Multimodal Behavioral Sensing for Precision Mental Health Care

Thesis Proposal By

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Proposal Outline

- Introduction
- The Curse of Dimensionality Challenge
- Completed Work
- Gaps in Completed Work
- Proposed Work
- Proposed Timeline
- Thesis Contributions

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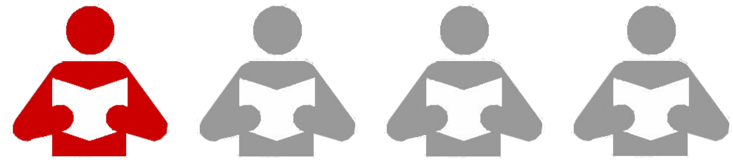
Mental Health Disorders are Very Prevalent!

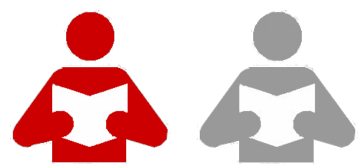
Lifetime occurrence within the US



Higher in certain groups.

- In any year, for college students

- Lifetime occurrence for patients with multiple sclerosis (pwMS)



Covid-19 and social distancing → increased prevalence

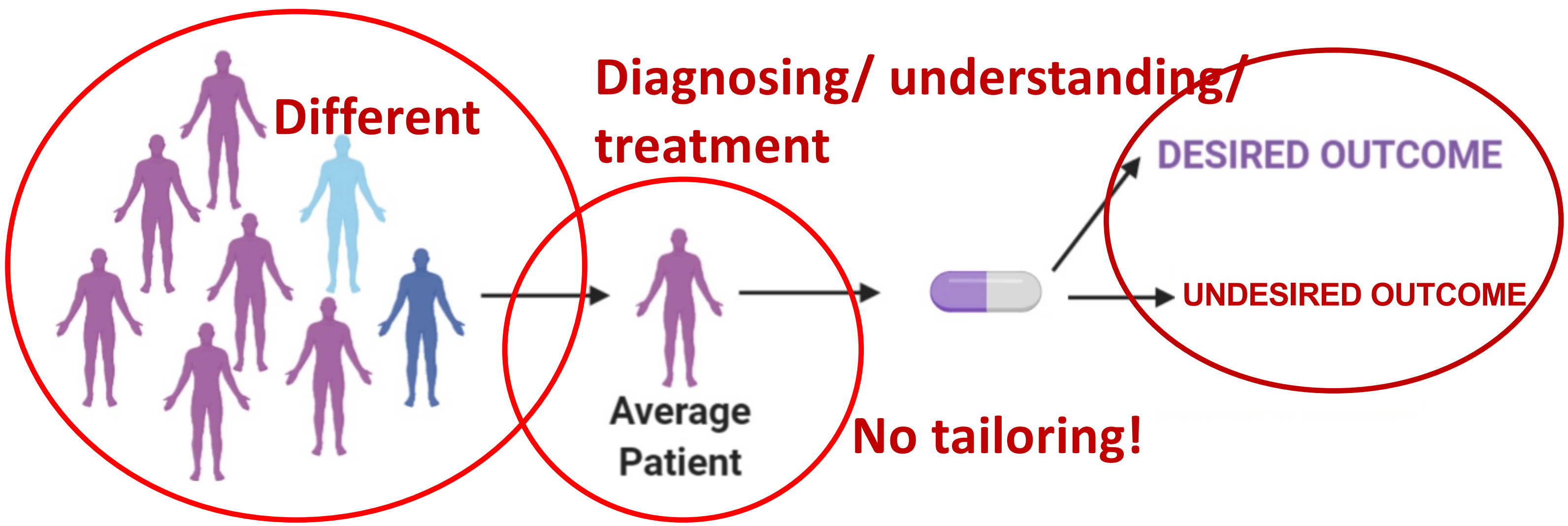
The Burden of Mental Illnesses is Huge!

- Leading cause of disability and suicide.
- Linked with lower productivity, performance, and participation in schools, universities, and workplaces.

Diagnosis, understanding, and treatment → A public health priority

Barriers for Mental Health Care

- Many people do not seek help and thus, go undiagnosed.
    - Lack of awareness, stigma, limited access



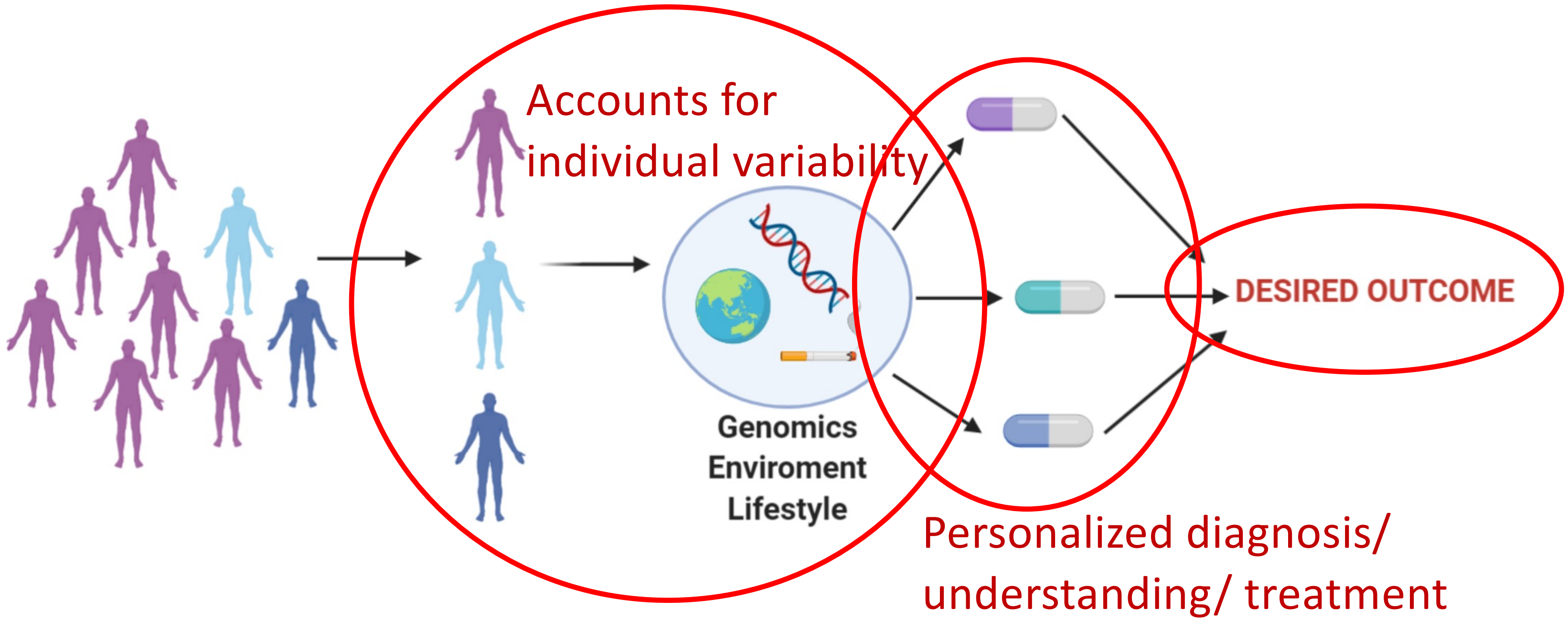
- For some people, diagnosis can take a long time → Delayed care.

The Need for Precision!

- Hence, there is a need to develop digital tools that
  - Increase access to mental health care,
  - while making diagnosis and treatment more precise by using data-driven insights and predictions.

Precision Health

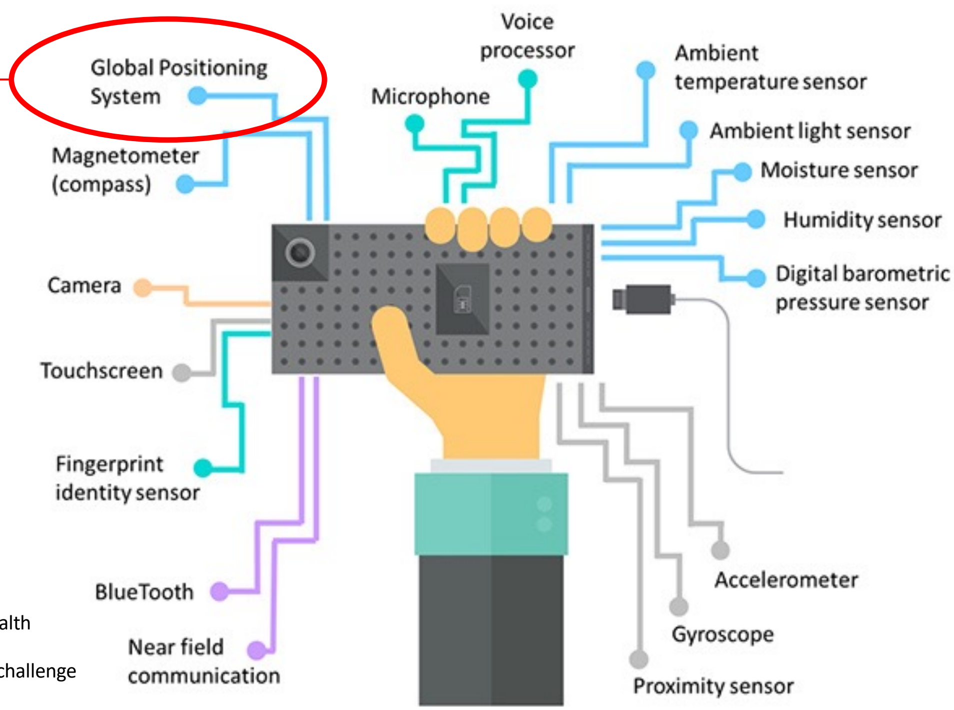
- An emerging data-driven approach to healthcare that:



Precision Mental Health (Precision MH)

- While genetics play a role in mental health, research has shown that behaviors, environment, and social context play a much larger role*. → Precision MH focus.
- Can be captured by smartphones and fitness trackers.

Time spent at home (rest/ engagement with the world)



*References:
1) Leonard Bickman, Aaron R Lyon, and Miranda Wolpert. Achieving precision mental health through effective assessment, monitoring, and feedback processes. 2016.
2) Michael Rutter. "The interplay of nature, nurture, and developmental influences: the challenge ahead for mental health". In: Archives of General Psychiatry 59.11 (2002), pp. 996–1000.

Precision Mental Health (Precision MH)

- While genetics plays a role in mental health, research has shown that behaviors, environment, and social context play a much larger role. → Precision MH focus.
- Can be captured by smartphones and fitness trackers.

The Biggest Problem in Precision MH

- Challenges
  - Variety of **data sources**
    - *e.g.*, data from many sensors in multiple devices.
  - From patients with different **multi-morbidities**
  - Patients in **different contexts**
    - e.g., demographics, medical history, past behaviors
- Such high-dimensional data
  - Creates new opportunities for precision
  - BUT makes it harder to derive robust insights and models for real-world scenarios.
  - Is the biggest problem in Precision MH!

    → **The Curse of Dimensionality Challenge**

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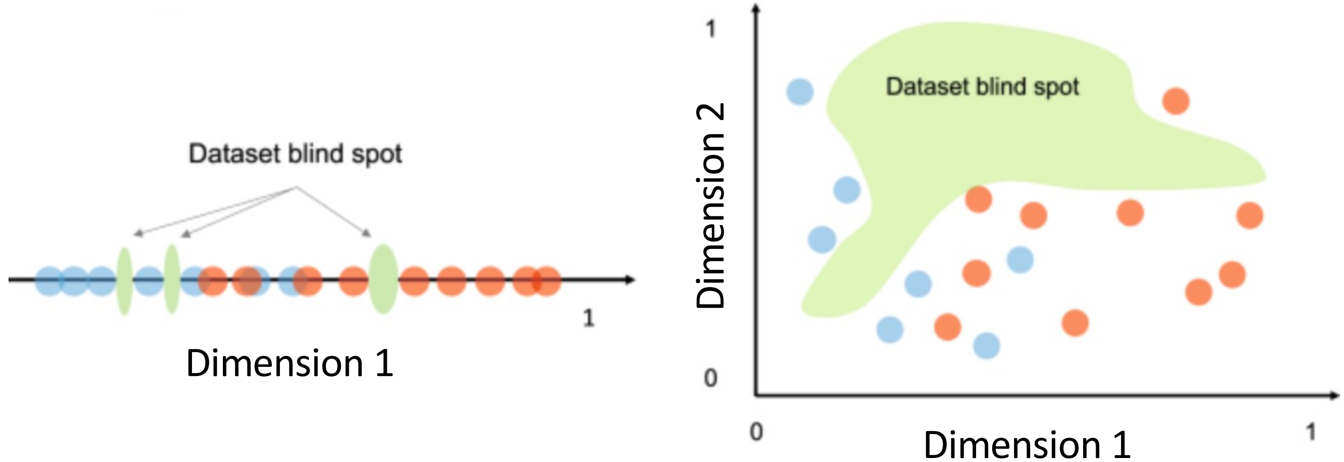
The Curse of Dimensionality Challenge

- Number of samples needed to estimate a function grows exponentially w.r.t. the number of input variables or features.

SAME NUMBER OF SAMPLES



- More blind spots → highly variable models (*e.g.*, vastly different selected features) and highly variable estimates of true model performance, across different subsamples of the same dataset.

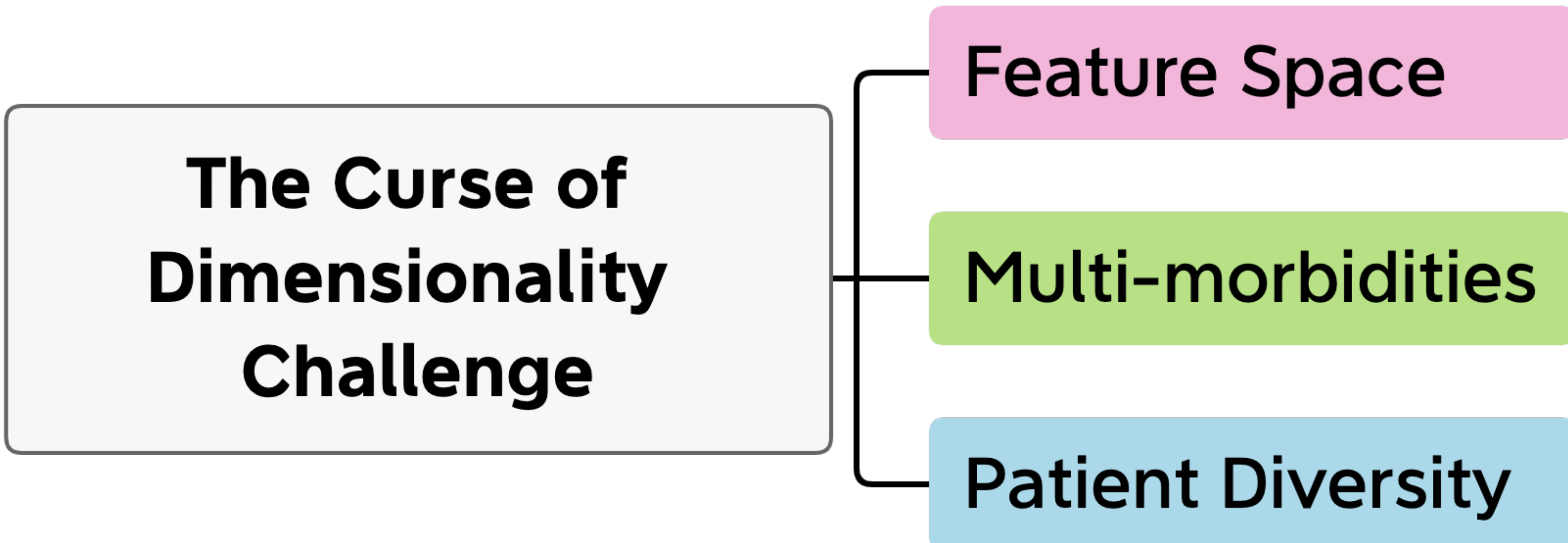
Thesis Problem Statement

This thesis focuses on developing and presenting novel methods that address **the curse of dimensionality challenge** with respect to:

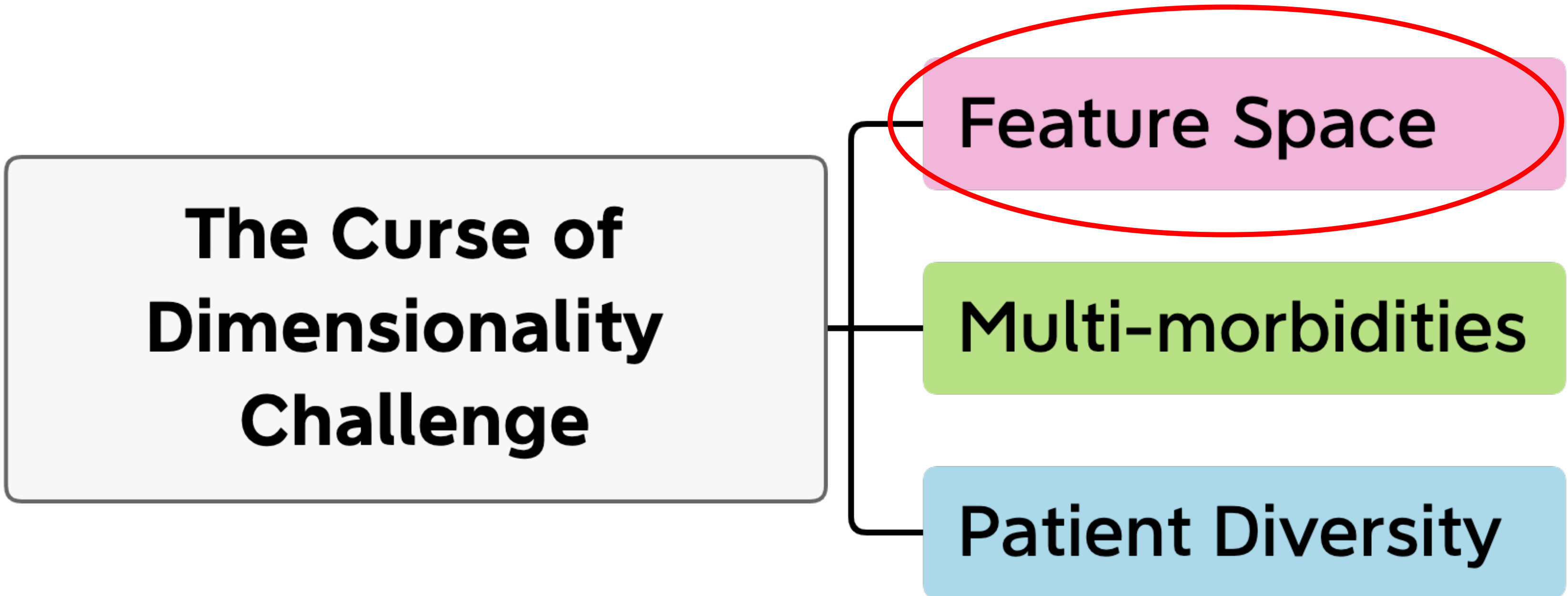
a) the feature space
b) multiple outcomes stemming from co-morbid medical conditions, and
c) diversity in patient contexts and characteristics.

Explanation to follow…

The Curse of Dimensionality Challenge Contd.

