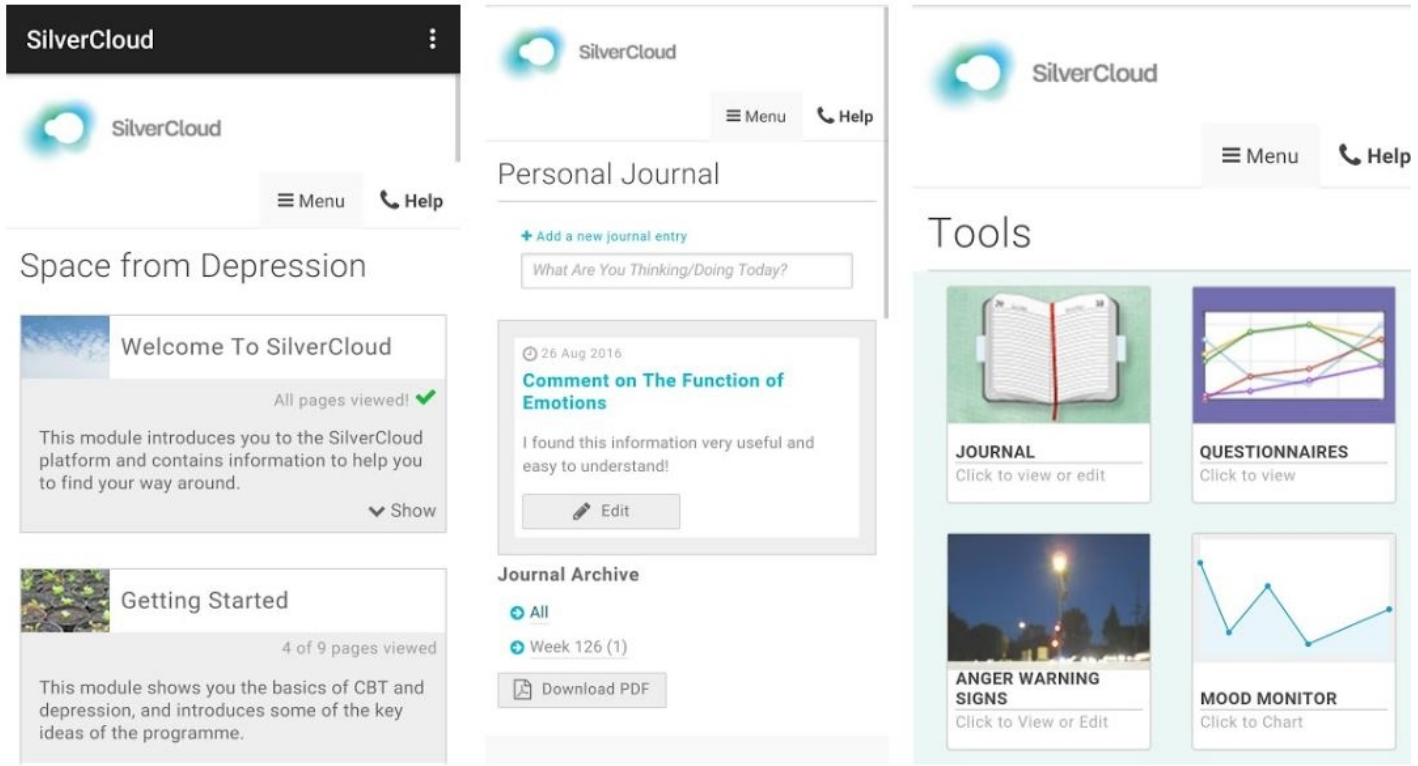
Space from **Chronic Illness**

Space from **Eating Issues**

Space from **Stress**

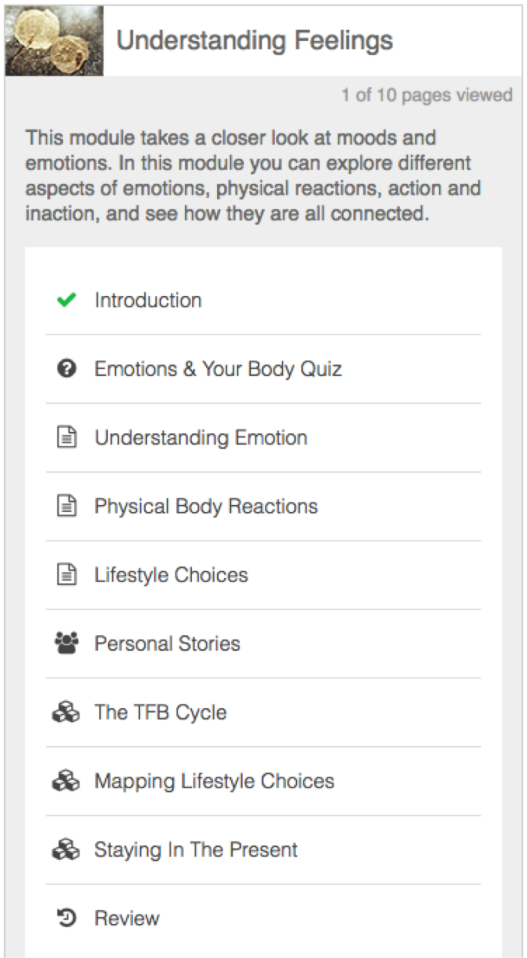
SilverCloud – An Introduction

- Content: a “online course” like structure.
- Tools: accessed any time.
- Supporter



SilverCloud – Content

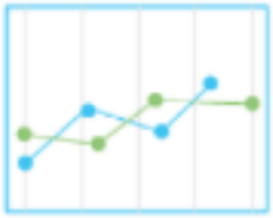
- “Space” or program dependent, and “prescribed”.



SilverCloud – Interactive Tools

- Accessible anytime


My Journal


Questionnaires


Backup and Support Network


Goals


Staying in the Present


Goals

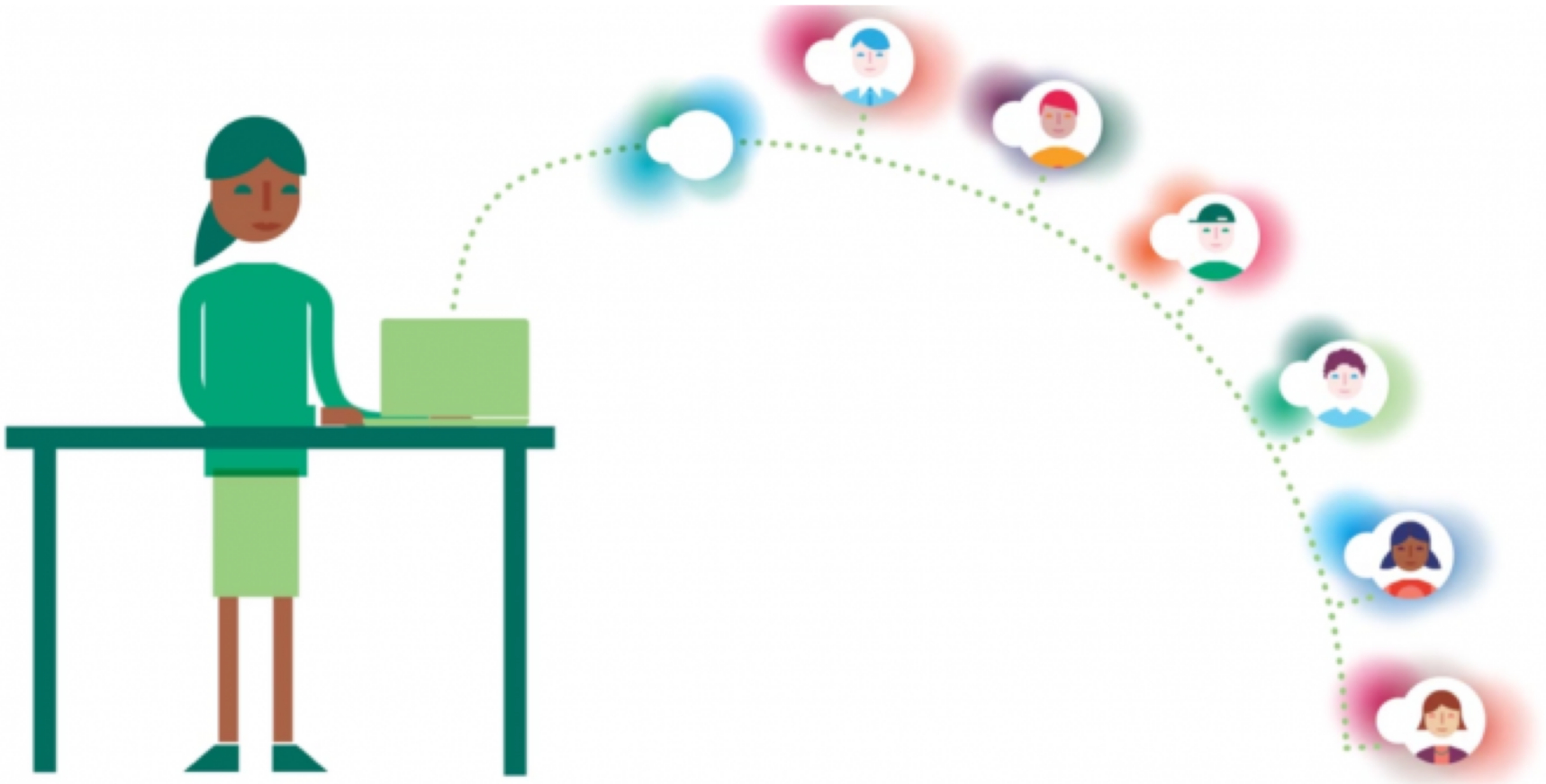

Mood Monitor


My TFB Cycles


Hierarchy of Fears

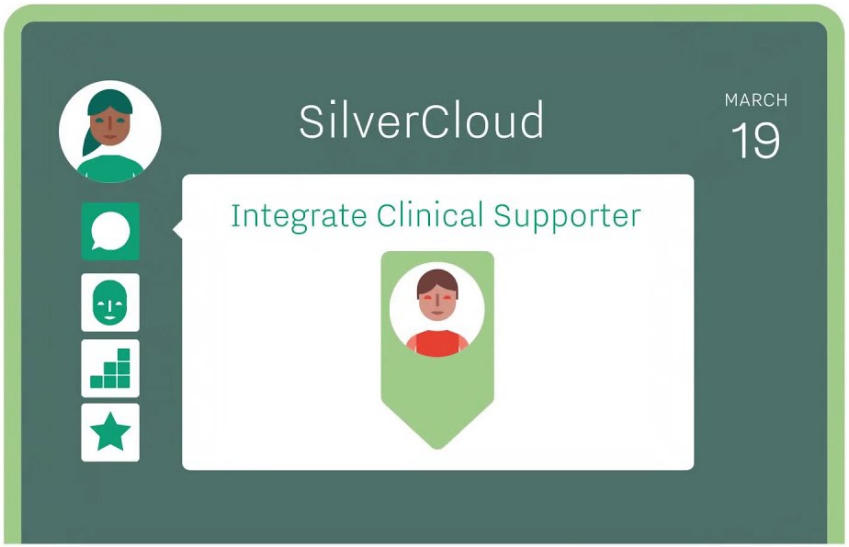
SilverCloud – Supporter

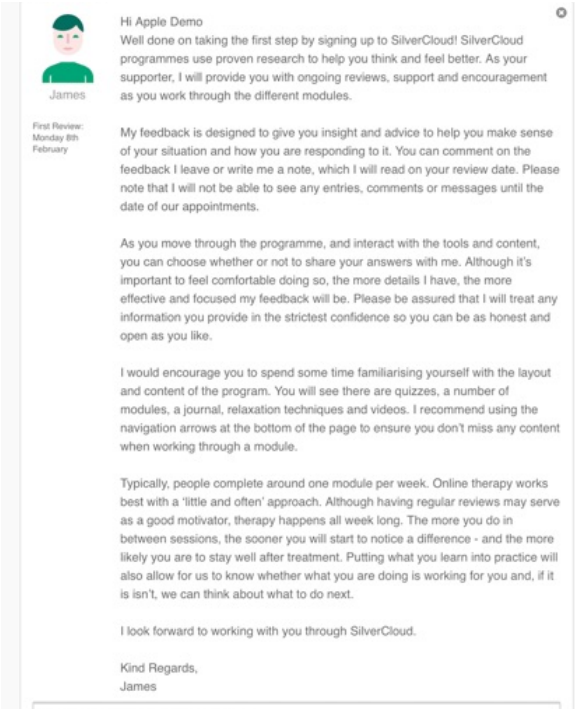
- Adherence and Attrition Issues
  → Human supporter
- Increased accountability



SilverCloud – Supporter (contd.)

- Reviews progress weekly. Provides feedback.
  - Should spend 10 min per message.
  - Should send 6-8 such messages.
  - Other guidelines (e.g. answer questions, promote engagement with platform, be positive)





SilverCloud – Outcome-based

- Clients also fill out weekly surveys that measure symptoms of depression and anxiety.

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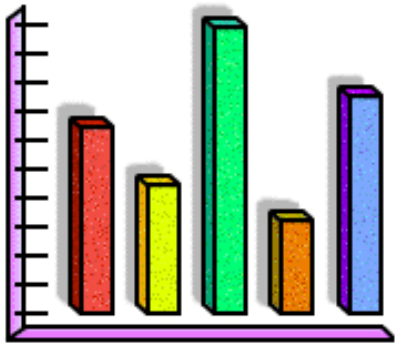
Previous Work – In Short

- Previous work focusses on duration and frequency of human support.



- Little is known about how supporter behaviors impact client outcomes.

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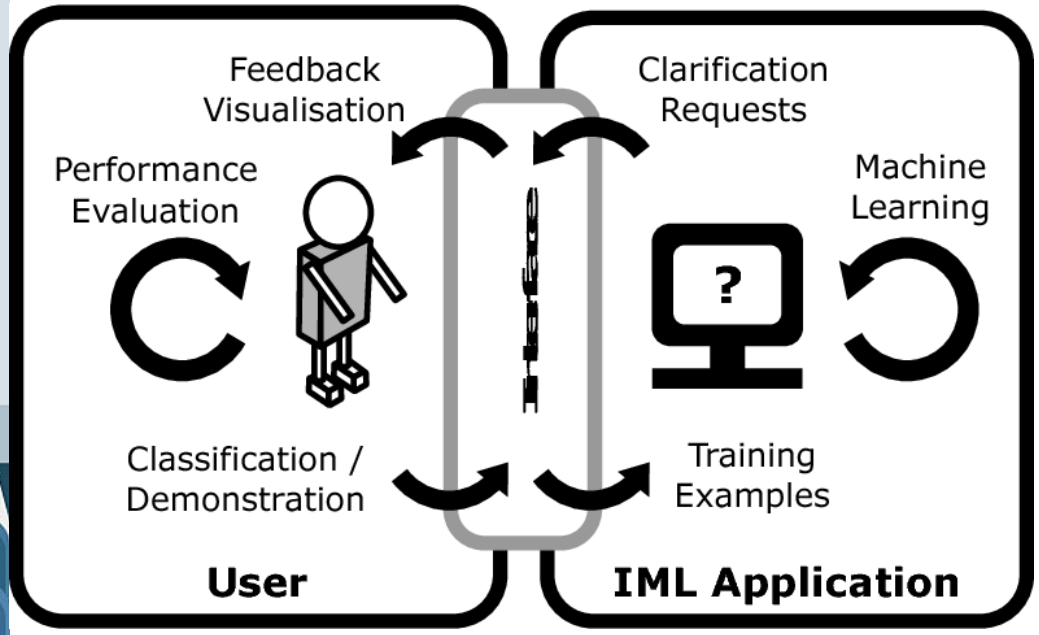
Research Goal

- More nuanced understanding of supporter behaviors:
  - → Better Supporter Training.
  - → ML for Recommending Supporter Behavior.



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Dataset

- Space for Depression and Anxiety.
- >200,000 messages sent by ~3500 supporters to ~50,000 clients.

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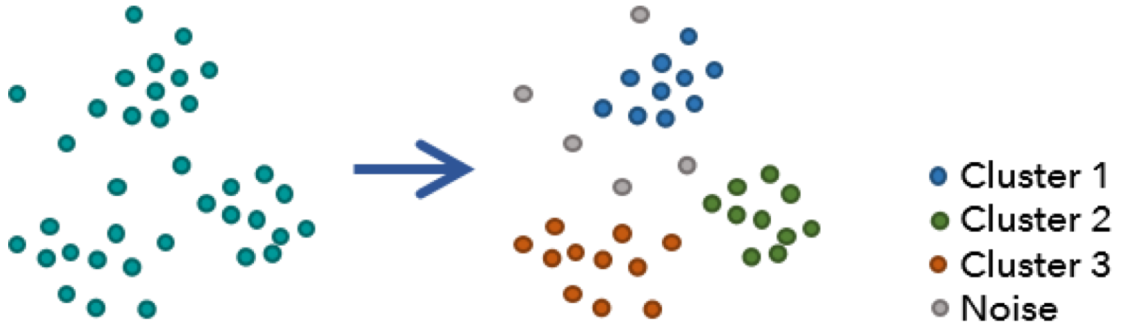
Contributions