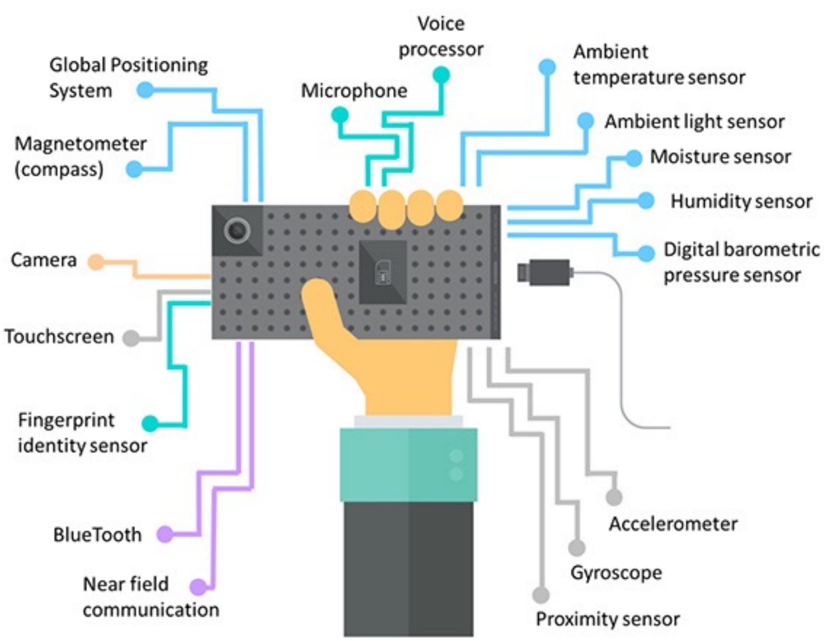


The Curse of Dimensionality Challenge Contd.



The Curse of Dimensionality w.r.t. the Feature Space

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Many sensors in multiple devices



The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - High cost of data collection → small sample size
  - Survey-based outcomes burden users

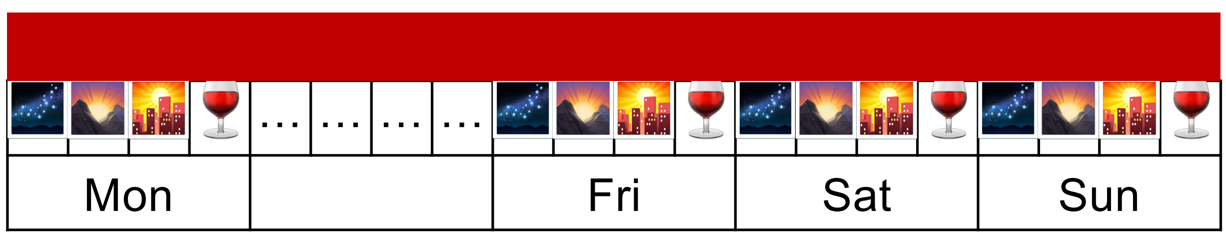
		Not at all	Several days	More than half the days	Nearly every day
1.	Little interest or pleasure in doing things	0	1	2	3
2.	Feeling down, depressed, or hopeless	0	1	2	3
3.	Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4.	Feeling tired or having little energy	0	1	2	3
5.	Poor appetite or overeating	0	1	2	3
6.	Feeling bad about yourself — or that you are a failure or have let yourself or your family down	0	1	2	3
7.	Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8.	Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3
9.	Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3

The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Same features from different temporal slices are useful

Step_Count_All_All:

- A measure of overall physical activity

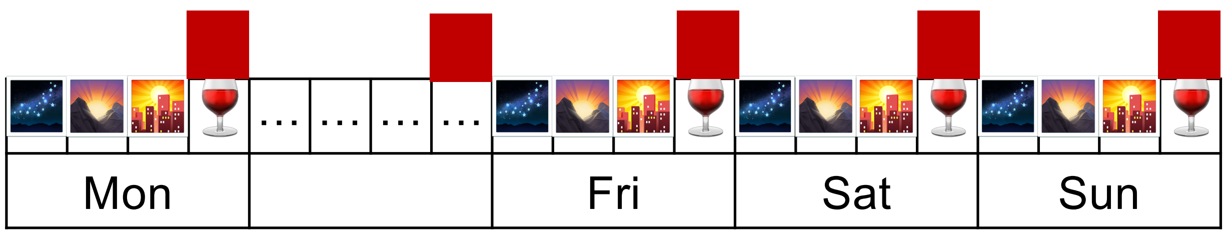


The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Same features from different temporal slices are useful

Step_Count_All_Evenings:

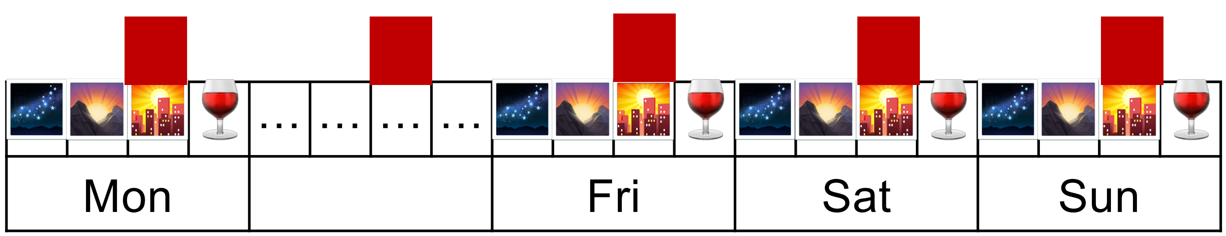
- may indicate after work exercise/ activities



The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Same features from different temporal slices are useful

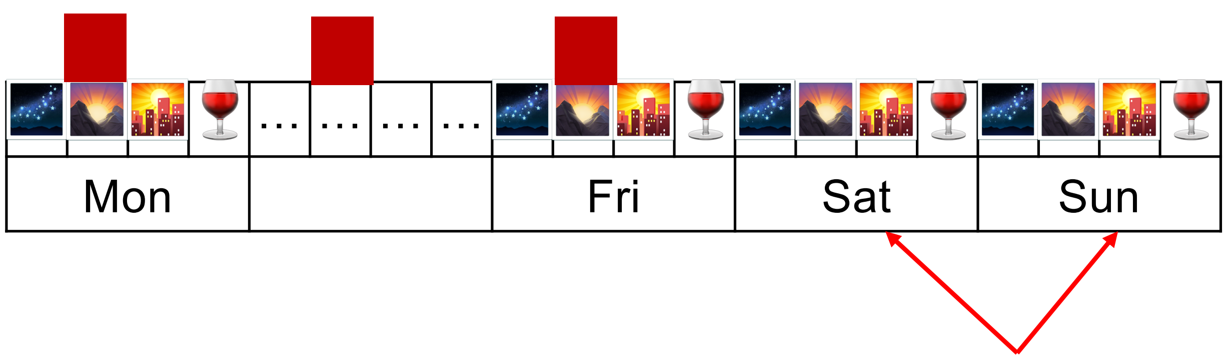
Whereas Step_Count_All_Afternoons:
- May be more related to occupation



The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Same features from different temporal slices are useful

Step_Count_Weekday_Mornings:
- May indicate active mornings

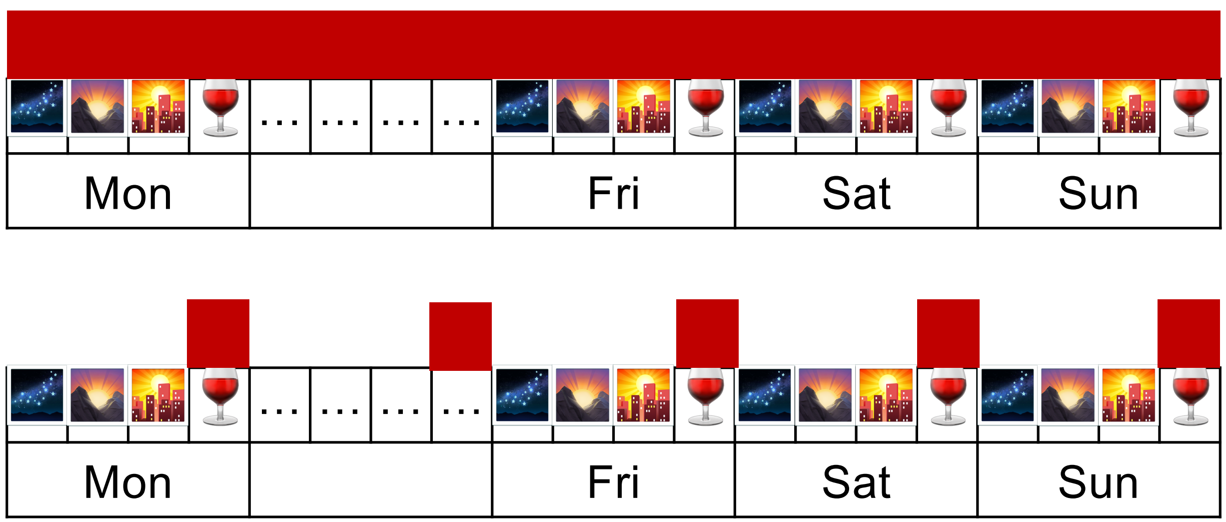


Doesn’t include weekend

The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Same features from different temporal slices are useful

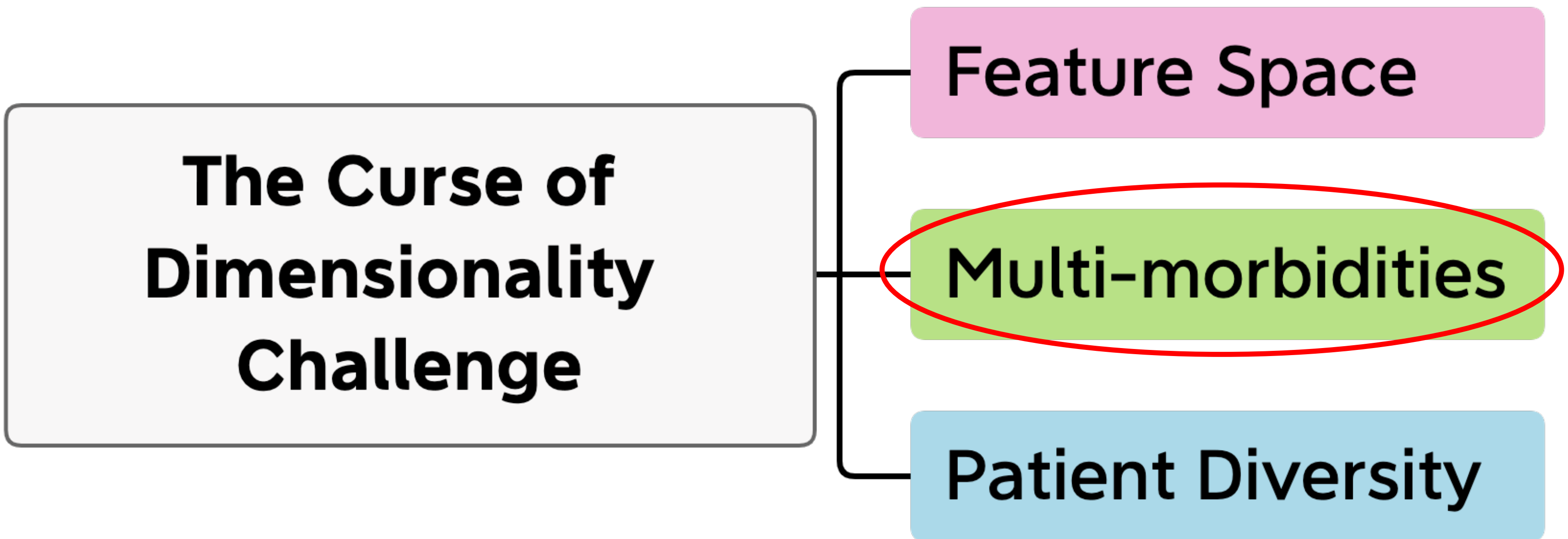
Note: Temporal slices overlap



The Curse of Dimensionality w.r.t. the Feature Space Contd.

- When analyzing sensor data or interaction logs, the number of features >> number of samples:
  - Same features from different temporal slices are useful
  - As they may indicate different things
  - But this further increases the size of the feature space
  - And adds to the curse of dimensionality in the feature space

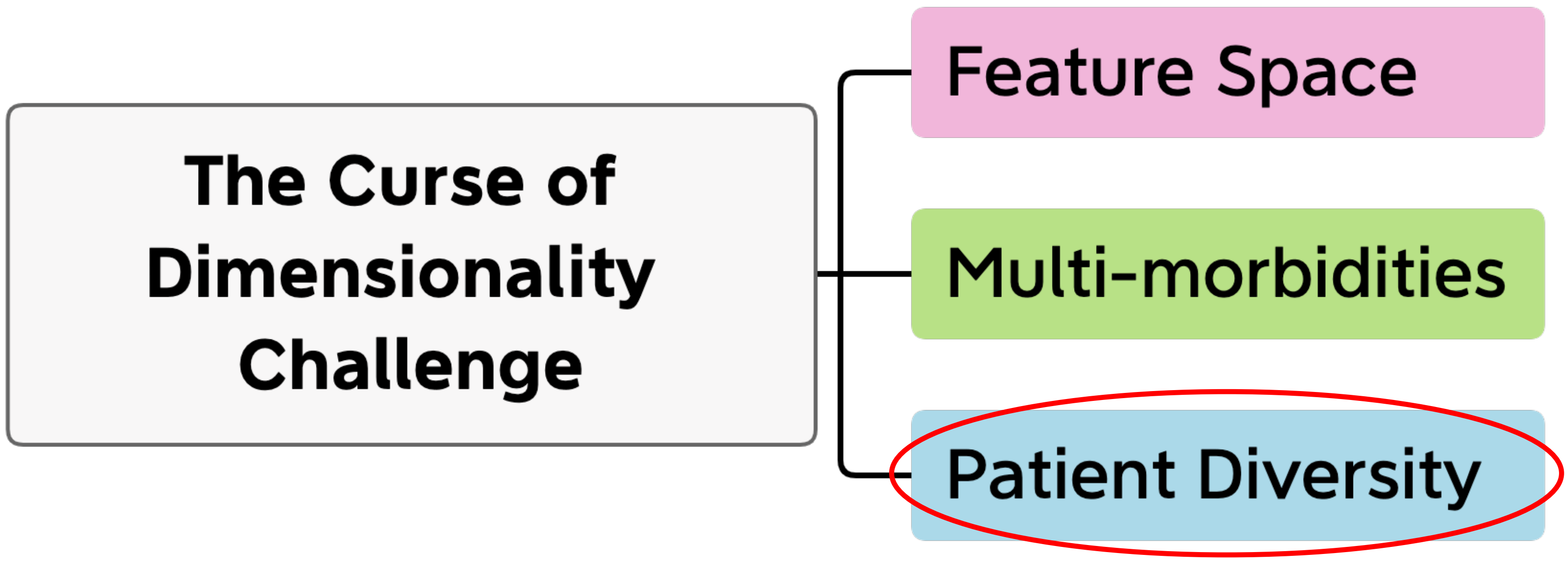
The Curse of Dimensionality Challenge Contd.



The Curse of Dimensionality w.r.t. Multi-morbidities

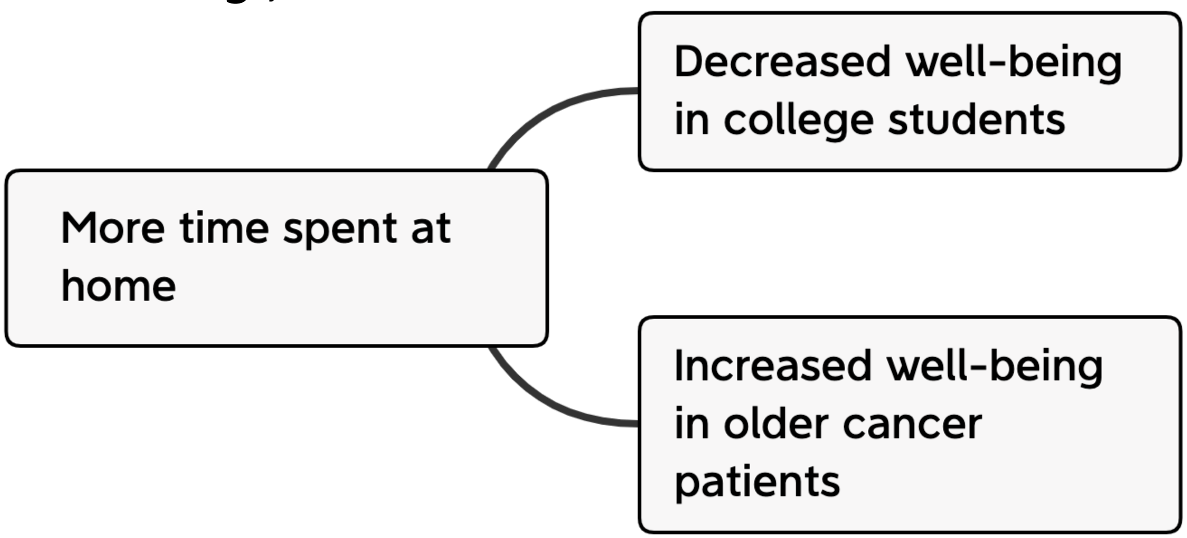
- Multimorbidity is the co-occurrence of >=2 chronic conditions.
- 70% of people with a MH disorder have co-morbidities.
- Co-morbid conditions could be the most important factor during diagnosis or treatment of the primary condition.
- Yet, they are often ignored in clinical trials and studies. In many studies, people with co-morbid conditions are explicitly excluded.
- Hence, it is important to consider conditions co-morbid with the primary condition, even though this will add to the curse of dimensionality by increases the number of outcomes.

The Curse of Dimensionality Challenge Contd.



The Curse of Dimensionality w.r.t. Patient Diversity

- Previous work shows that the relationship between behaviors and outcomes may be dependent on patient context and characteristics. *E.g.,*



- → Accounting for the patient's context is important.