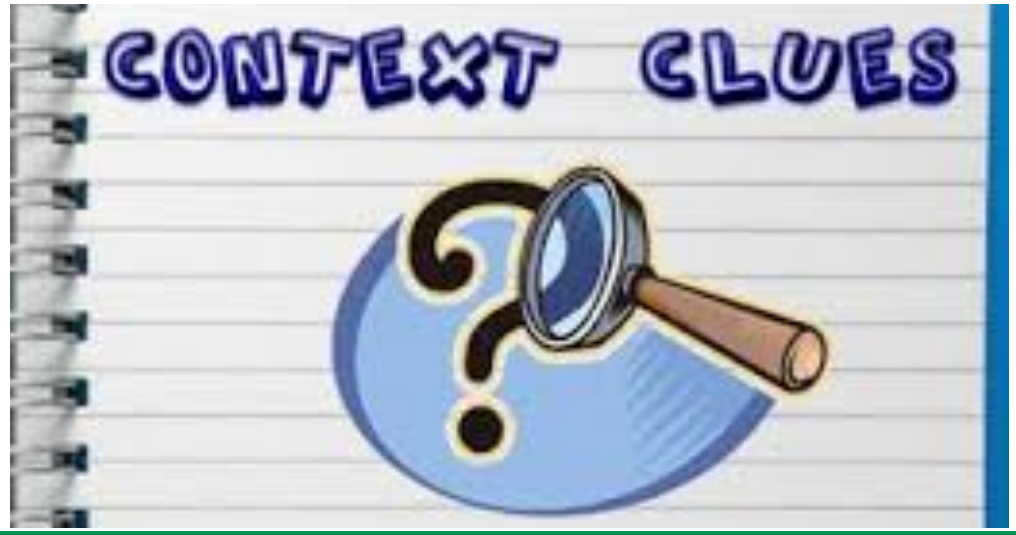
1. *Cluster supporters* based on how their support messages correlate with client outcomes.



2. *Extract linguistic features* indicative of supporter behaviors that correlate with "high" outcomes across clients in different contexts.

Contributions (Contd.)

3. *Identify salient context-specific patterns of support*, while taking into account co-occurrent patterns of different context variables.



Spoiler ☺ *Concrete, positive, and supportive* messages from supporters that reference *social behaviors* are strongly associated with better outcomes.

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- Methods and Results: Clustering Supporters
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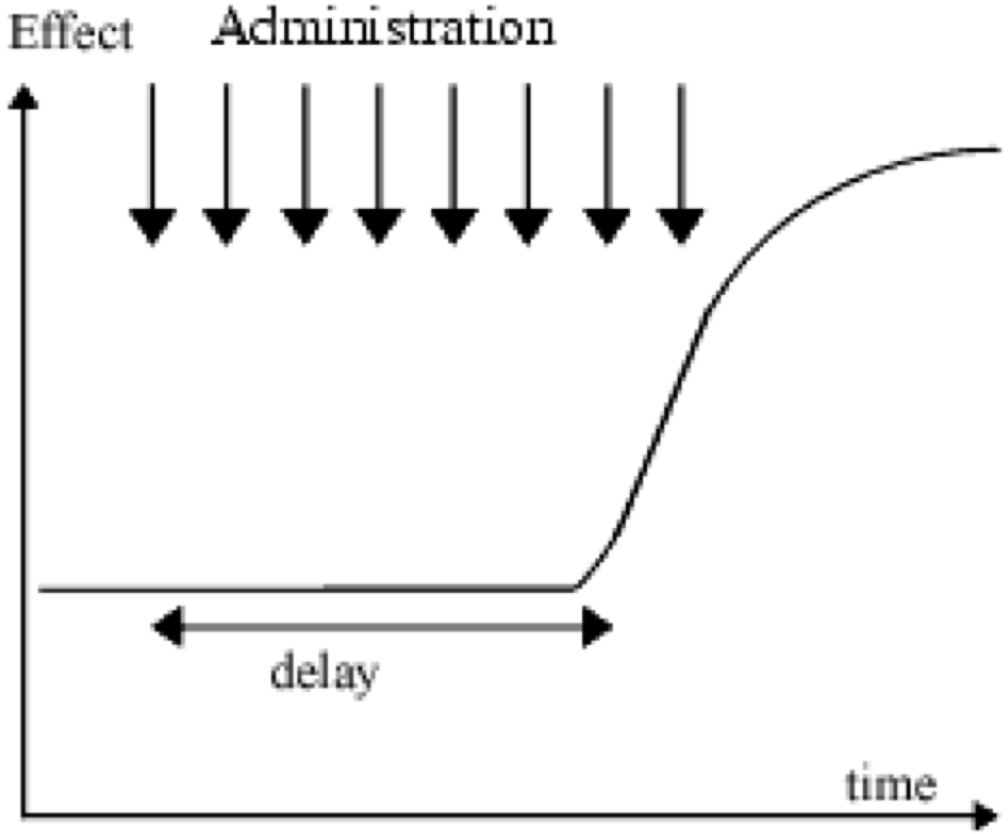
Clustering Supporters – Motivation

Support messages may not directly impact immediate outcomes → **Focus on improvement over time**.

E.g.

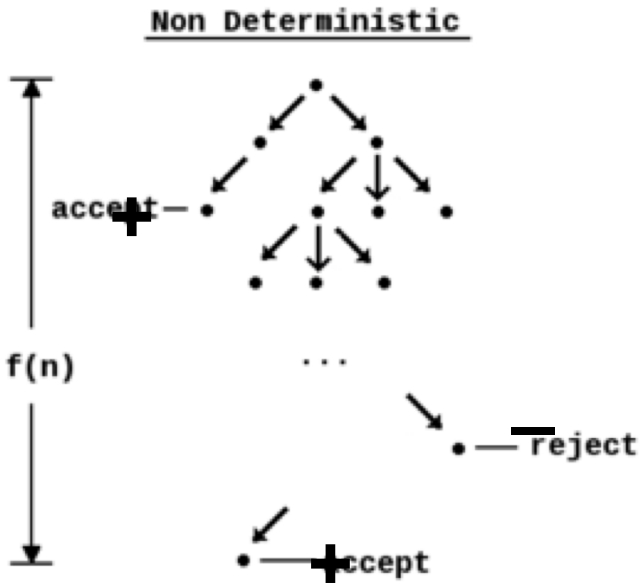


Clustering Supporters – Motivation (contd.)

Some clients will not improve despite the use of good support strategies in supporter messages.

But, good strategies used consistently with a set of clients will lead to improvement for the majority.

→ **Focus on the supporters.**



Clustering Supporters – Motivation (contd.)

- Hence, we cluster supporters into supporters based on the success of their strategies.
- Success?

Clustering Supporters – Method

Compute 4 outcome measures for each supporter and cluster them using K-means with K=3.

Message-level change	Client-level change
Message-level improvement rate	Client-level improvement rate

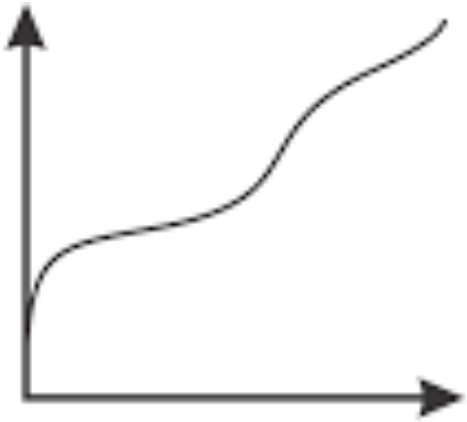
Clustering Supporters – Method (contd.)

1. Message-level Change (MC): Average change in scores across all messages sent by supporter *s*.
2. Message-level Improvement Rate (MR): Percentage of messages sent by supporter *s* that were followed by an improvement.

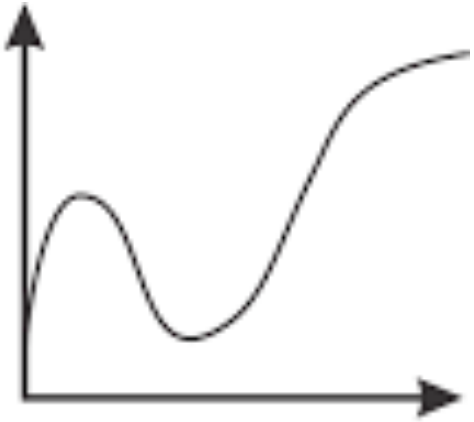
Clustering Supporters – Method (contd.)

Message-level outcomes don't capture client-level differences.

E.g.



Good things happened!



Something bad happened

Clustering Supporters – Method (contd.)

Better account for client-level differences:

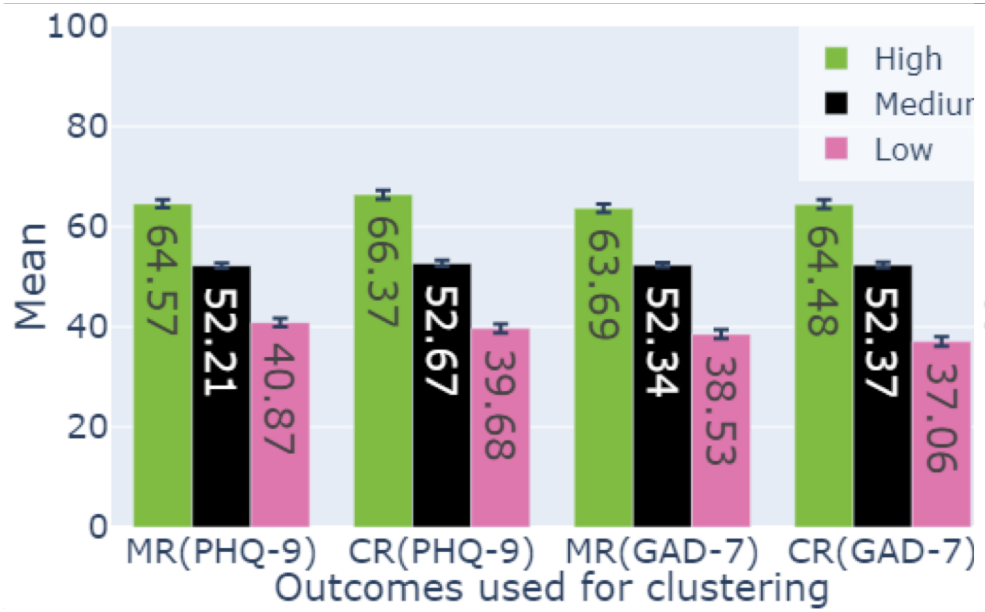
3. Client-level Change (CC): Compute Message-level Change for each client, and average it.
4. Client-level Improvement Rate (CR): Compute Message-level Improvement Rate for each client separately, and average it.

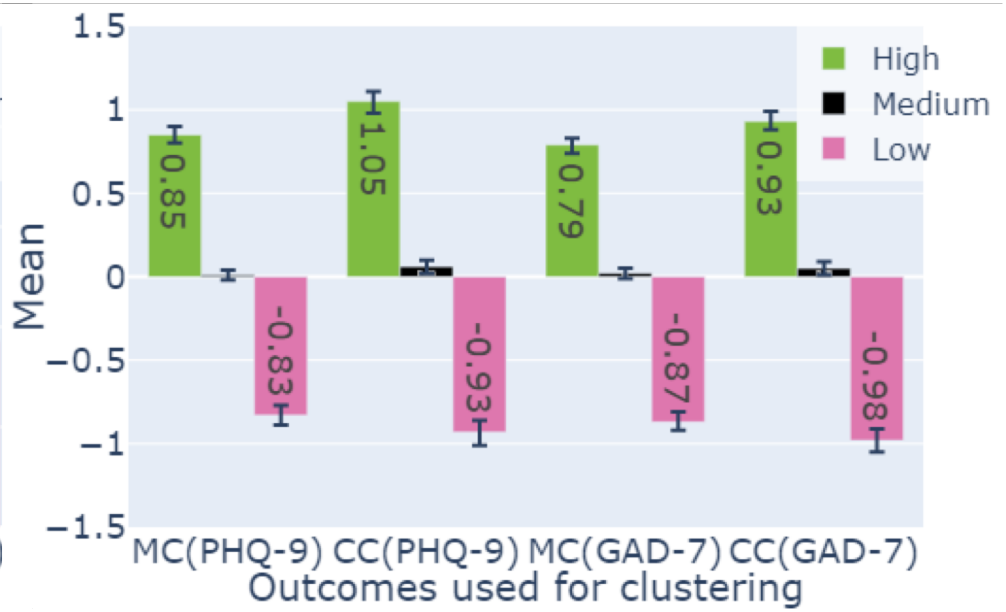
Clustering Supporters – Results

K-means with K=3

Clustering Supporters – Results (contd.)

Cluster	#Supporters	#Clients	#Messages	#Messages Labeled
High	438	11068	42734	14519
Medium	767	31789	123303	42740
Low	393	10828	47023	14266





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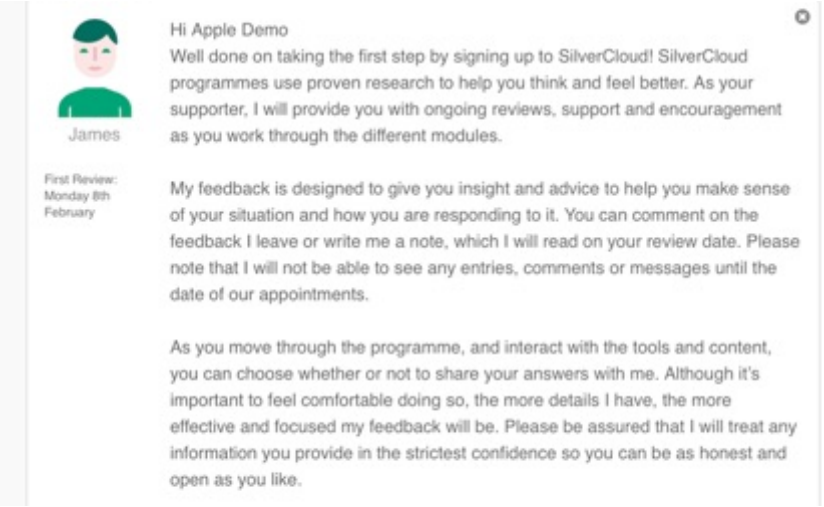
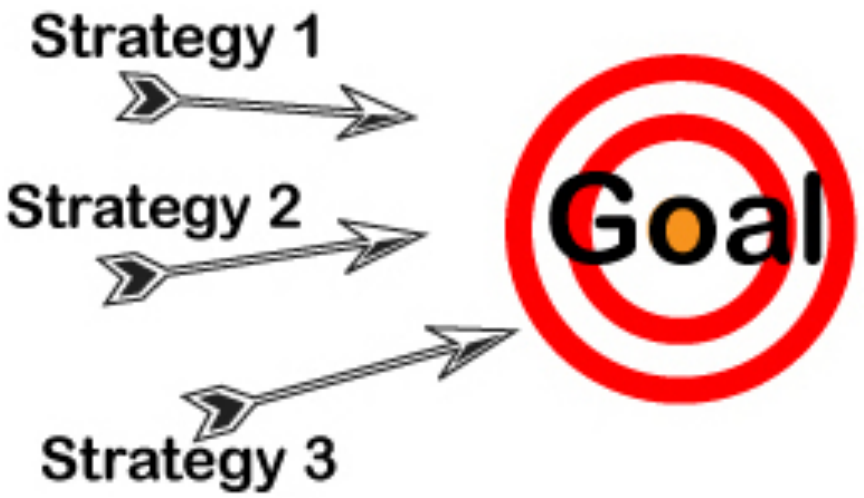
Successful Support Strategies – Features

- Client <Context> Variables:
  - 5 Variables: ContentViews, Shared, MessageNumber, CurrentPHQ-9, and CurrentGAD-7.
  - BINNED

Successful Support Strategies – Features (contd.)