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Completed Work

- S1: Detecting Depression and Loneliness In College Students
- S2: Forecasting End of Semester Depression In College Students
- S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period
- S4: Understanding Client Support Strategies to Improve Clinical Outcomes in an Online Mental Health Intervention

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S1: Detecting Depression and Loneliness In College Students

Capture behavior and symptoms

Detect Depression

Detect Loneliness

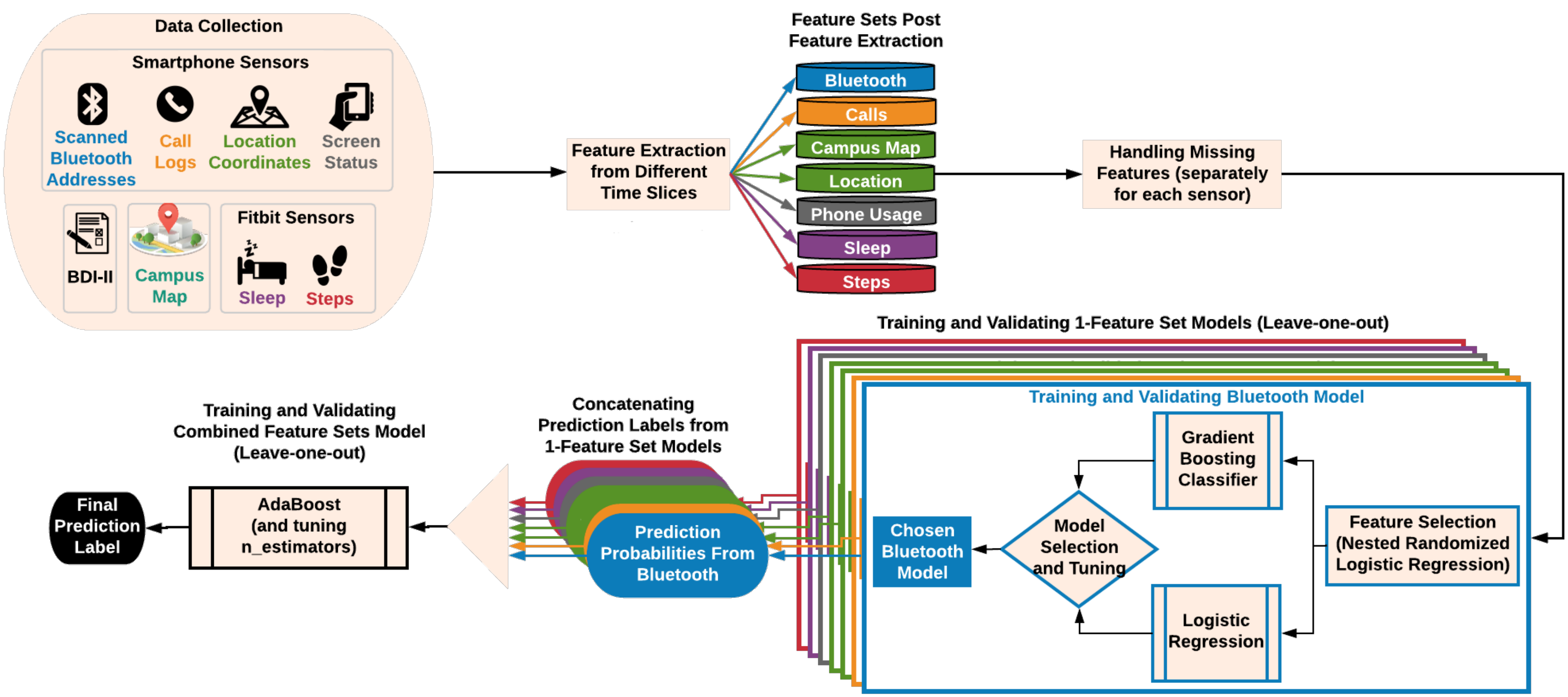
S1: Gaps in Previous Work

- Does not address situations where we have limited ground truth as compared to the feature space:
  - Relies on frequent measurement (*e.g.* every week) → burden
  - Limits the number of features (*e.g.* no temporal slicing)
  - → doesn't face the curse of dim. w.r.t. the feature space
- Rarely evaluates if the same approach can be used to detect multiple co-morbid outcomes.
  - → doesn't face the curse of dim. w.r.t. multi-morbidities

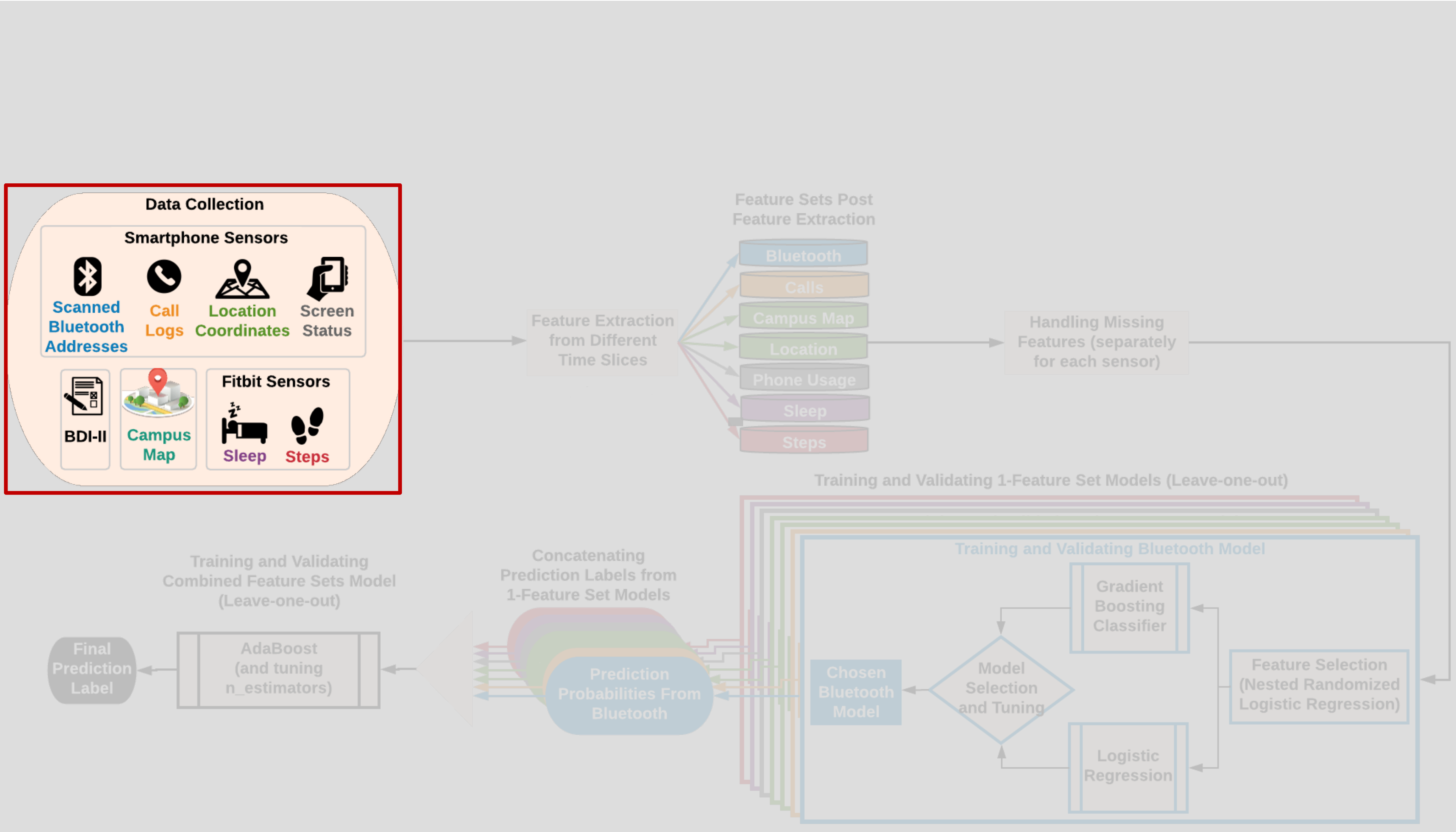
References

- Luca Canzian and Mirco Musolesi. 2015. Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. In Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing. ACM, 1293–1304.
- Asma Ahmad Farhan, Chaoqun Yue, Reynaldo Morillo, Shweta Ware, Jin Lu, Jinbo Bi, Jayesh Kamath, Alexander Russell, Athanasios Bamis, and Bing Wang. 2016. Behavior vs. introspection: refning prediction of clinical depression via smartphone sensing data.. In Wireless Health. 30–37.
- Sohrab Saeb, Mi Zhang, Christopher J Karr, Stephen M Schueller, Marya E Corden, Konrad P Kording, and David C Mohr. 2015. Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. Journal of medical Internet research 17, 7 (2015).
- Fabian Wahle, Tobias Kowatsch, Elgar Fleisch, Michael Rufer, and Stef Weidt. 2016. Mobile sensing and support for people with depression: a pilot trial in the wild. JMIR mHealth and uHealth 4, 3 (2016).
- Rui Wang, Weichen Wang, Alex daSilva, Jeremy F Huckins, William M Kelley, Todd F Heatherton, and Andrew T Campbell. 2018. Tracking Depression Dynamics in College Students Using Mobile Phone and Wearable Sensing. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 2, 1 (2018), 43.

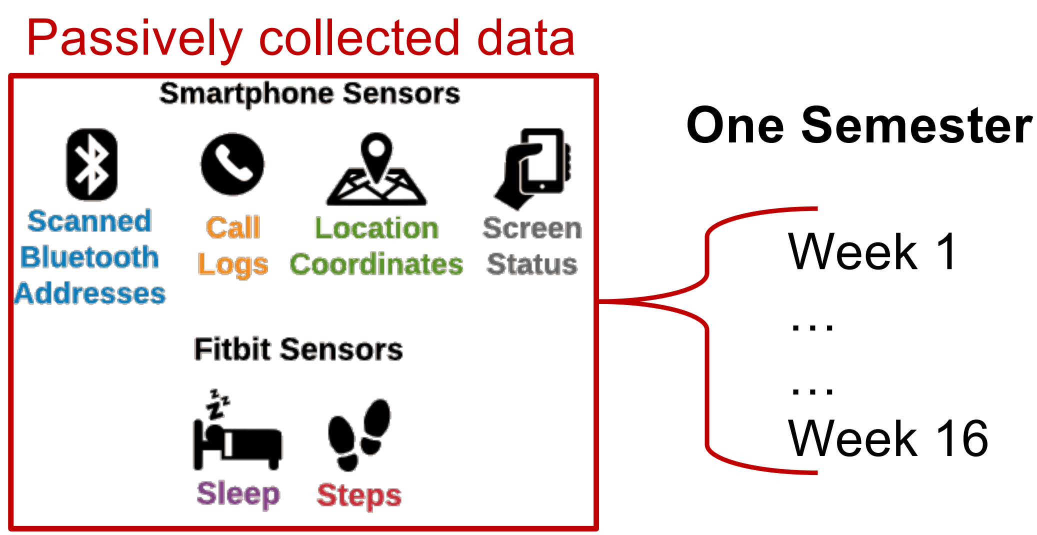
S1: Methodology



S1: Methodology

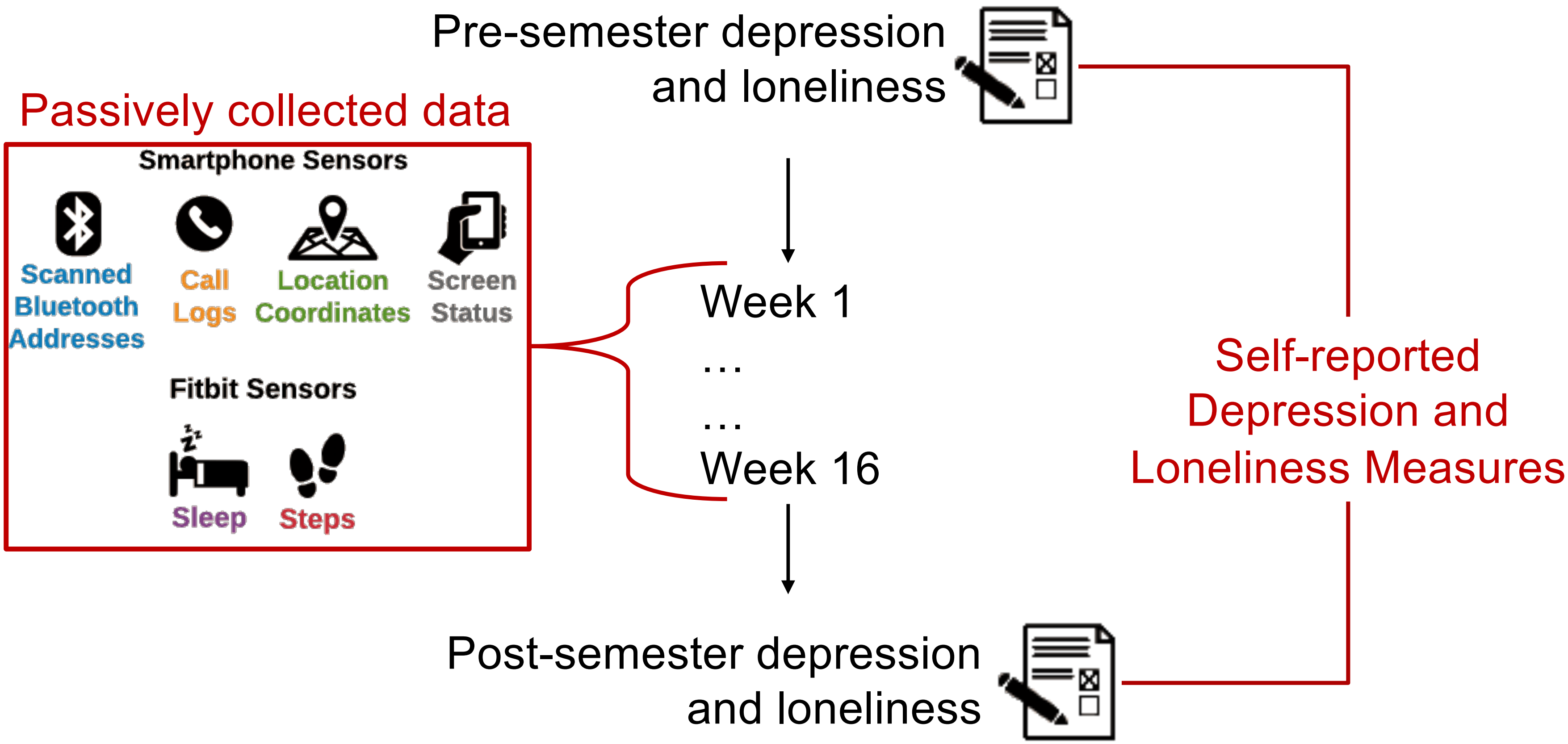


S1: Methodology – Data Collection



- 138 First Year College Students at the same University
- Aware API for iOS and Android, and Fitbit

S1: Methodology – Data Collection

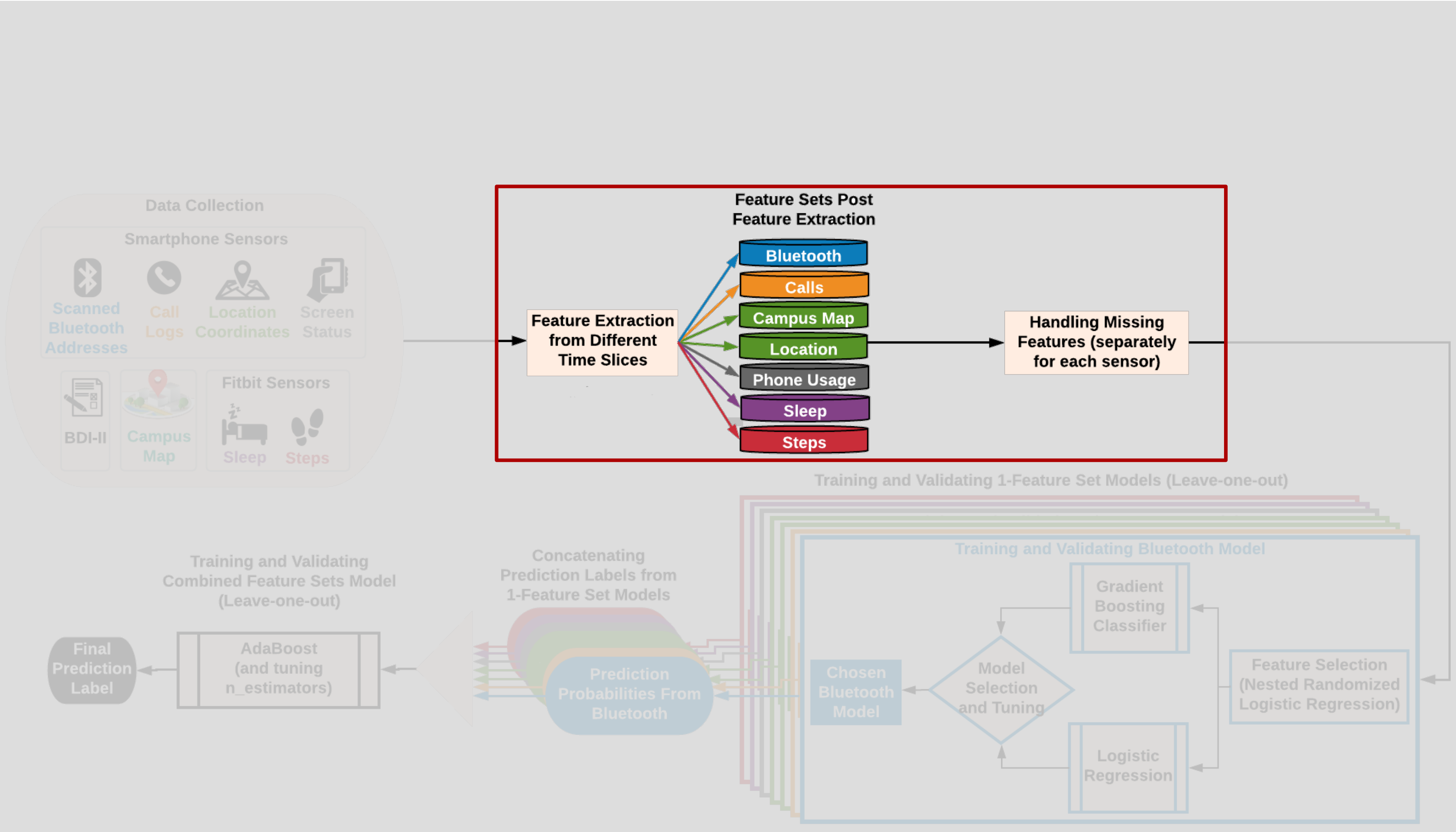


- 138 First Year College Students
- Aware API for iOS and Android, and Fitbit

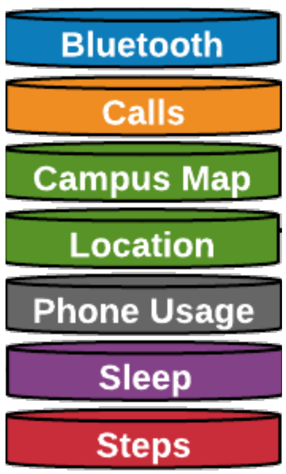
S1: Methodology – Data Collection Outcomes

- Post-semester Depression
  - Binary: “no depression” vs. “has depression”
- Change in Depression
  - Binary: “severity level remains the same” vs. “severity level worsens” (No one improved)
- Post-semester Loneliness
  - Binary: “high loneliness” vs. “low loneliness”
- Change in Loneliness
  - 3-class: “increased” vs. “decreased” vs. “remained the same”