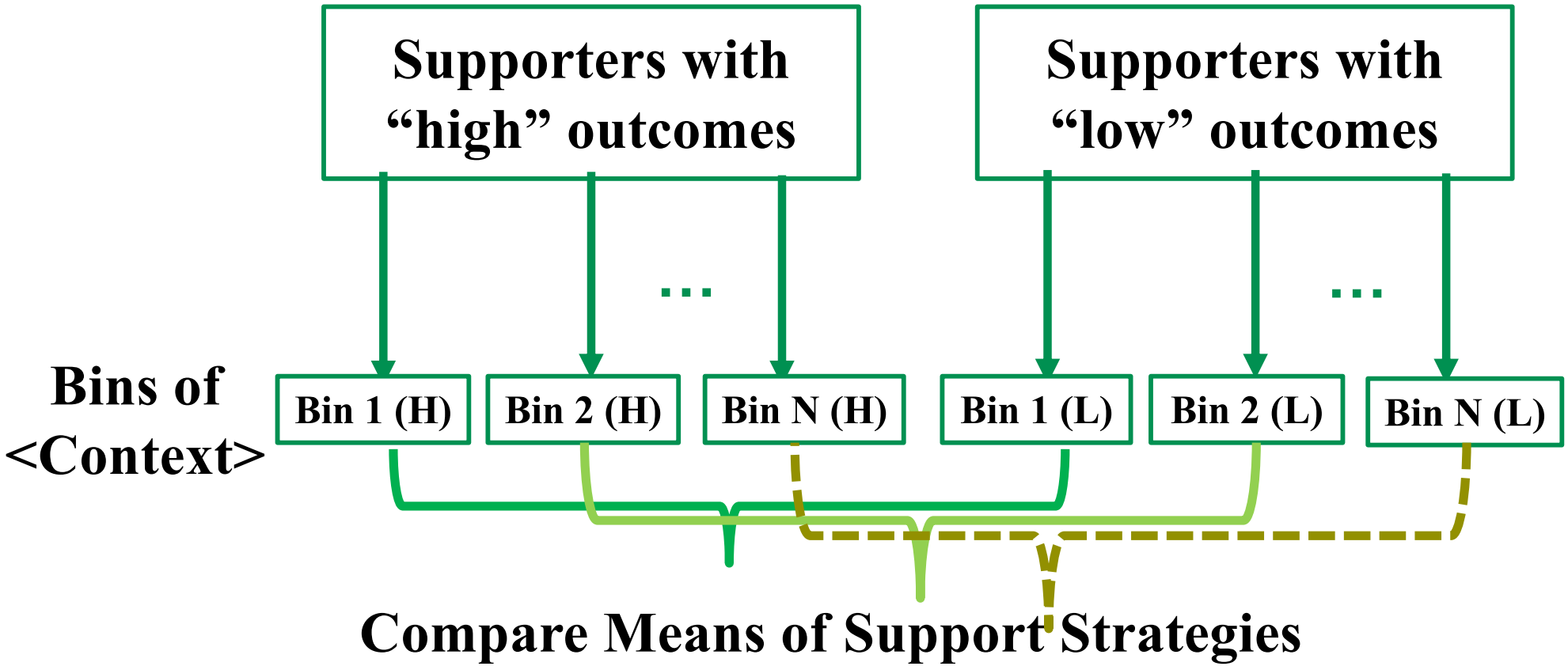




- Support <Strategy> Variables:
  - 23 variables calculated using validated lexicons and NLP techniques.
  - Can be divided into 6 categories: Sentiment, Emotion, Pronouns, Encouraging Phrases, Mental Processes & Behaviors, and Quantity.

Successful Support Strategies – Method

- For each <context, strategy> pair (NP=23*5=115),
  - Divide messages as follows:



Successful Support Strategies – Method

- To compare Means for messages in each bin:
  - 95% bootstrapped confidence intervals for “high” and “low” clusters.
  - Using bootstrapped resampling test.

- Bootstrapping was done on the supporters.
  - Gold standard for similar hierarchical data.
  - (i.e. Supporter → Client → Message)
  - No independence assumption for messages.

Successful Support Strategies – Method

- We make these comparisons using:
  - By comparing means obtained through hierarchical bootstrapping.
  - We compute the p-values and 95% confidence intervals to assess the significance of these findings

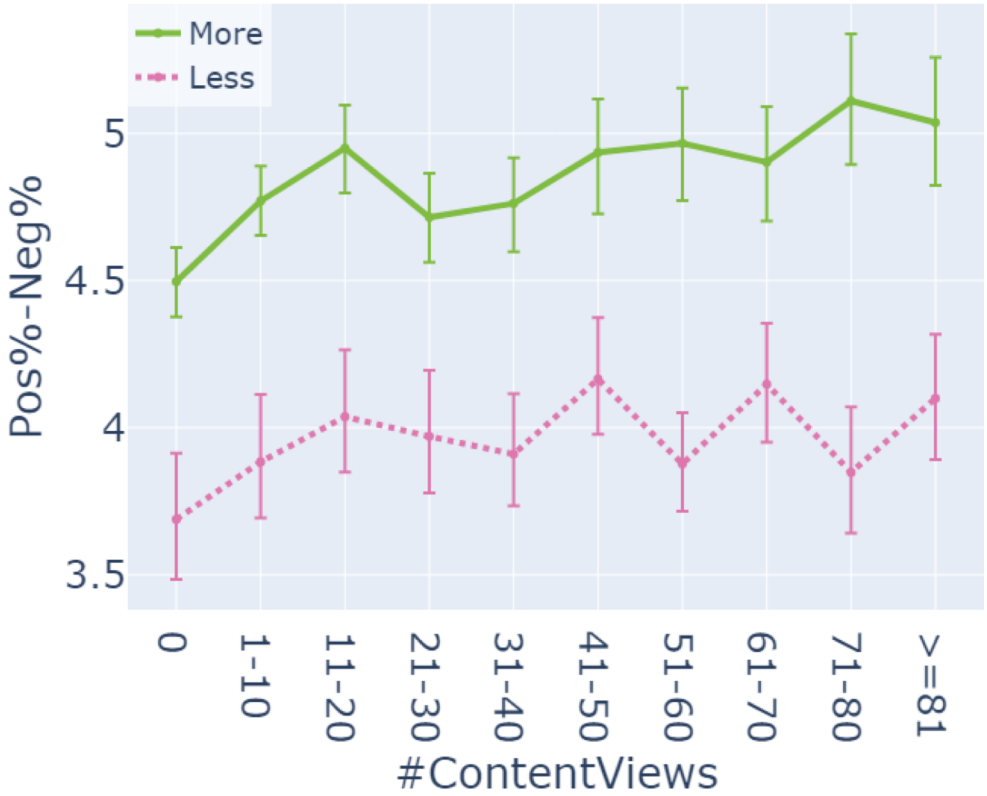
Successful Support Strategies – Method

- Compare Means: For messages in each bin, compute the following:
  - 95% bootstrapped confidence intervals for “high” and “low” clusters, and check for overlap.
  - Compare means across the “high” and “low” clusters using bootstrapped resampling test.

- Messages are Hierarchical Data (i.e. Supporter → Client → Message)
  - Bootstrapping was done on the supporters.

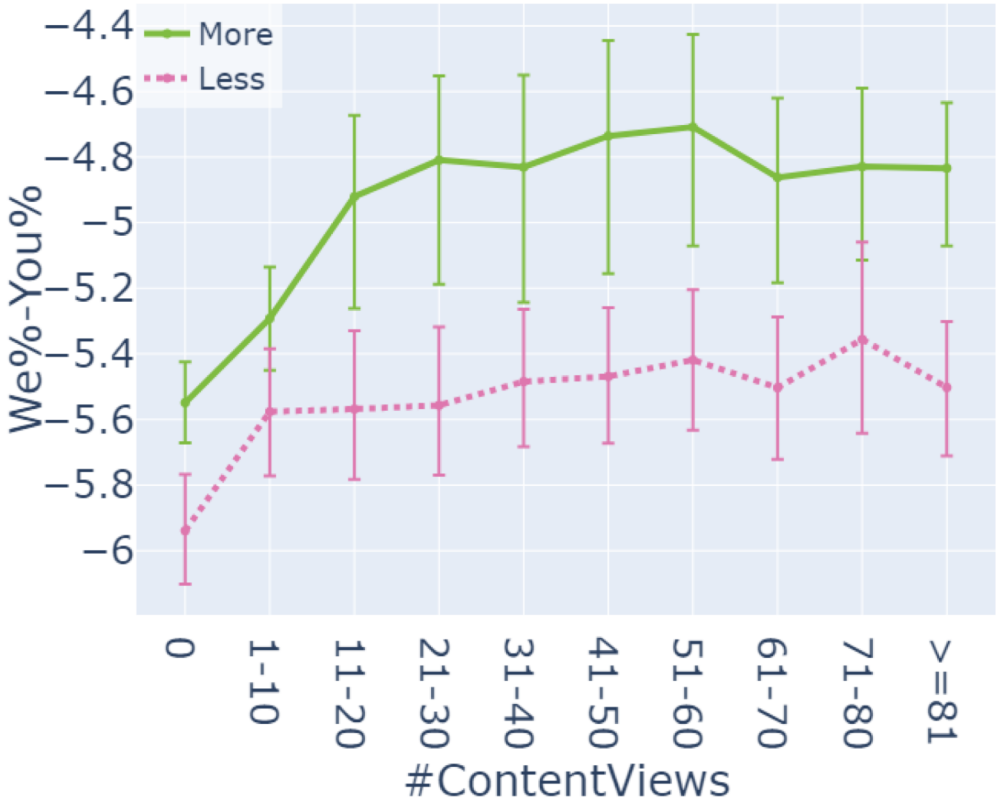
Successful Support Strategies – Results

- More successful messages had:
  - Used **more positive** and **less negative** words.
  - Used **less** words associated with negative emotions such as **sadness** and **fear**.



Successful Support Strategies – Results

- More successful messages had:
  - Used **more 1st person plural pronouns** (e.g. we), and had greater difference between frequencies of 1st person plural pronouns and 2nd person pronouns.

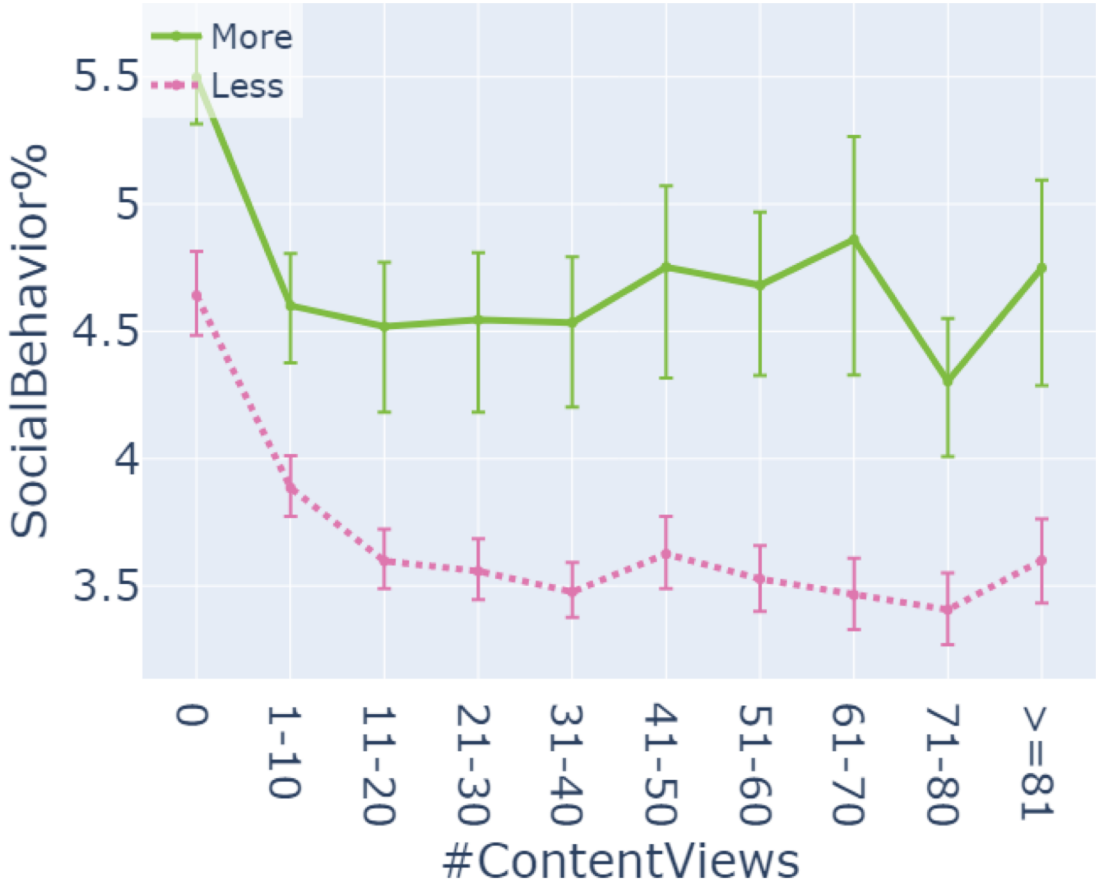


Successful Support Strategies – Results

- More successful messages had:
  - Used **more encouraging phrases** (e.g. well done, good job).

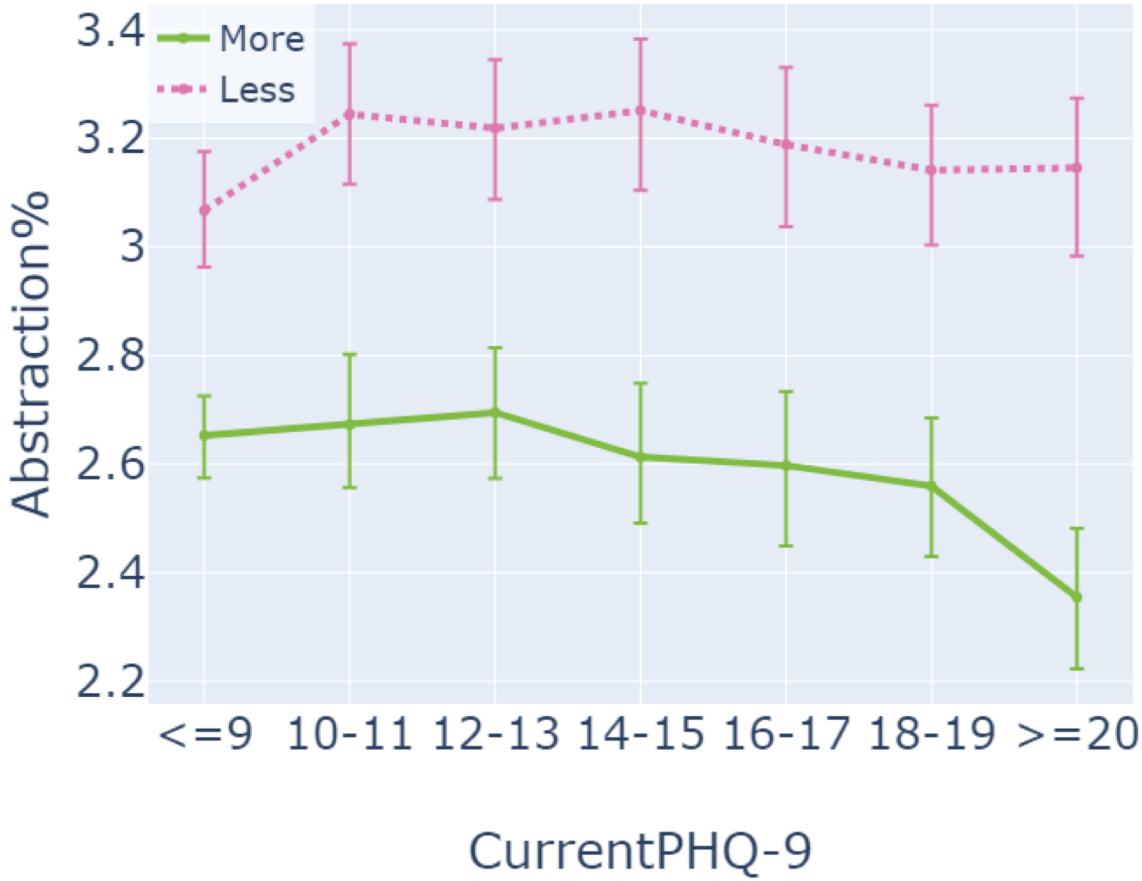
Successful Support Strategies – Results

- More successful messages had:
  - Used **more** words associated with **social behavior (***E.g. help, call, discuss*, and *share.)*



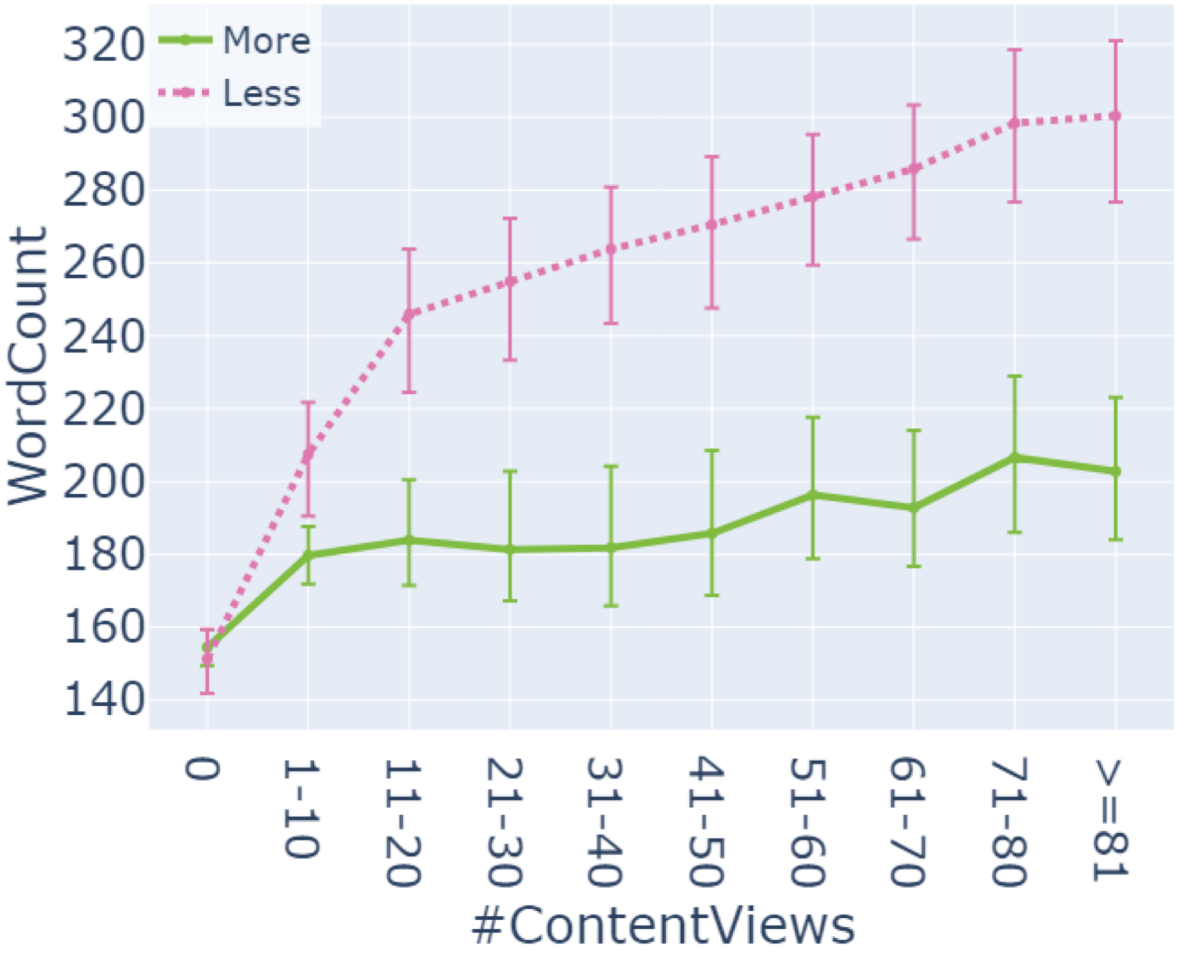
Successful Support Strategies – Results

- More successful messages had:
  - Used **less** words associated with **abstraction.**
    (E.g. think/thought, know, understand, and learn)



Successful Support Strategies – Results

- More successful messages were **shorter**!