S1: Methodology

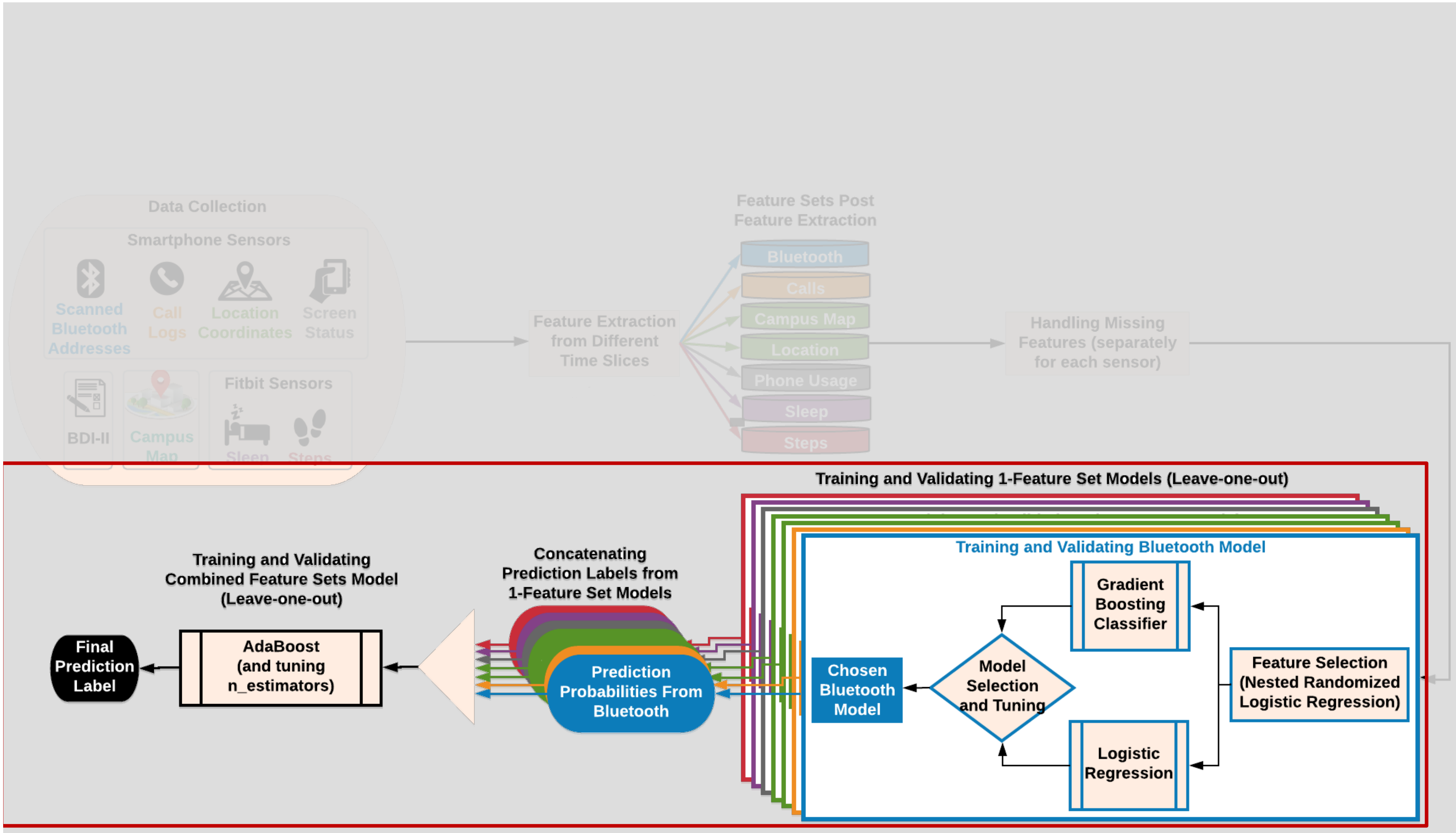


S1: Methodology – Feature Extraction



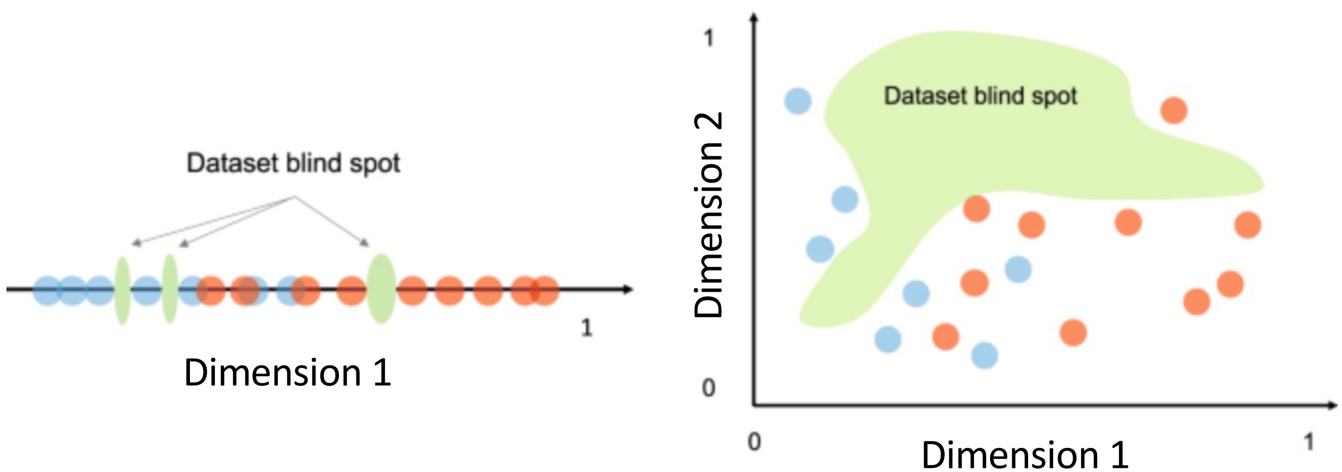
- We collect data from 7 feature sets/ sensors.
- From each, we extract features from 45 temporal slices.
- 50K features and only 79 people from all feature sets!
  → The curse of dim. w.r.t. the feature space applies.

S1: Methodology



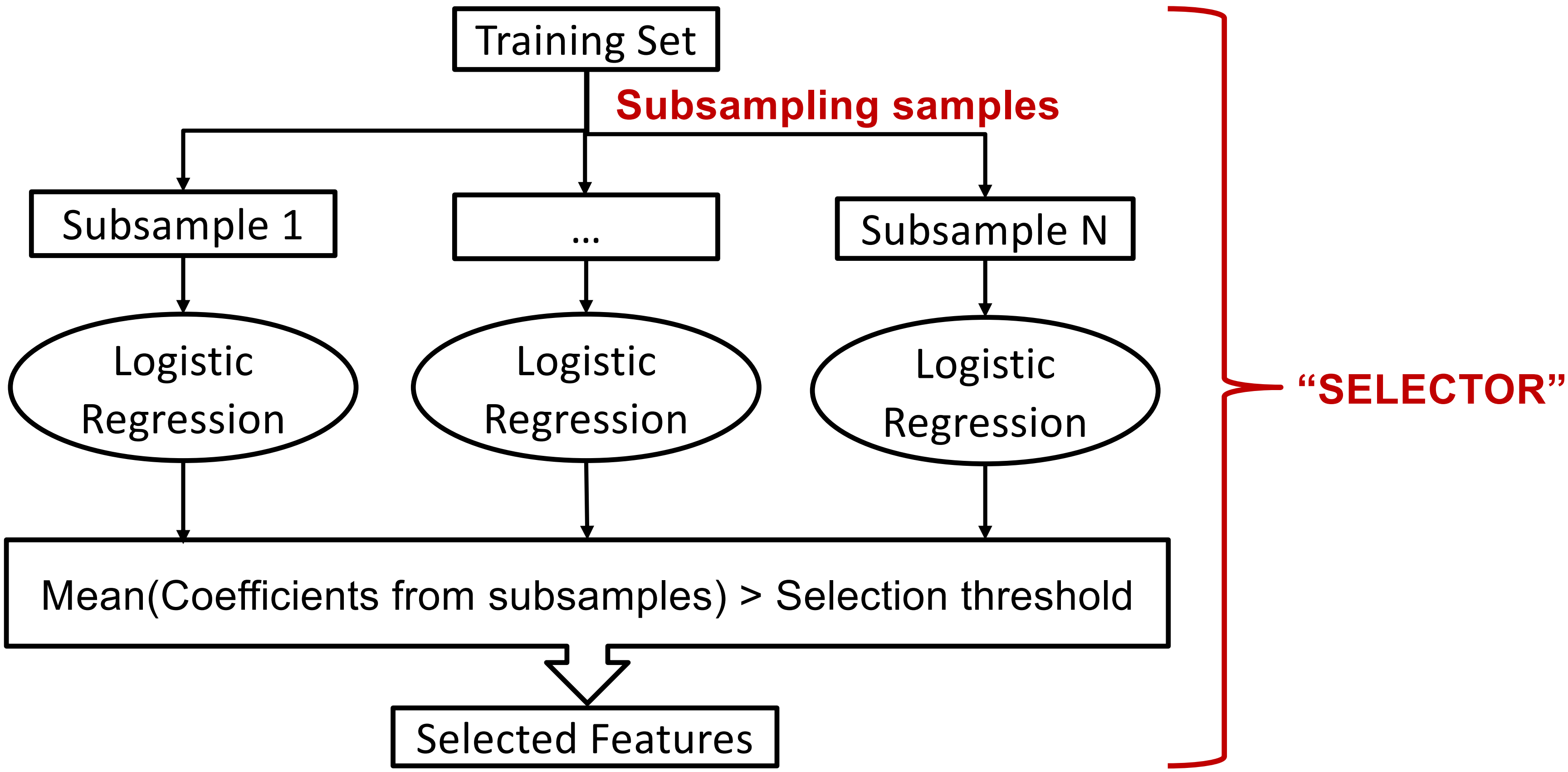
S1: Methodology – Feature Selection & Modeling Contd.

- Even 1-sensor models: 6-10K features and only ~110 people
- Off-the-shelf approaches for 1-sensor predictions:
  - Poor accuracy
  - High variability in selected features across LOO folds
  - RECALL: Blind spots → high variability, low robustness



- Need a new method for stable feature selection
  - Feature space decomposition → reduce blind spots

S1: Methodology – Feature Selection & Modeling Contd.



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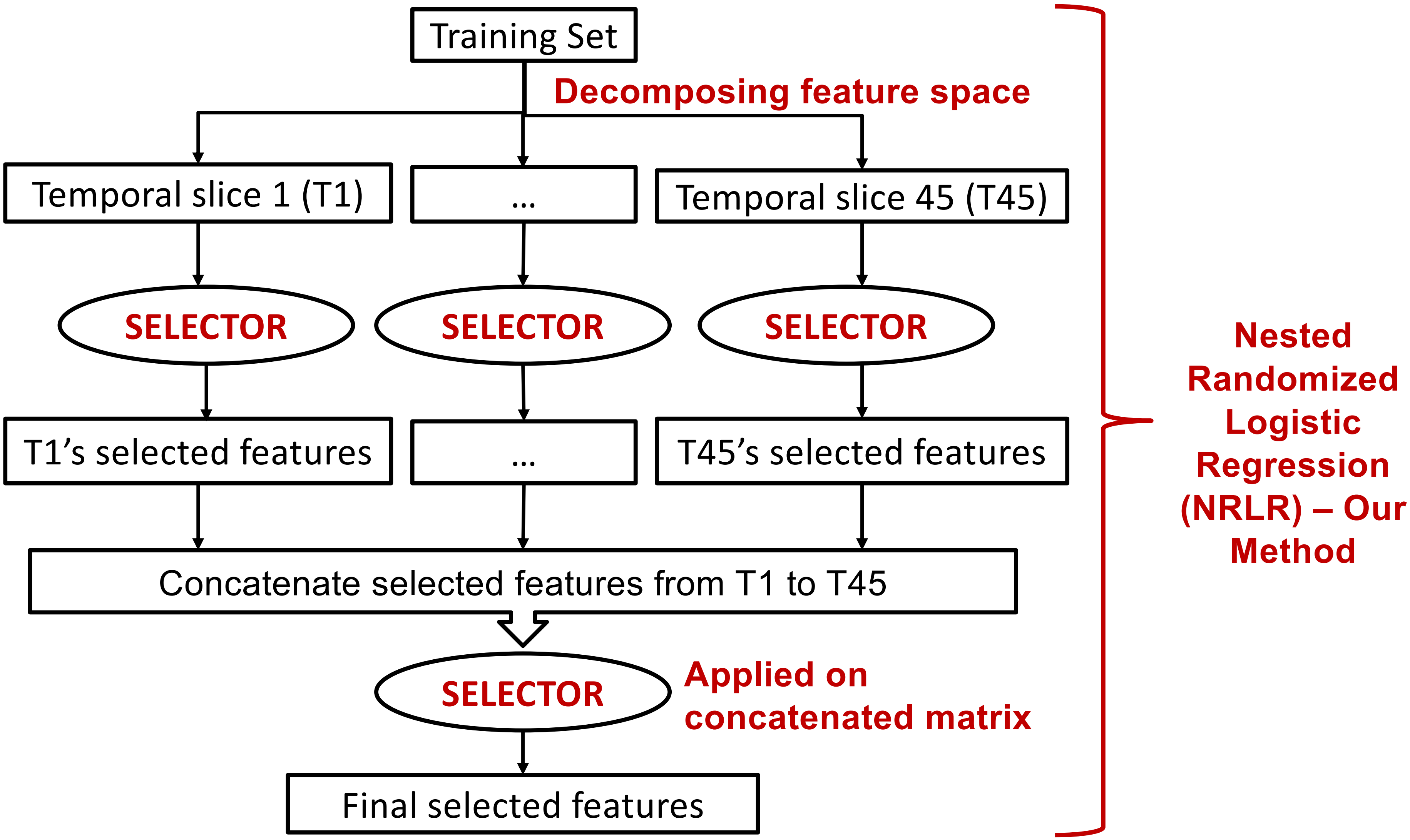

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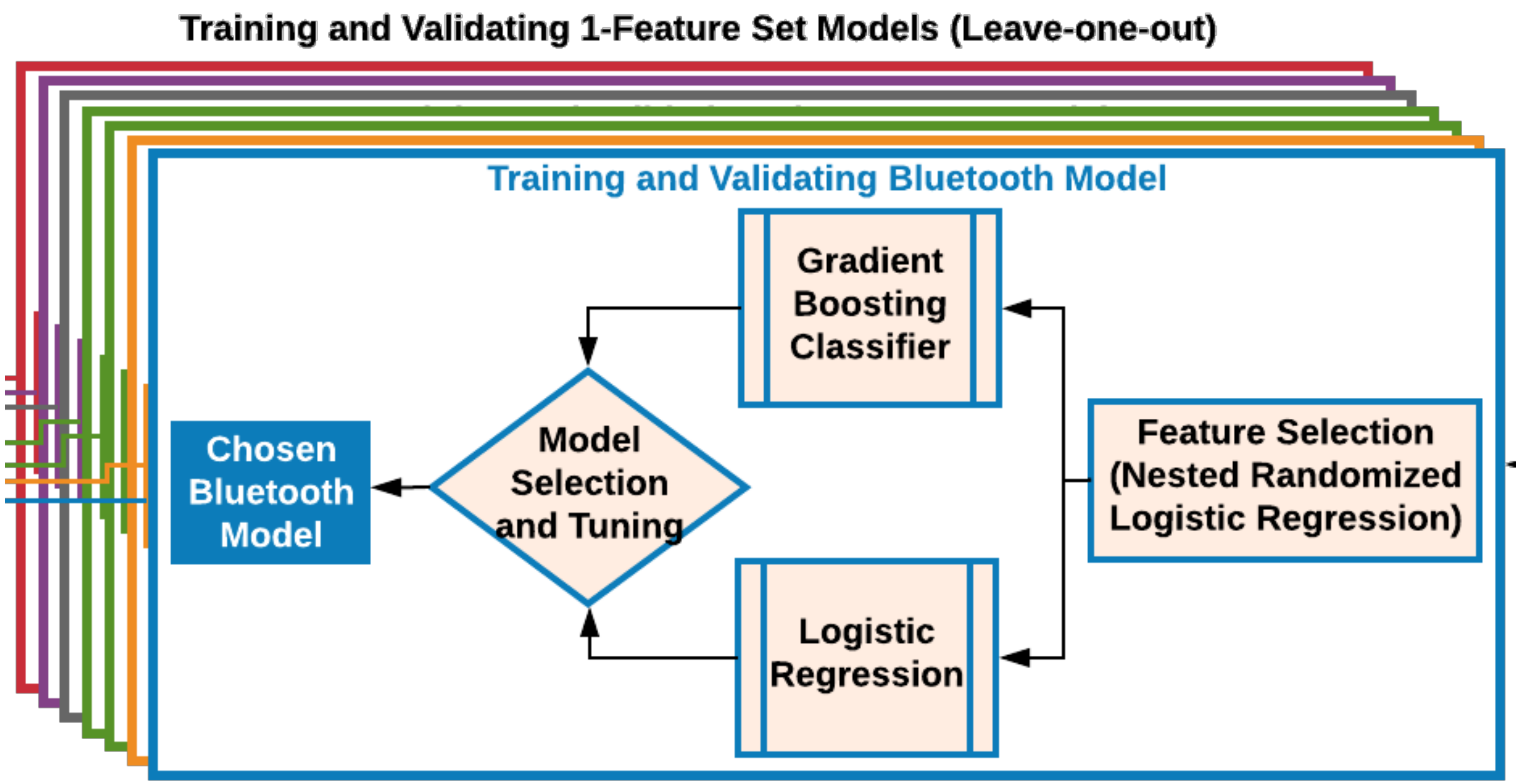
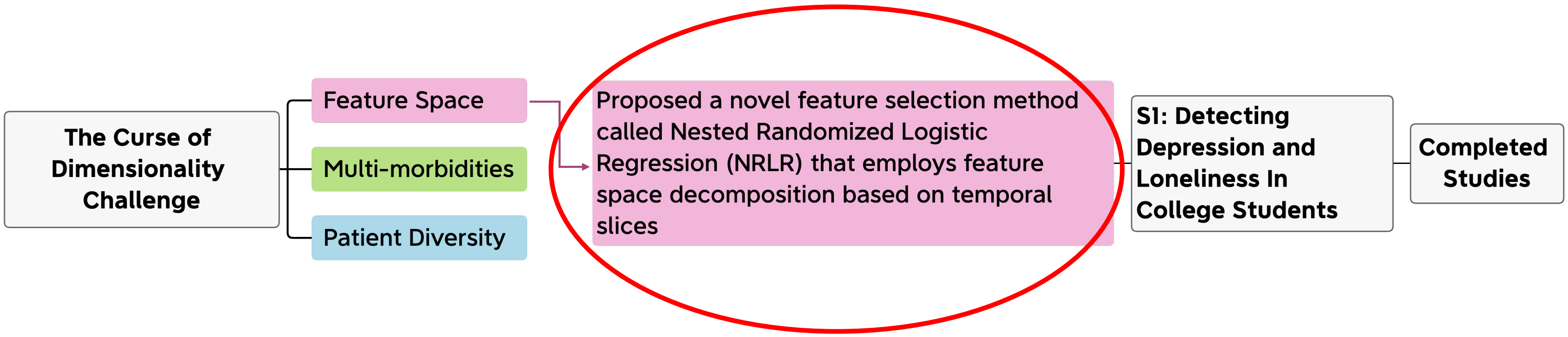


S1: Methodology – Feature Selection & Modeling Contd.

How does this address the curse of dimensionality?



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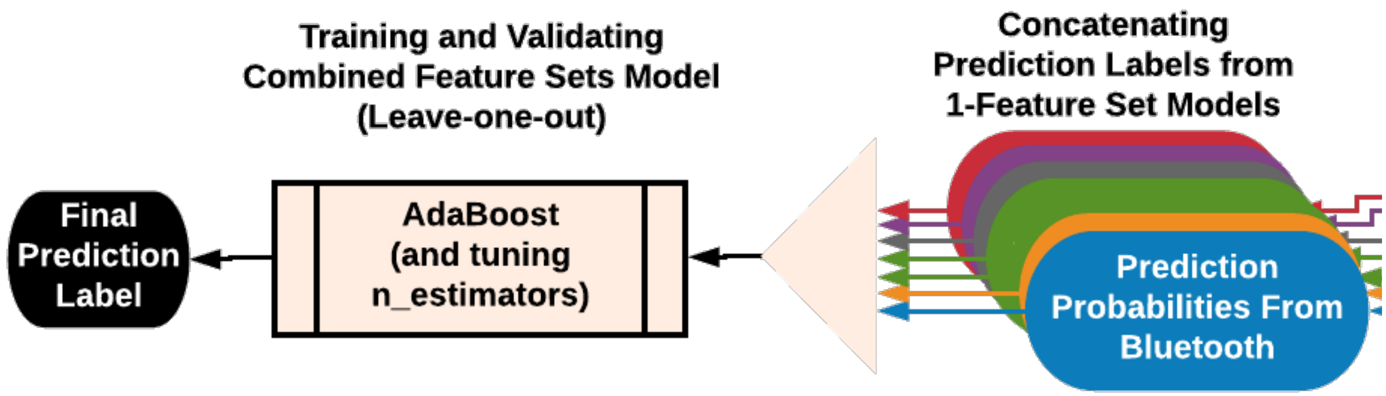
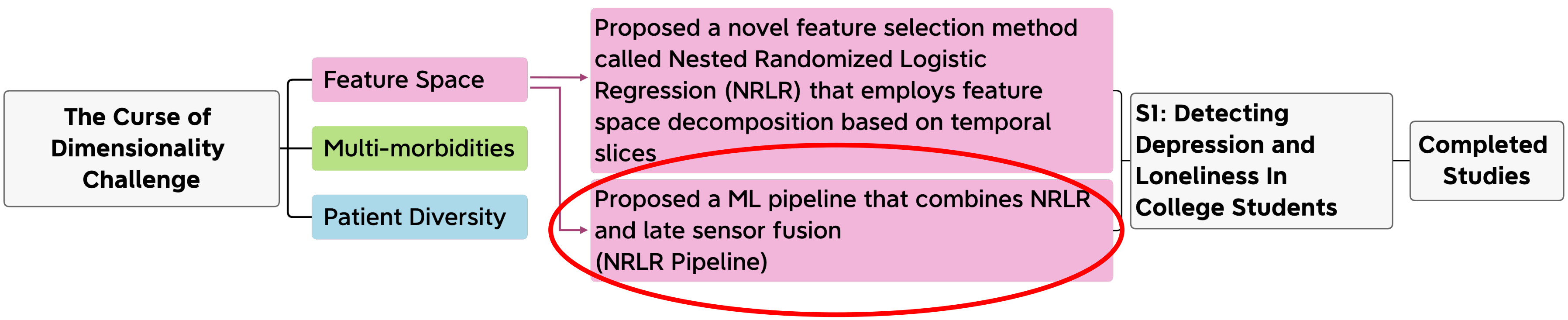


- Two methods for combining sensors:
  - Early sensor fusion: Combine sensor data or features, and then do ML to get the final prediction.
  - Late sensor fusion: We use ML to get a prediction for each sensor, and later, combine those predictions.
- We do late sensor fusion → aids in feature space decomposition.

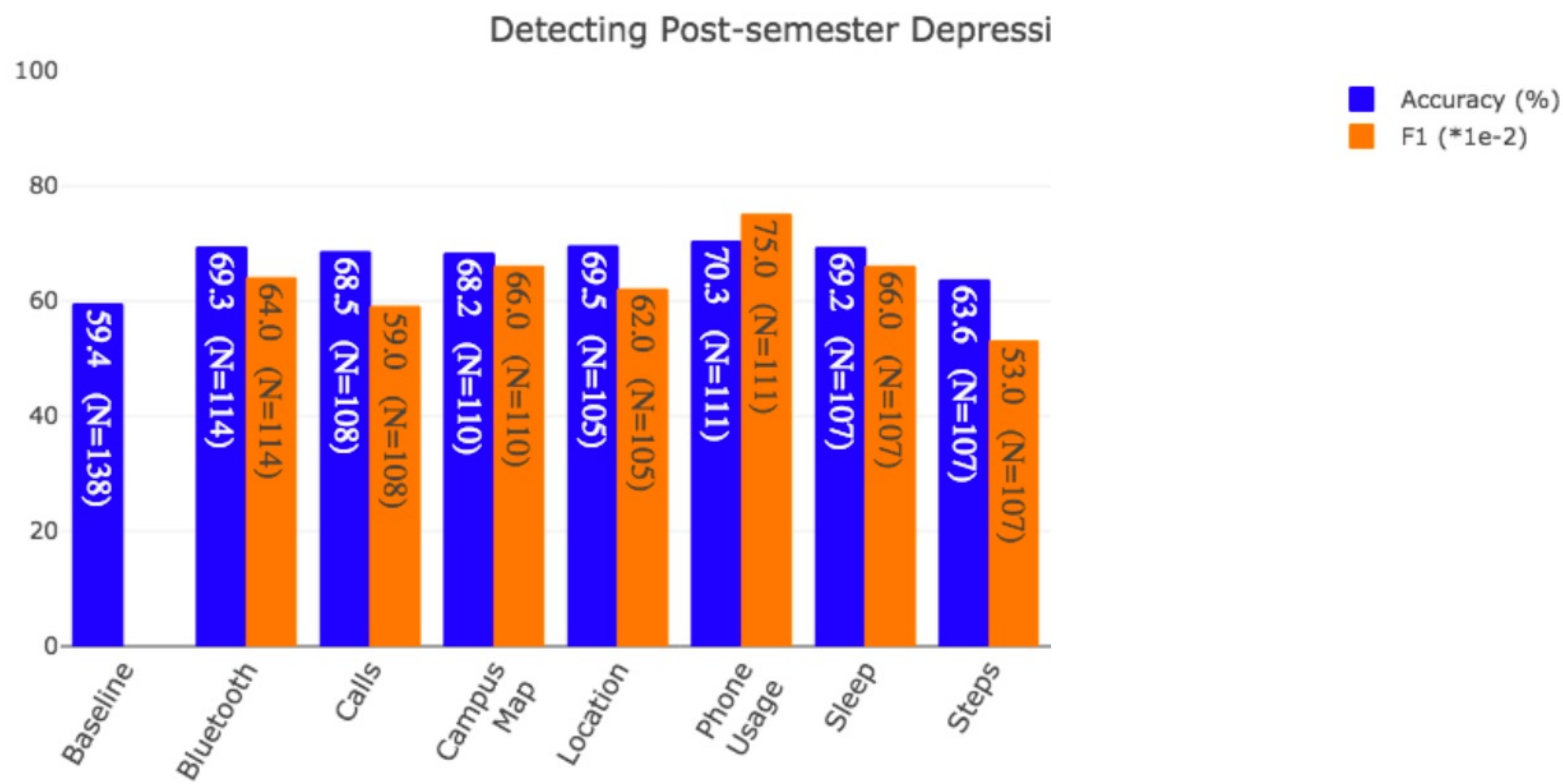
S1: Methodology – Feature Selection & Modeling Contd.

How does this address the curse of dimensionality?

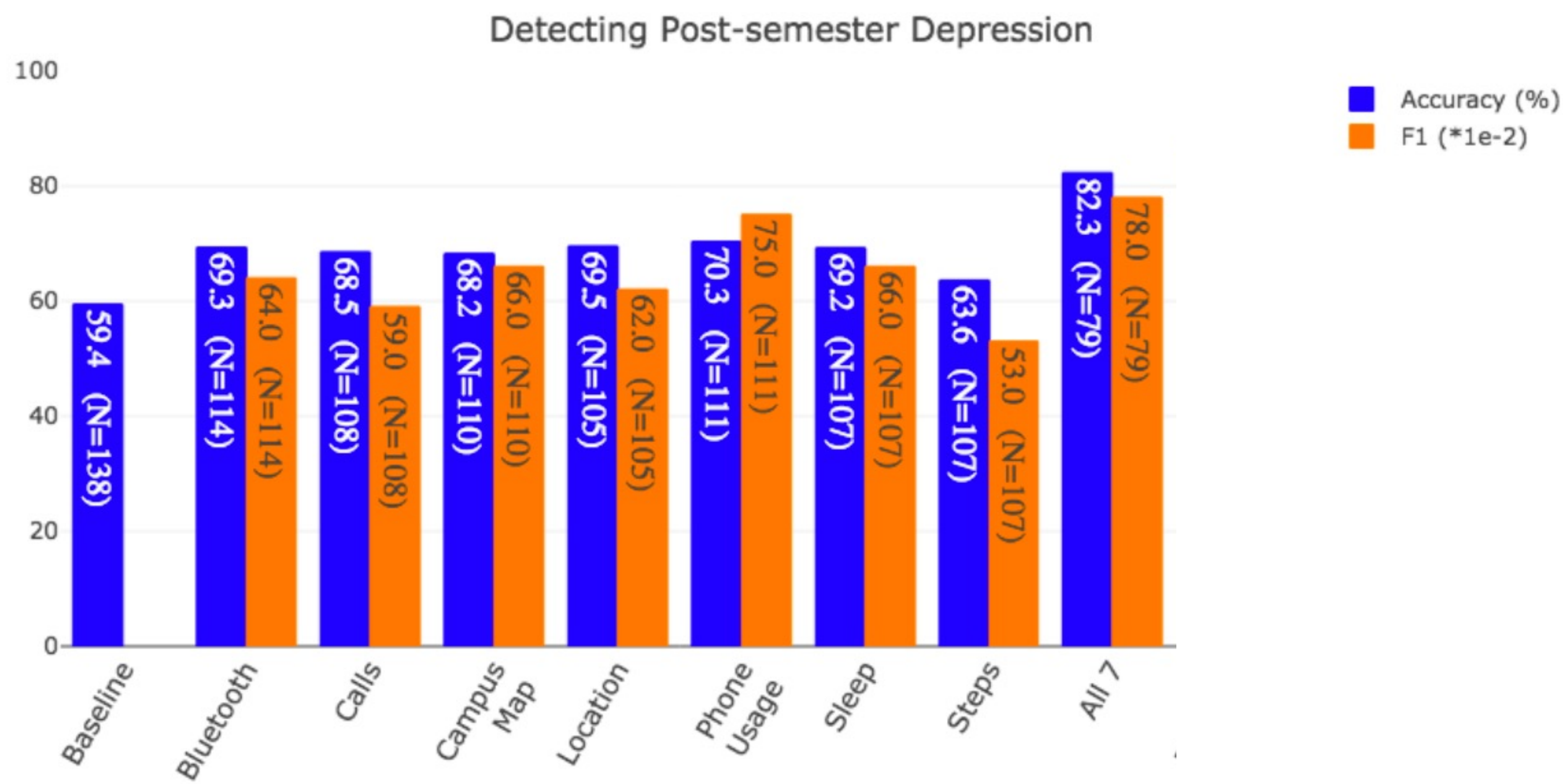


S1: Results – Post-semester Depression

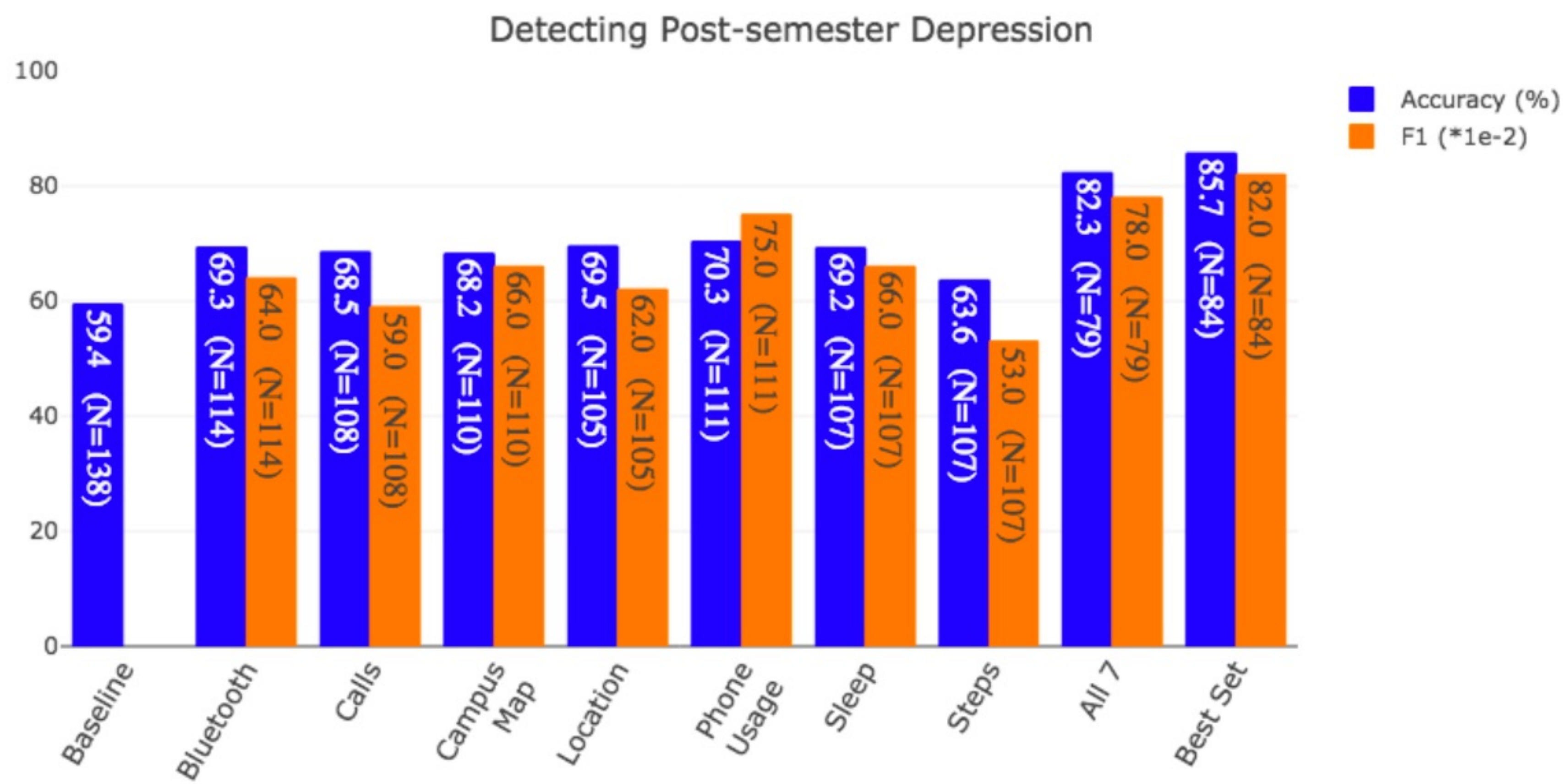
S1: Results – Post-semester Depression Contd.



S1: Results – Post-semester Depression Contd.



S1: Results – Post-semester Depression Contd.



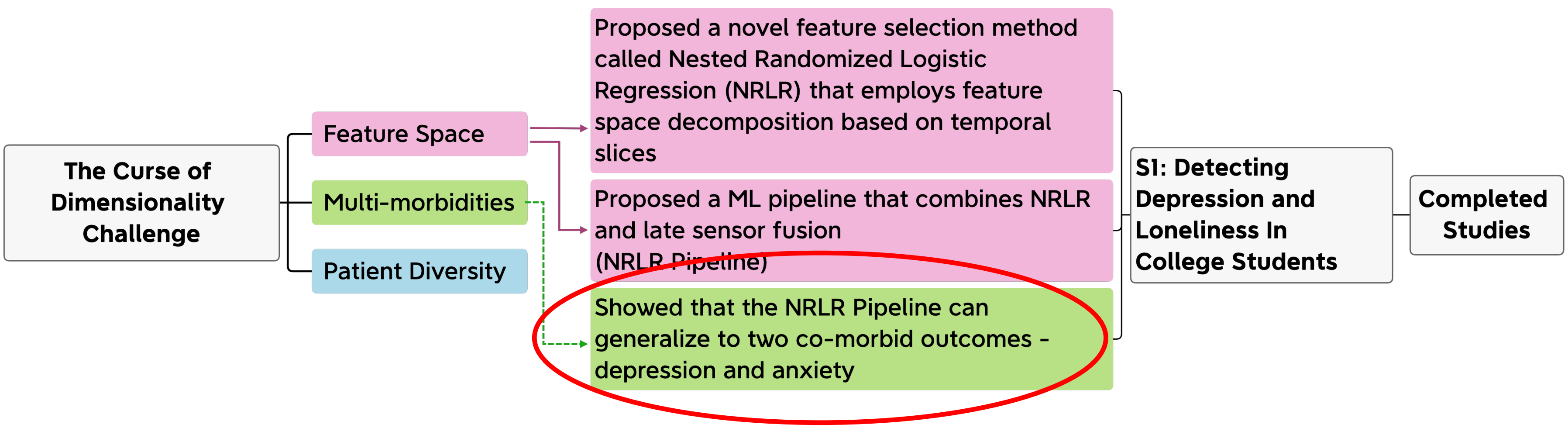
S1: Results – All

- Post-semester depression (binary): 85.7% accuracy
- Change in depression (binary): 85.4% accuracy
- Post-semester loneliness (binary): 80.2% accuracy
- Change in loneliness: 88.4%% accuracy

- Results in comparison with existing methods:
  - Our method outperformed Lasso and KNN for all except one sensor.
  - It also selected fewer features than Lasso and KNN.
  - These findings were consistent for depression and loneliness.

S1: Addressing the Curse of Dimensionality

How does this address the curse of dimensionality?



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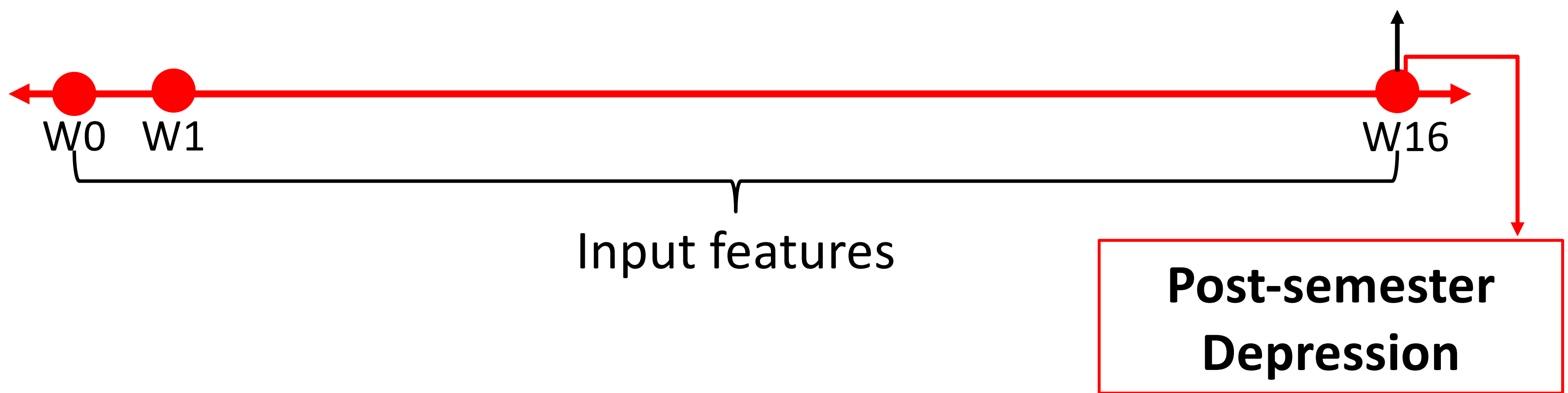
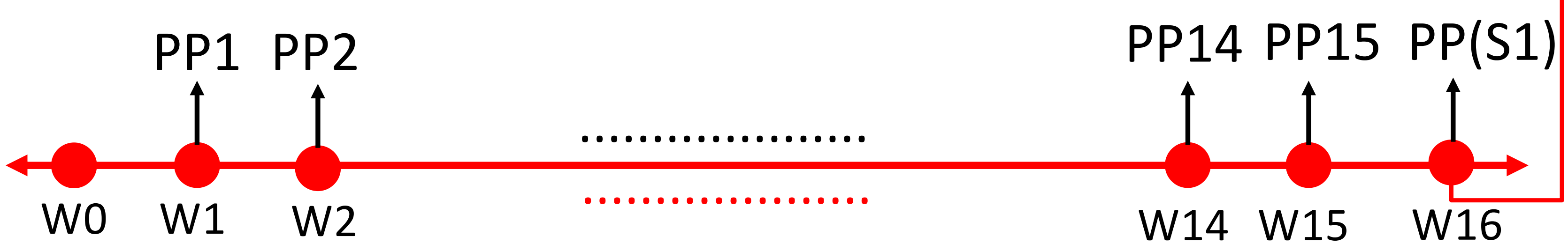
S2: Forecasting End of Semester Depression In College Students

- Study 1
    - Concluded: NRLR works for large feature spaces.