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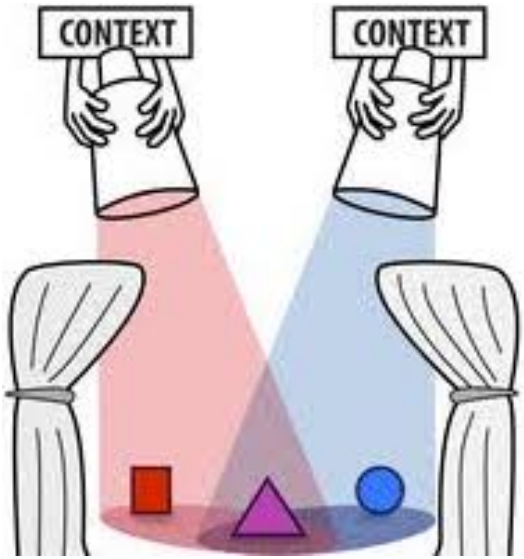
Salient Context-Specific Support Strategies

- Client Context, Supporter Behavior, and Client Outcomes → More complex relationship
  - E.g. Multidimensional Context.

Salient Context-Specific Support Strategies



- Multidimensional Context
  - How may considering the combination of multiple context variables shift how salient a specific support strategy is?
  - Interesting for personalization!

Salient Context-Spec. Supp. Strategies – Method

- Apriori algorithm to mine frequent co-occurrent patterns of multidimensional contexts.
- For each frequent multidimensional context *MC* and each individual support strategy *S*, we can compute *P(S|MC)* for *"high"* and *"low"* clusters separately.

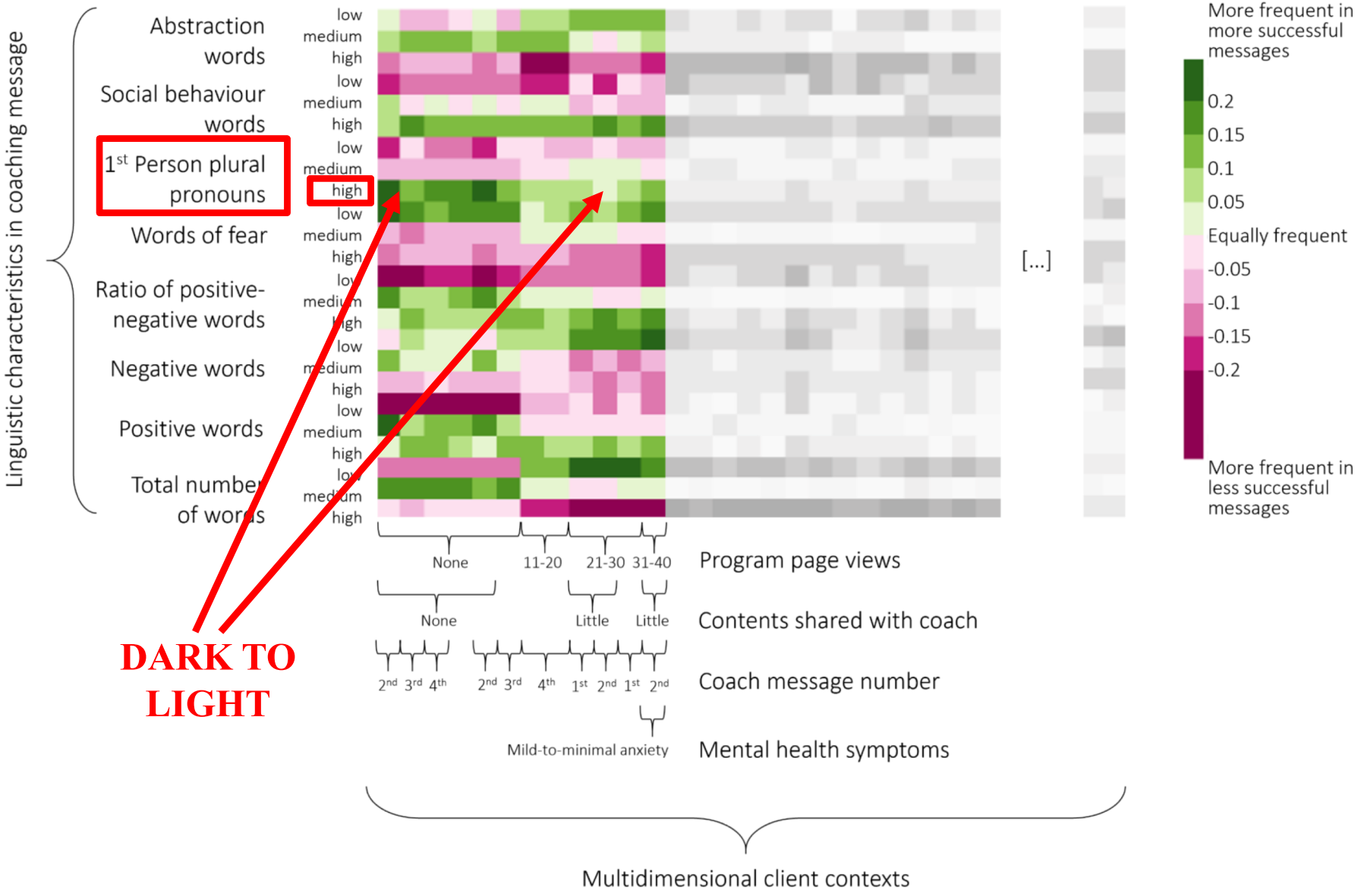
- **Confidence Diff = $P_{high}(S|MC) - P_{low}(S|MC)$**

- **Salience = abs(Confidence Diff)**

Salient Context-Spec. Supp. Strategies – Results

Salient Context-Spec. Supp. Strategies – Results

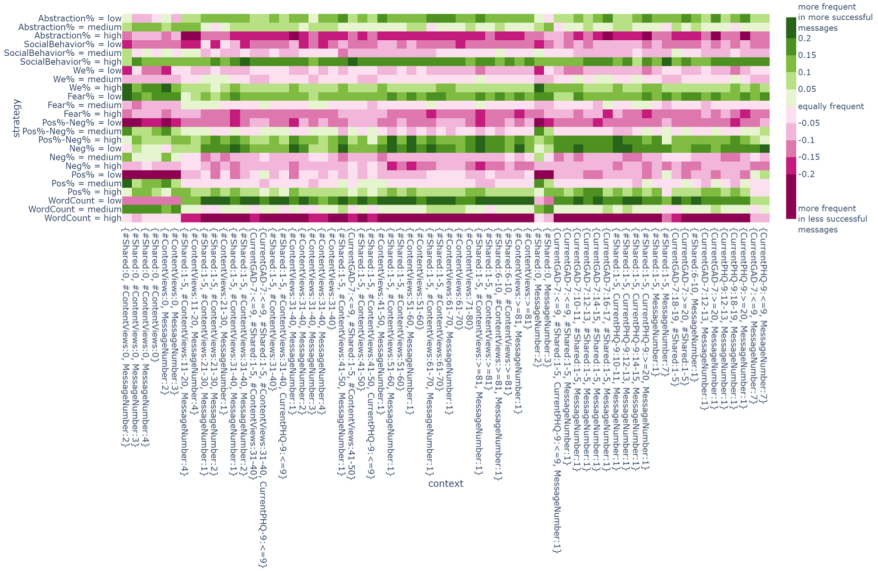
Salient Context-Spec. Supp. Strategies – Results



Salient Context-Spec. Supp. Strategies – Results

- For **less engaged clients**, writing **longer**, **more positive** and **more supportive** reviews is linked with greater outcomes.
- **More engaged clients** appear to benefit more from messages with **less negative words**, **less abstraction**, and **more references to social behaviors**.