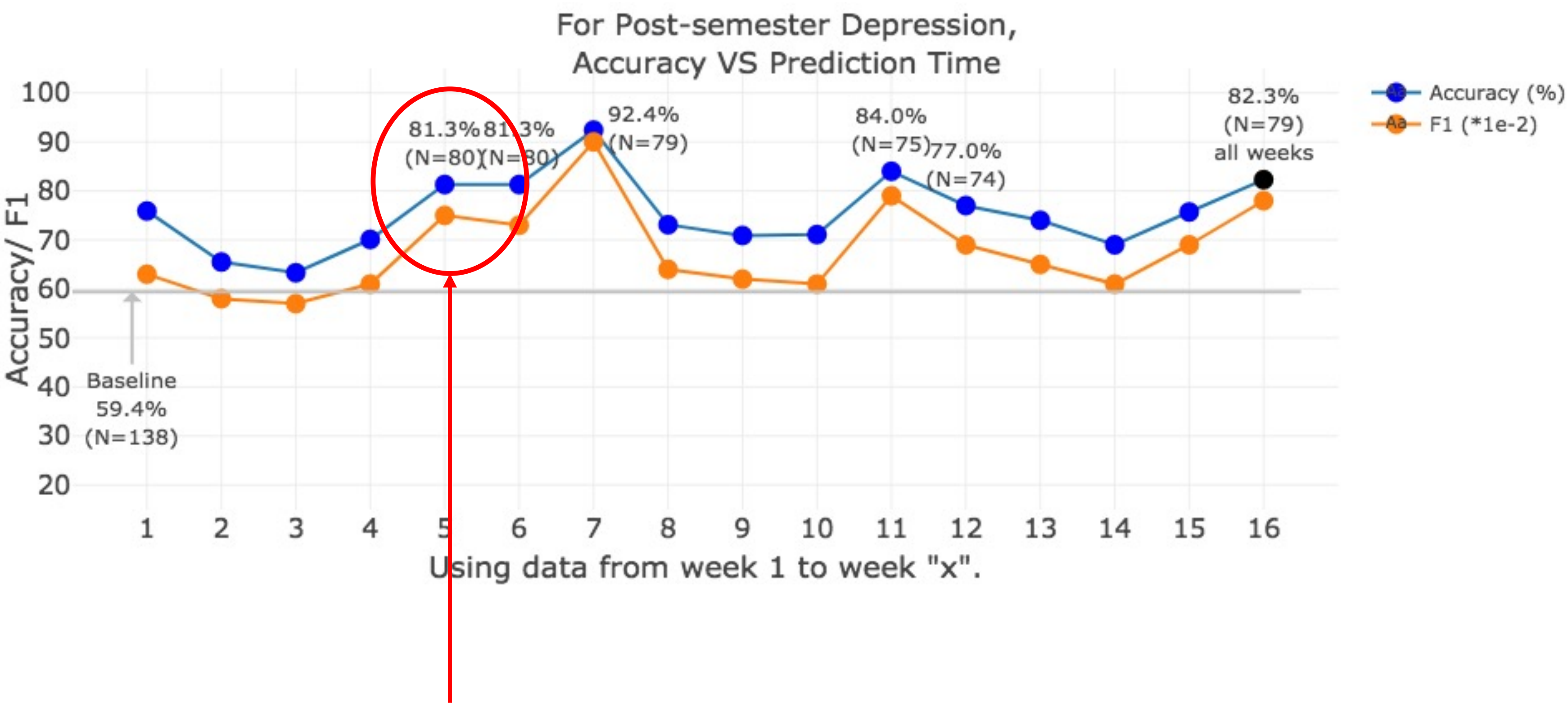
- Q) If our feature space is smaller, would NRLR work?
    - Inspired by the prediction/ forecasting problem



S2: Forecasting End of Semester Depression In College Students

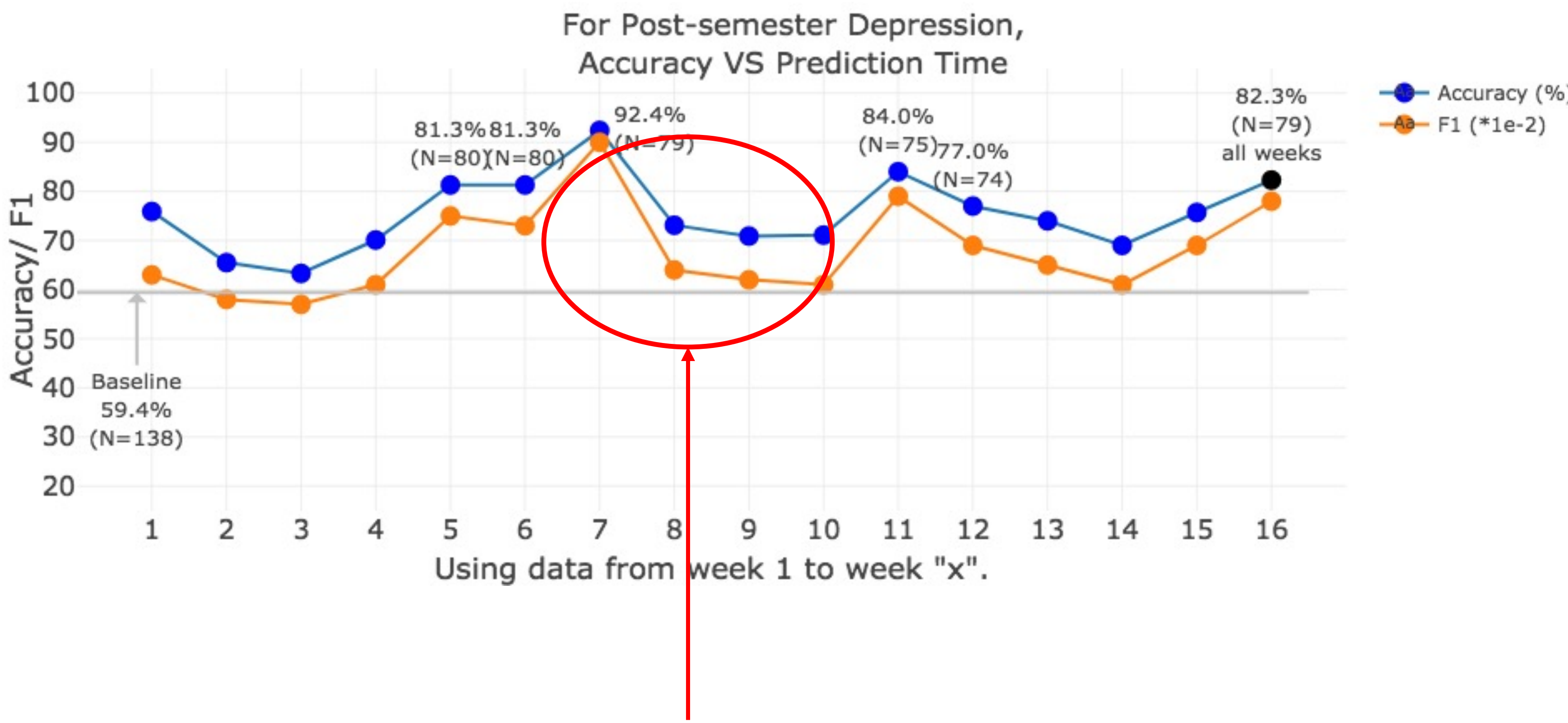
- Study 2:
  - Forecasting NOT weekly prediction
  - Same data as study 1

S2: Results



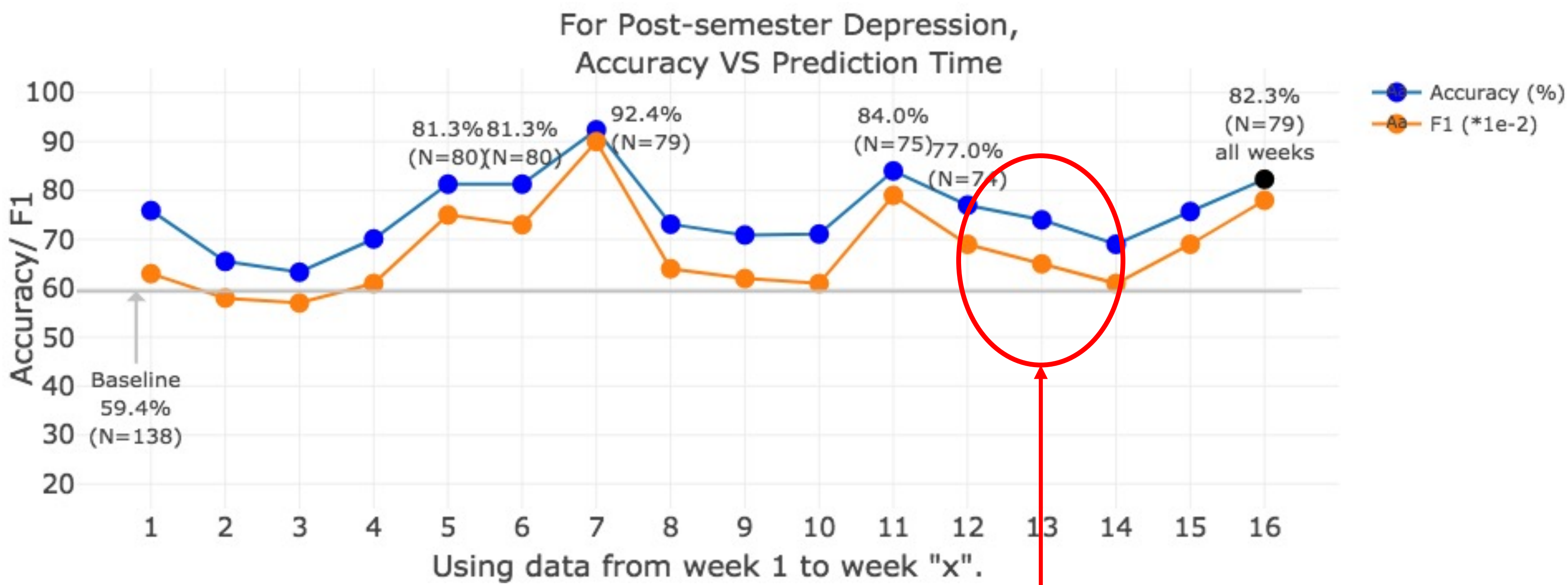
- We achieve an accuracy of 81.3% as early as the end of week 5.

S2: Results



- Drop in accuracy during the spring break and midterms.

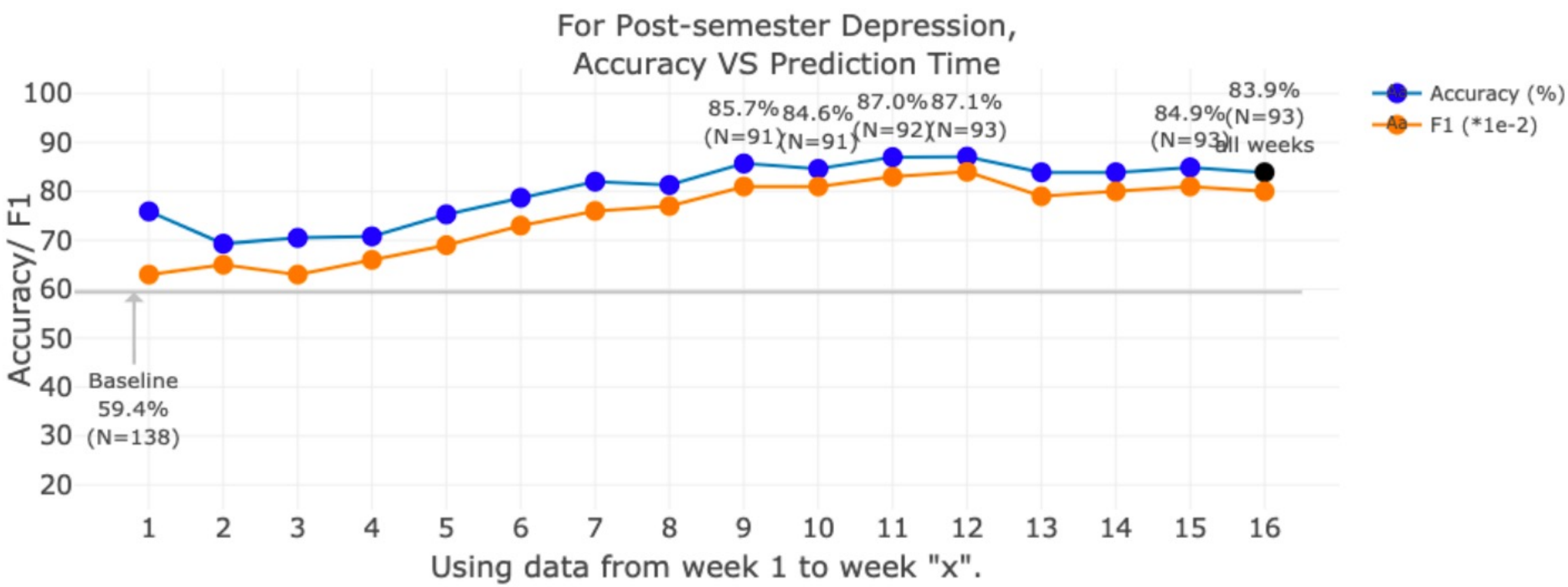
S2: Results



- Hard to say what's happening here without more background information → majority voting

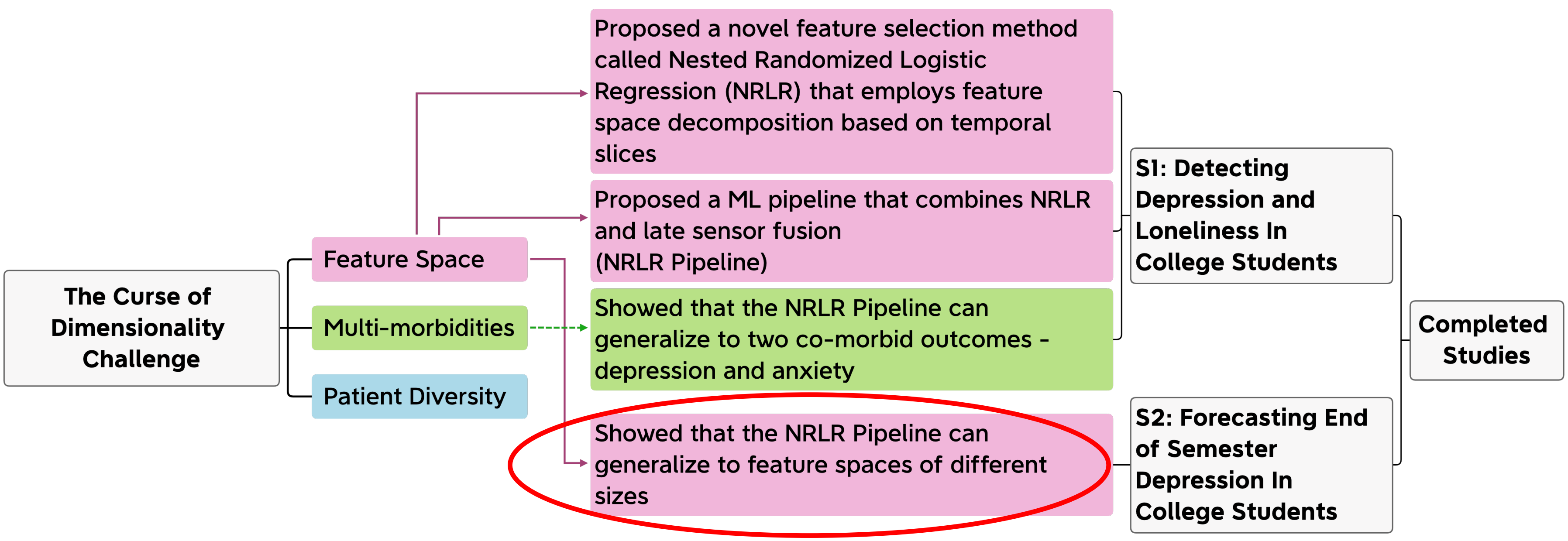
S2: Results

- After majority class voting:



S2: Addressing the Curse of Dimensionality

How does this address the curse of dimensionality?

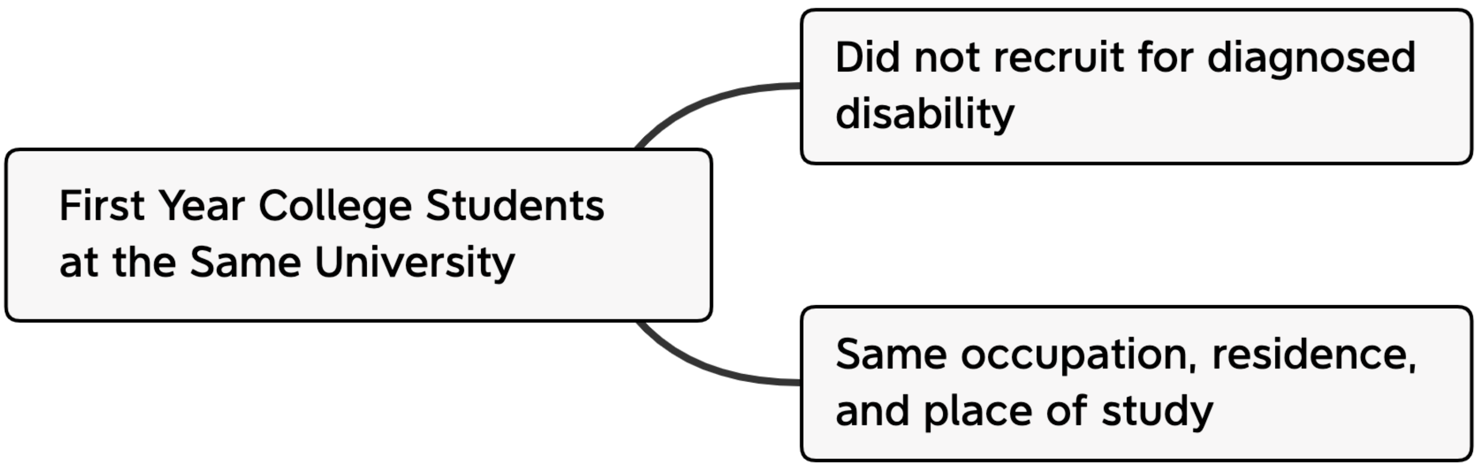


Completed Work

- S1: Detecting Depression and Loneliness In College Students
- S2: Forecasting End of Semester Depression In College Students
- **S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period**
- S4: Understanding Client Support Strategies to Improve Clinical Outcomes in an Online Mental Health Intervention

S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period

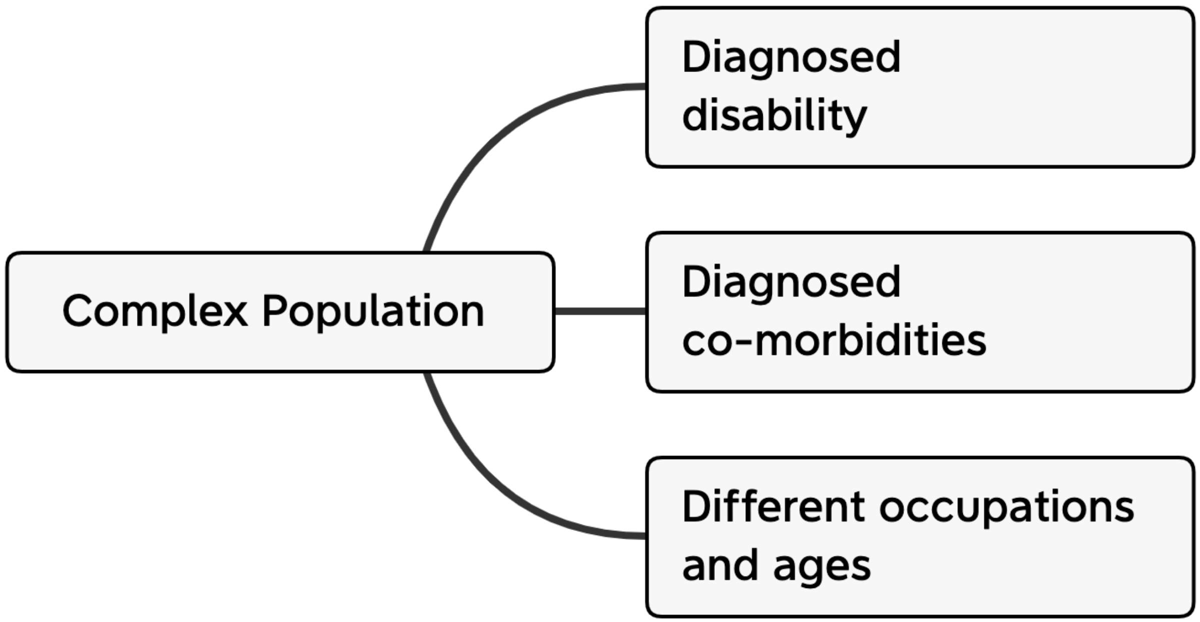
- Study 1 and 2:
  - Participants are likely to have similar behaviors.
  - → it makes sense for our population model (NRLR) to work.



- Q) Would NRLR generalize to a more complex population?

S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period

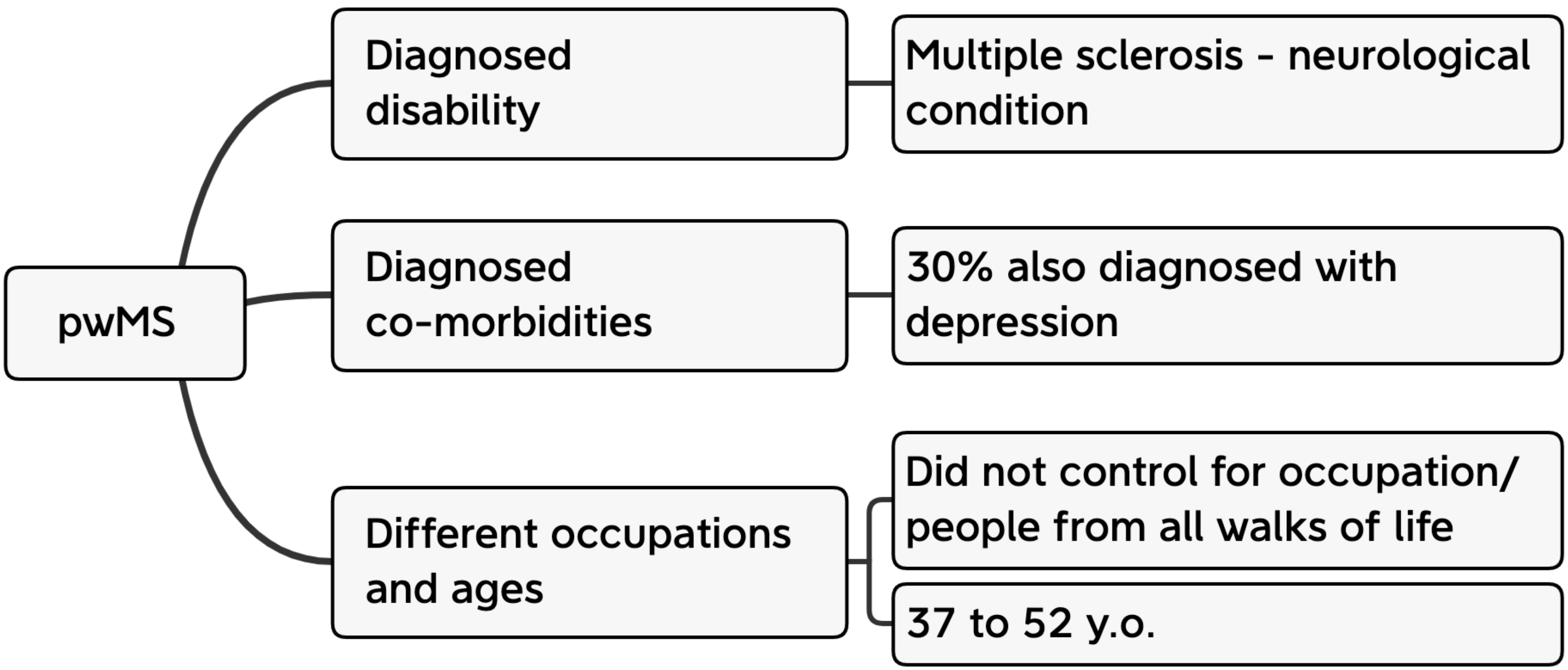
- What factors would make a population “complex”?



- Would NRLR generalize to such a population?
    - One such population is patients with Multiple Sclerosis.

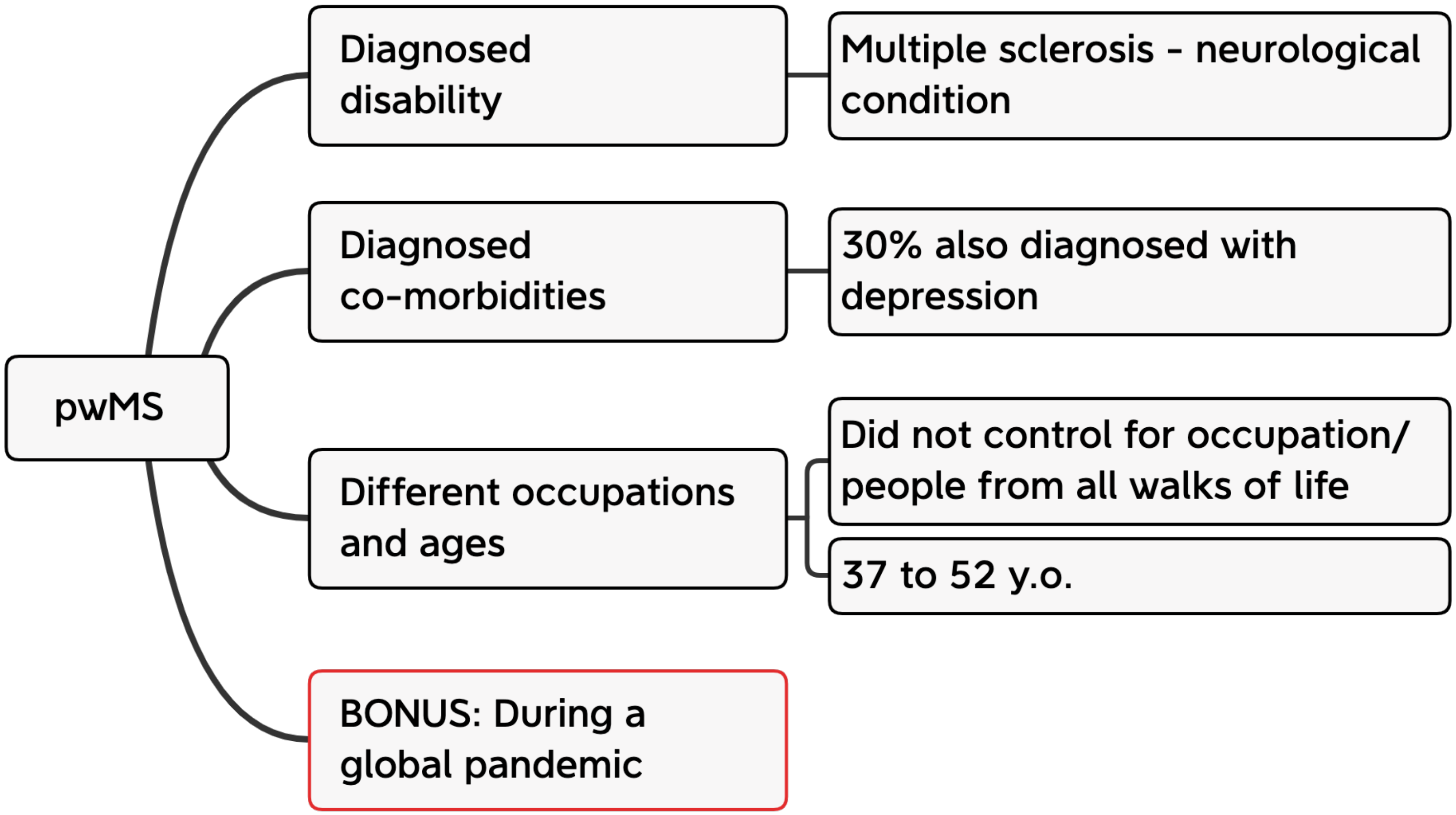
S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period

- Patients with Multiple Sclerosis (pwMS)



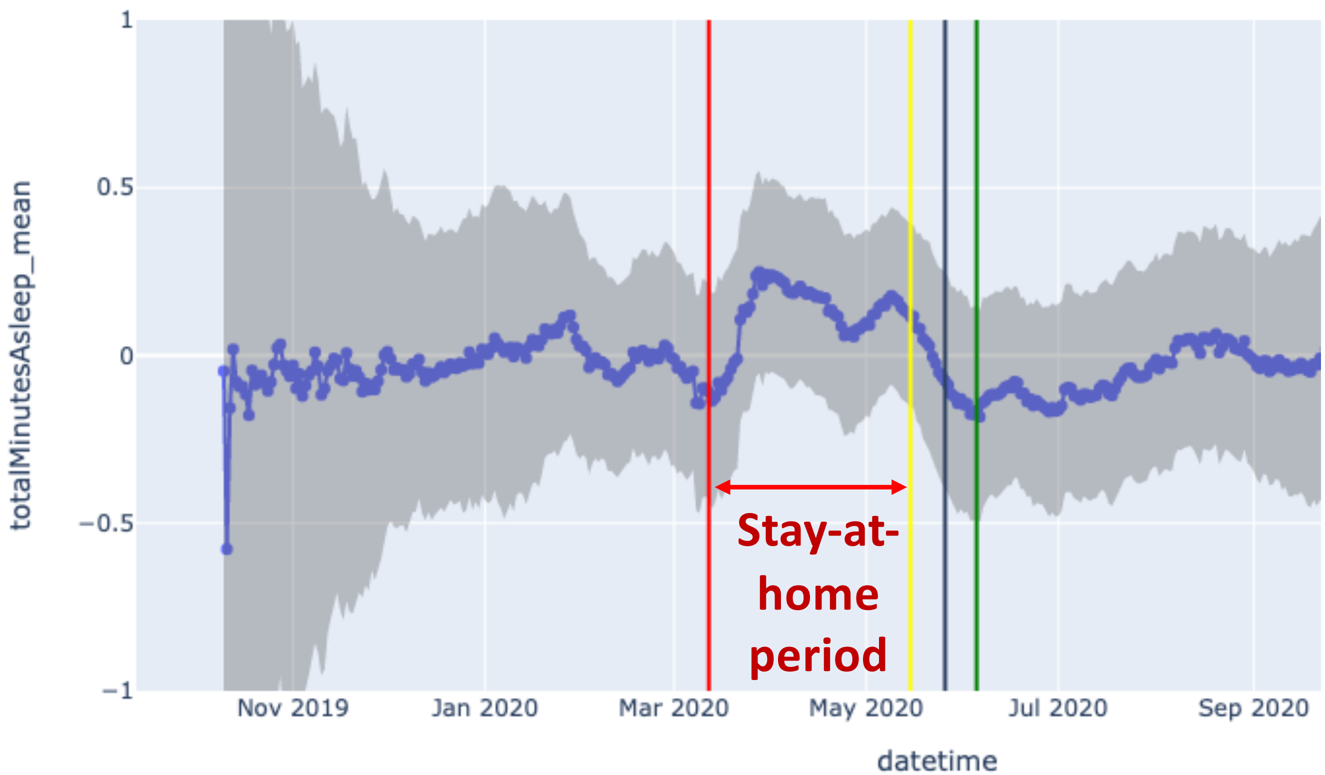
S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period

- Patients with Multiple Sclerosis (pwMS)



S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period

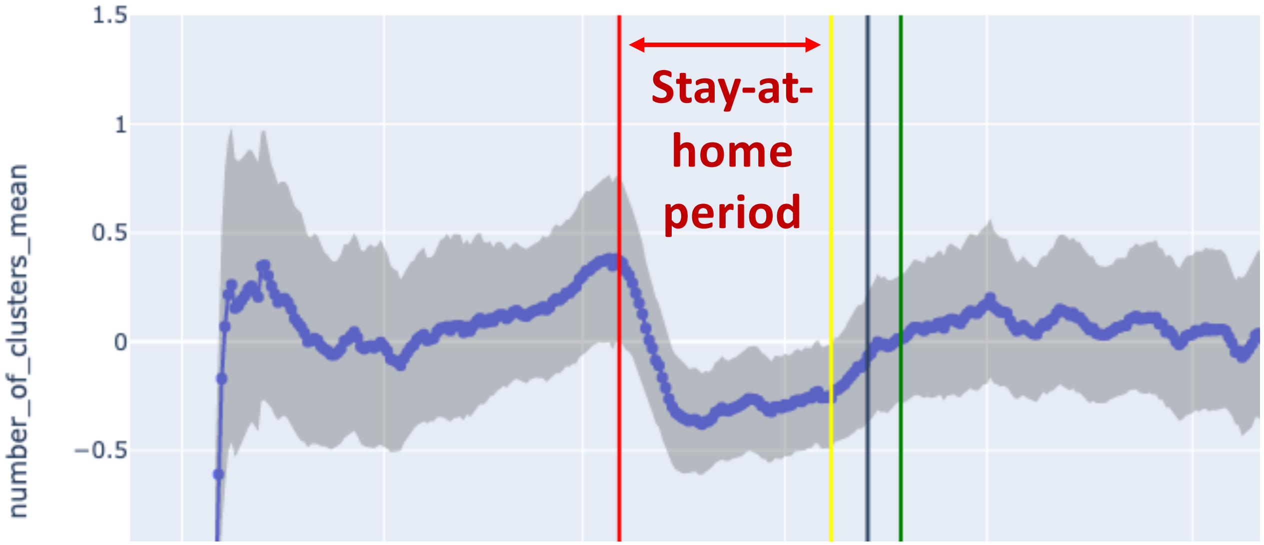
- We found that the stay-at-home period imposed during the pandemic had a major effect on people's behaviors.



Time spent asleep per day (normalized per person)

S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period

- We found that the stay-at-home period imposed during the pandemic had a major effect on people's behaviors.



Number of significant locations (normalized per person)

What does this mean for
Multimodal Behavioral Sensing research?

S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period Contd.

- Q) Can we use changes in behavior that occurred after the stay-at-home period was imposed to predict health outcomes during the stay-at-home period?

Change in behaviors before and after the "stay-at-home" order is instated

- Detect Depression
- Detect Fatigue
- Detect Global MS Symptom Burden
- Detect Sleep Quality

Multiple ground truth values are averaged over the Covid-19 stay at-home period to get outcomes

- 56 Patients with Multiple Sclerosis (pwMS)

S3: Methodology – Feature Extraction

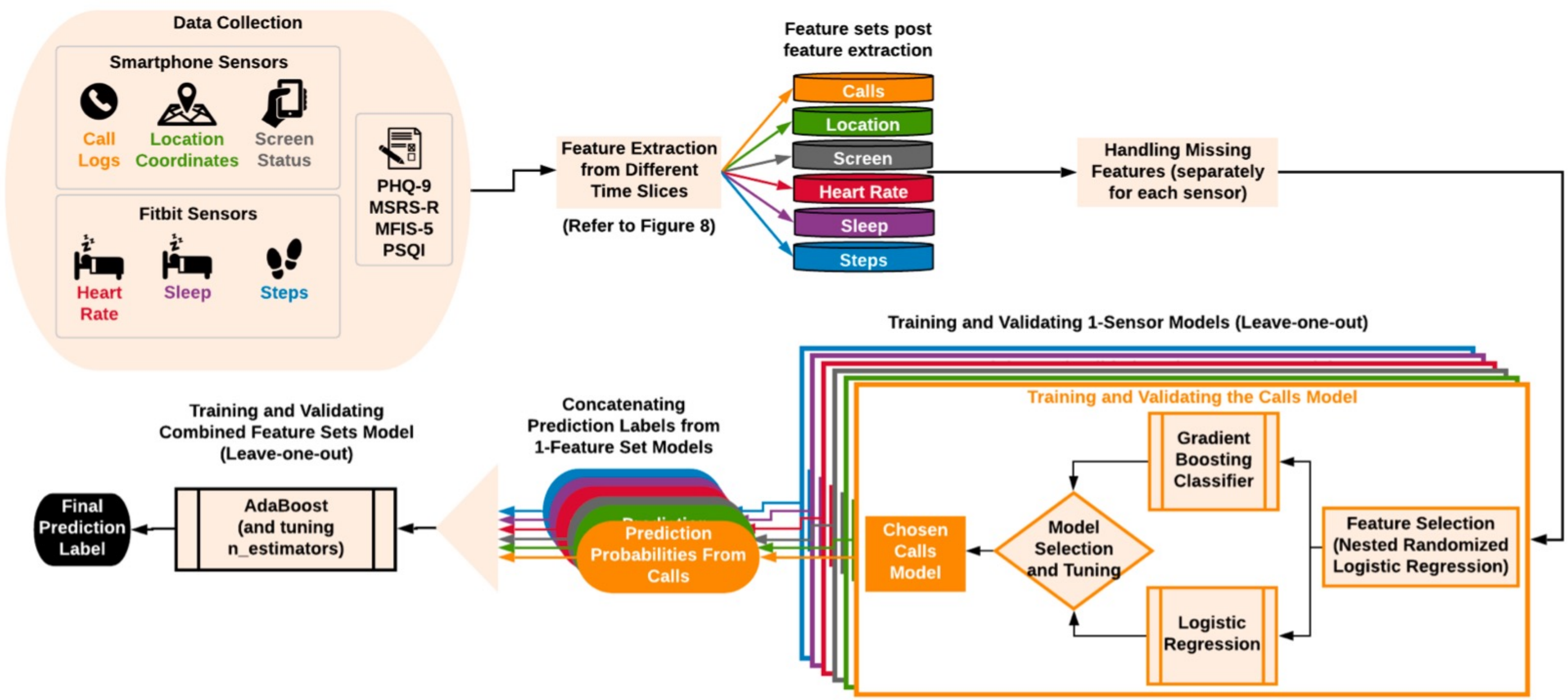
- Collected data from 6 sensors.
- For every sensor, extracted features from 15 time slices from the pre-covid-19 and stay-at-home periods.