See Paper! ☺



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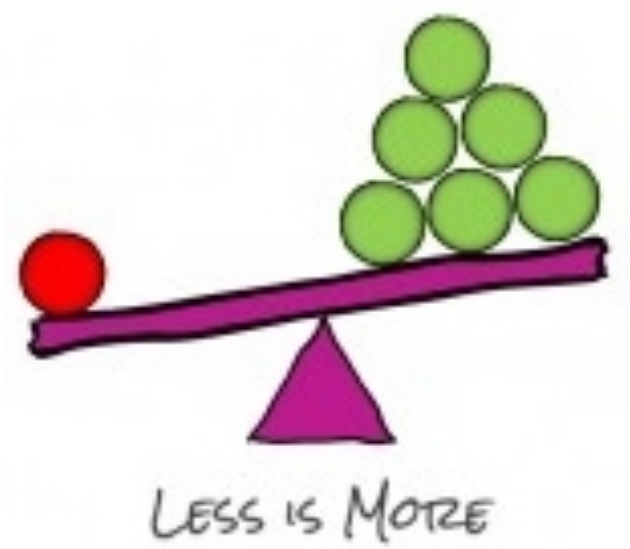
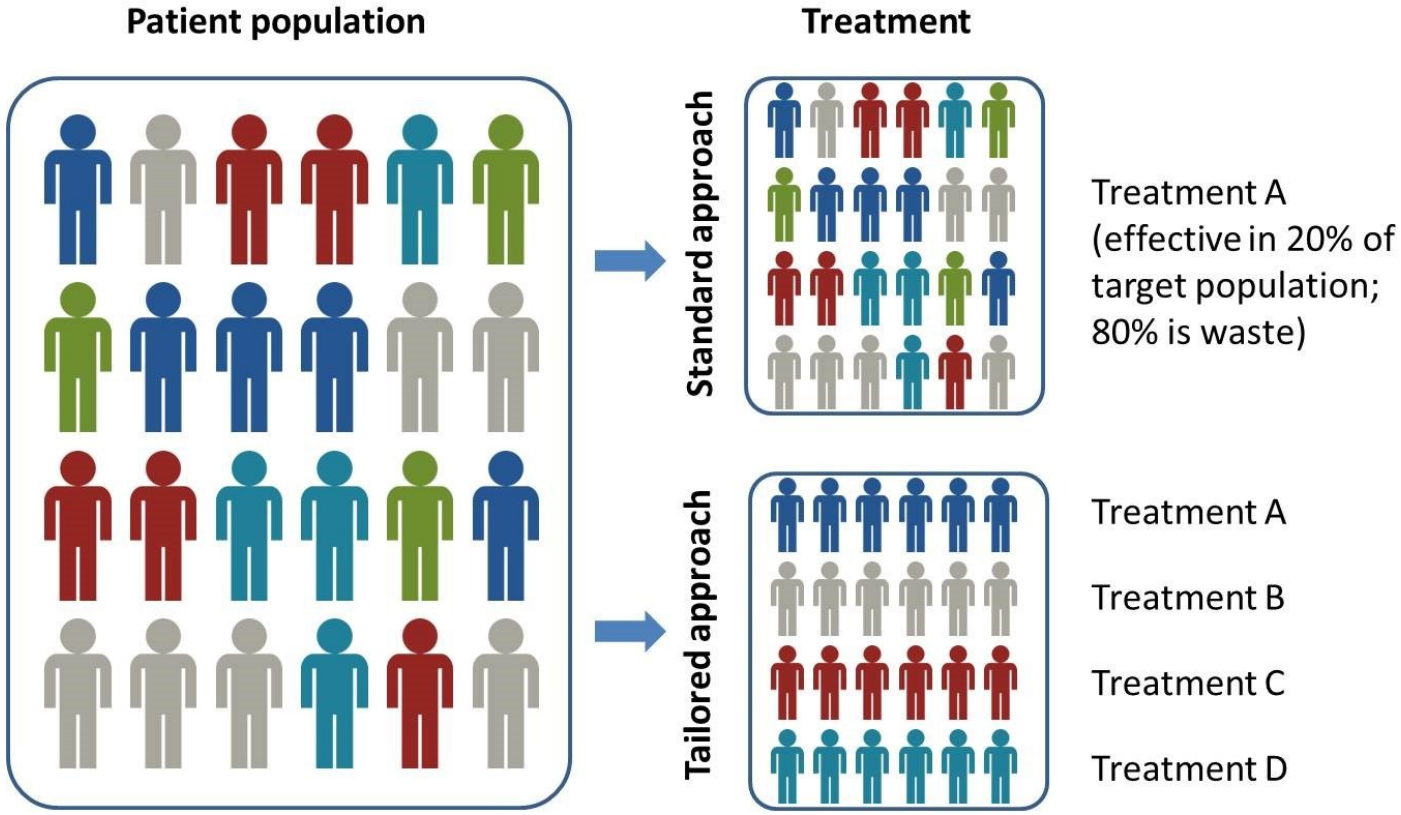
Discussion – Summary of Findings

- Supporter messages that typically achieve higher client outcomes contain more words that are **positive, supportive, related to social behaviors**, and **less abstract**; and those messages tend to be **shorter** than less successful message.



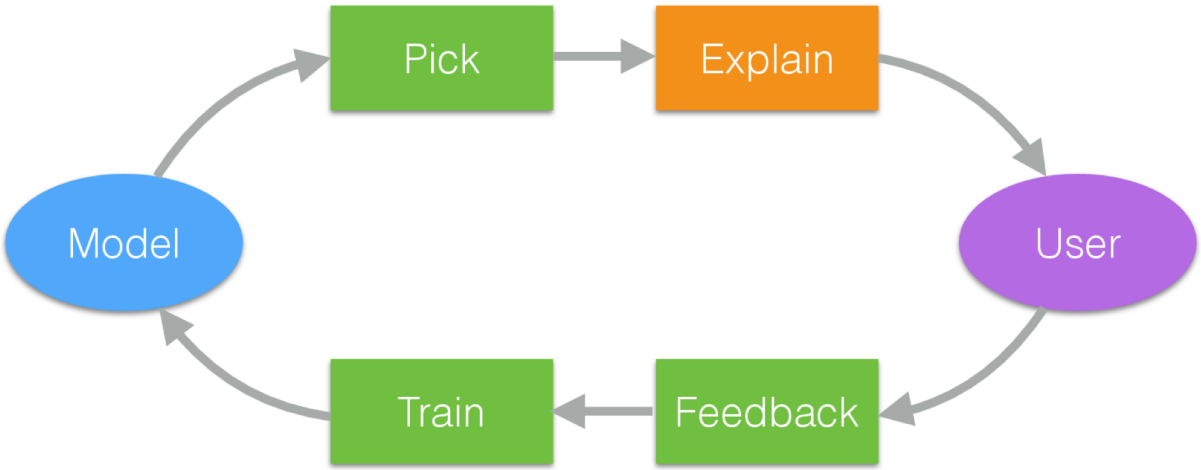
Discussion – Implications for Personalization

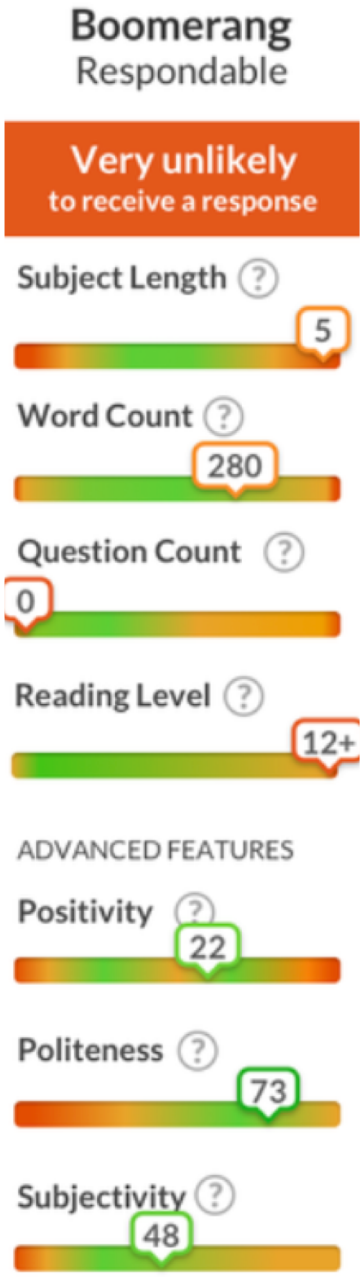
- Further, we demonstrated how the salience and associated success of identified **support strategies can vary dependent on a specific client context**.



Discussion – Conclusion

- Maintaining the Human Touch & Enhancing Supporter Agency
  - Genuine human connection important for working alliance.
  - Creates opportunities to empower supporters → better training or data-driven tools for supporters.





Thank you! ☺

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