Final Feature Matrix = Stay-at-home Feature Matrix – Pre-Covid-19 Feature Matrix

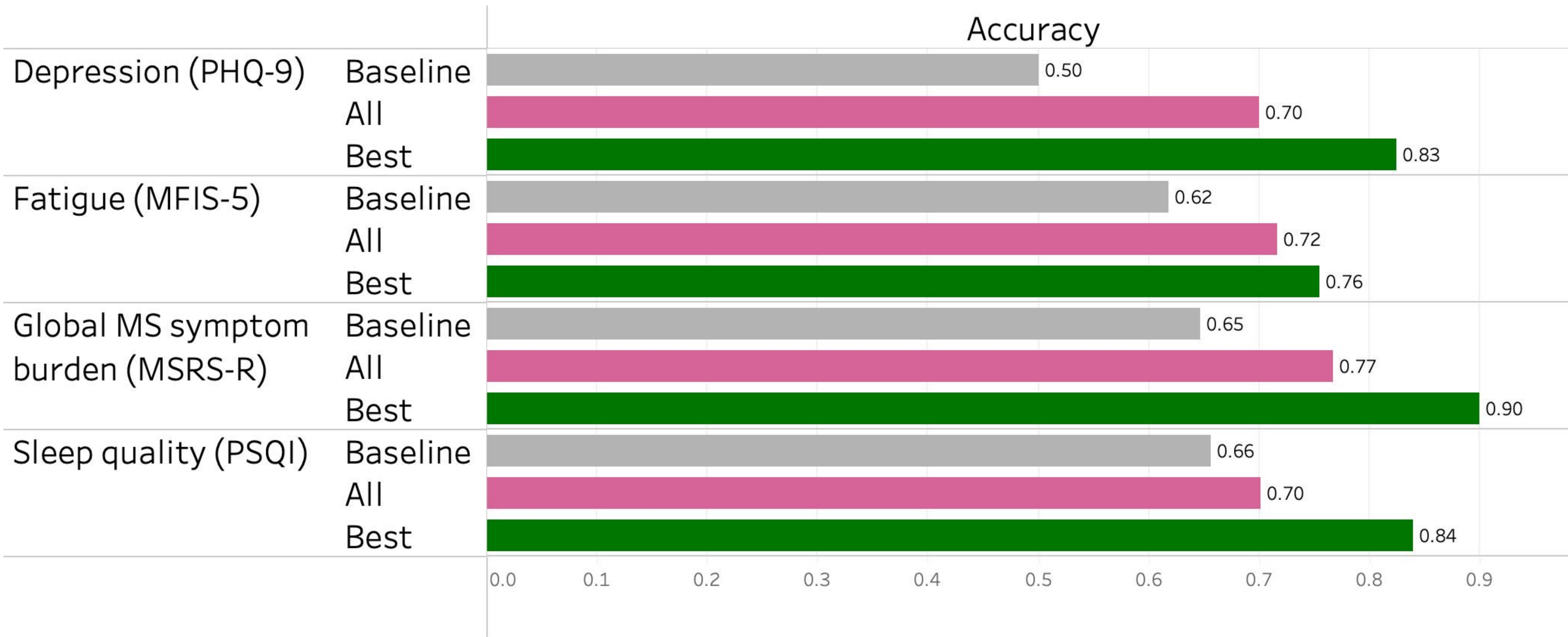
- E.g., for person A:
  - Average Steps Pre-Covid-19 = 7000
  - Average Steps during the Stay-at-Home Period = 4000
  - Final Feature = -3000

S3: Methodology - Modeling

- Same modeling approach as before



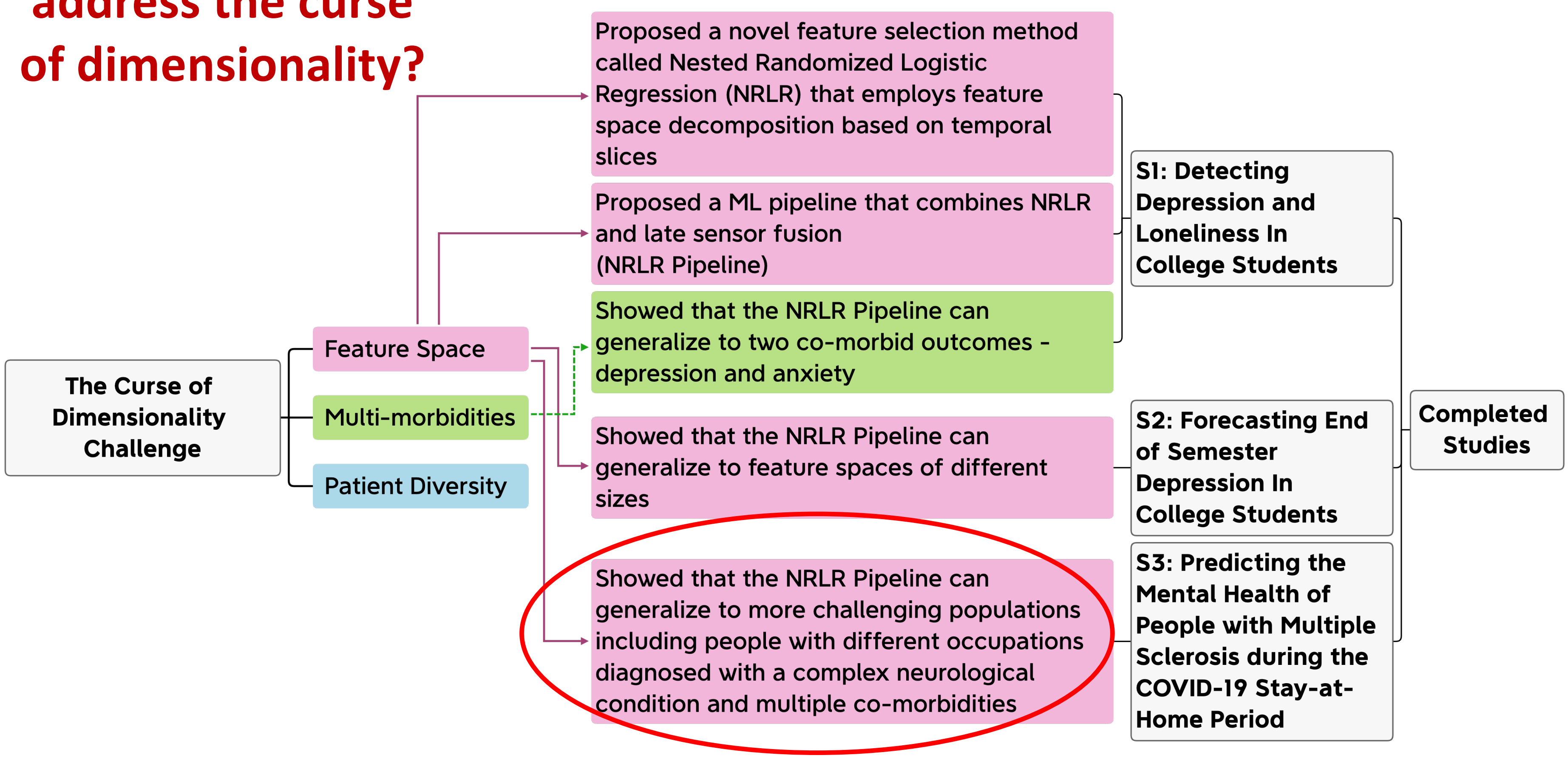
S3: Results



Baseline: Majority class
All: All 6 sensors
Best: Best combination of sensors

S3: Addressing the Curse of Dimensionality

How does this address the curse of dimensionality?



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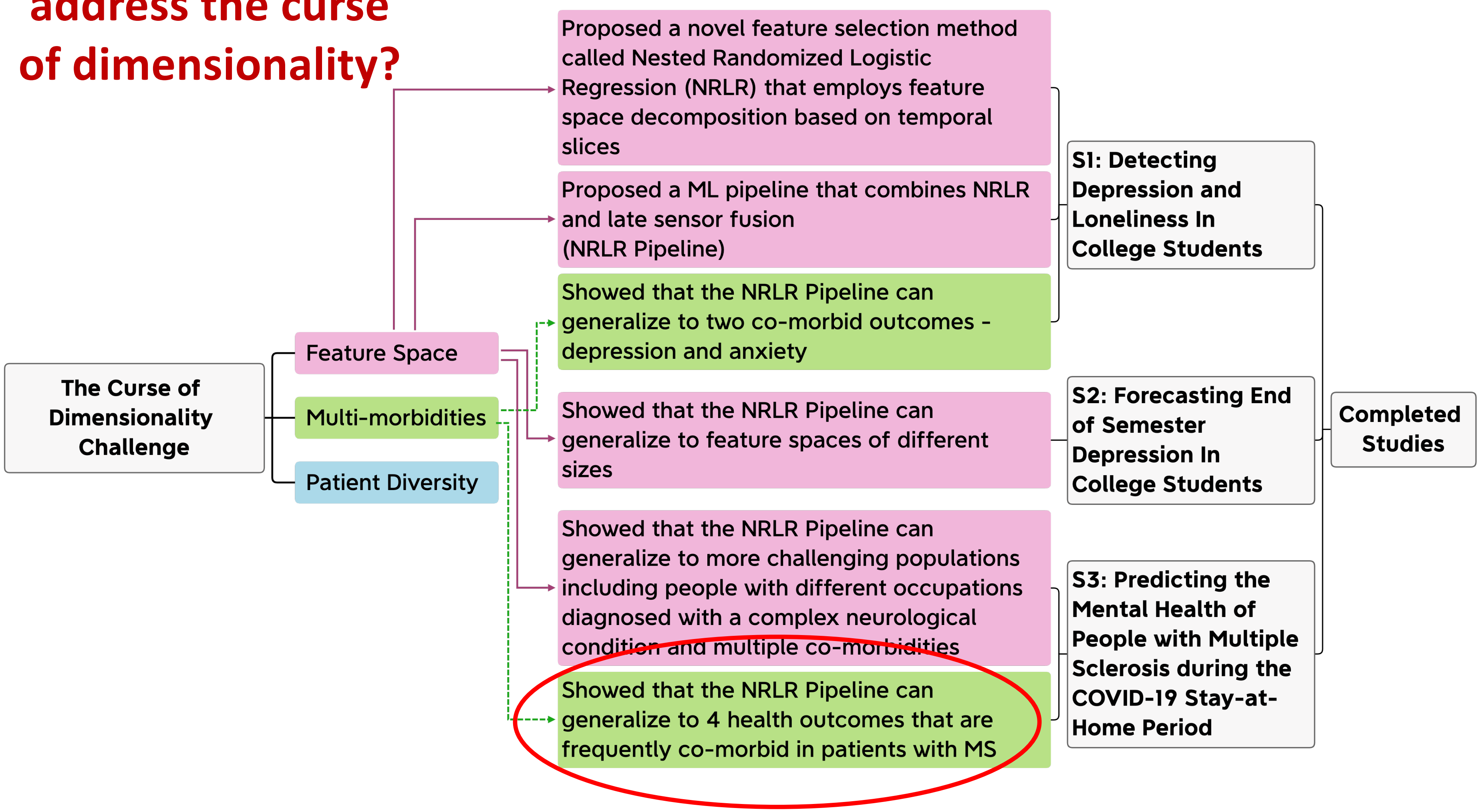

Completed Work

- S1: Detecting Depression and Loneliness In College Students
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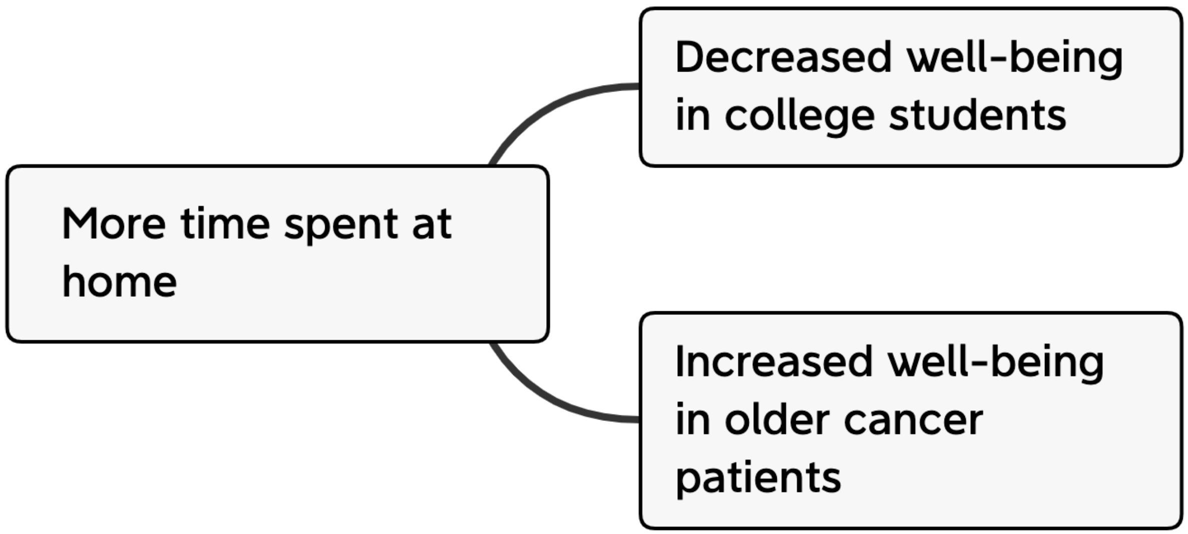
- S3: Predicting the Mental Health of People with Multiple Sclerosis during the COVID-19 Stay-at-Home Period
- **S4: Understanding Client Support Strategies to Improve Clinical Outcomes in an Online Mental Health Intervention**

S4: Understanding Client Support Strategies to Improve Clinical Outcomes in an Online Mental Health Intervention

- **RECAP:** The relationship between behaviors and outcome may be dependent on patient context and characteristics.



- We have not yet addressed the curse of dimensionality in the diversity in patient context and characteristics.

S4: Understanding Client Support Strategies to Improve Clinical Outcomes in an Online Mental Health Intervention

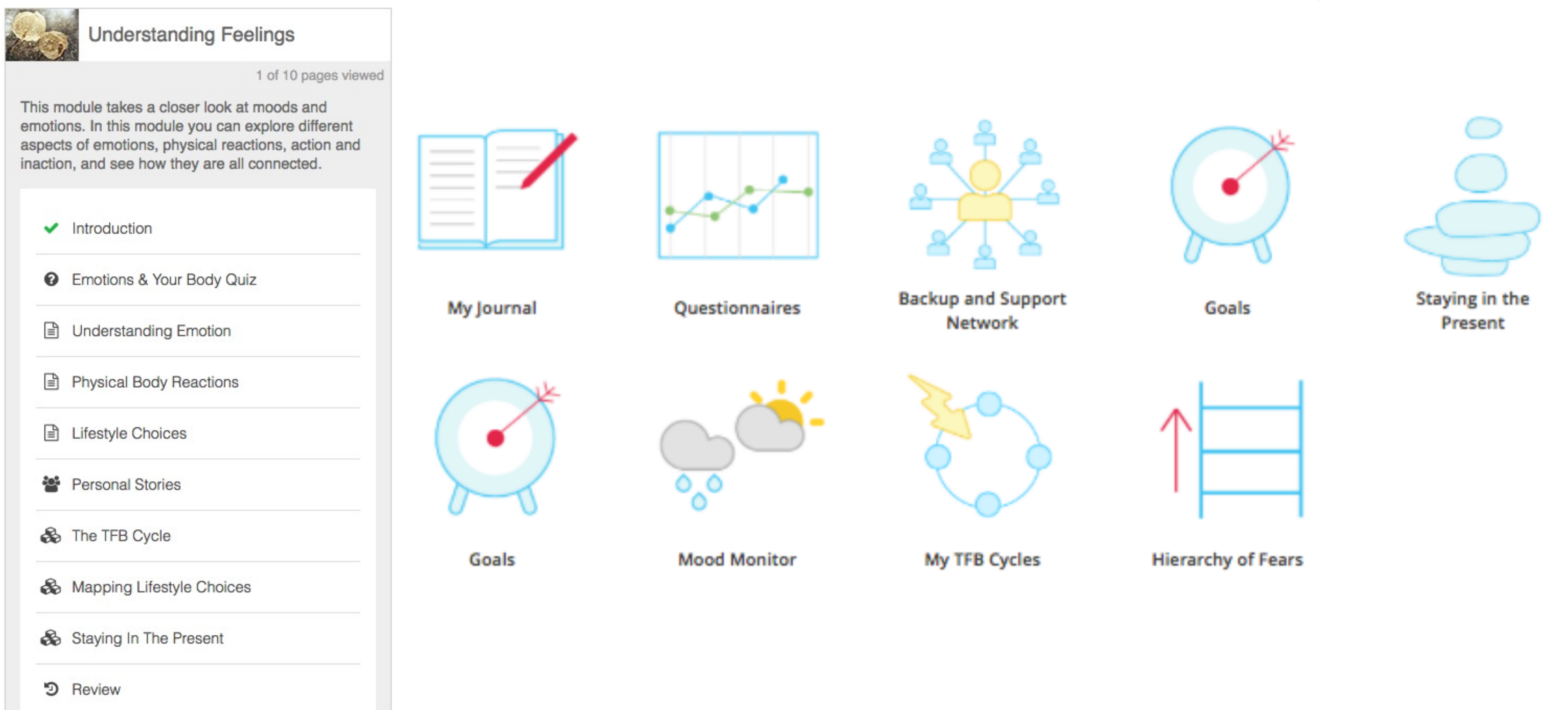
- Further, interventions are an important part of this kind of work.
- Hence, I'd like to switch gears and talk about interventions

- Analyzing behaviors in the context in which they occur, can lead to more interpretable insights,
  - Interventions require more trust and transparency.
  - So, interpretability is even more important for interventions.

- **S4's GOAL:** Analyze the users' interaction with a MH intervention app and the human supporters on the app to understand how supporter behaviors correlate with patient outcomes for patients in different contexts or situations.

S4: Background

- Patient is engaged with an online mental health intervention based on Cognitive Behavioral Therapy (CBT).
- Patient has access to course content and tools through the app.



S4: Background Contd.

- A human supporter reviews the patient’s clinical scores, progress on course material and tools usage, and sends a personalized message offering feedback, **each week for 6-8 weeks**.
- Supporters use their experience and discretion to employ a wide variety of strategies in their messages.

~3,500 supporters → ~200,000 messages → ~50,000 patients

S4: Background

- Patients also fill out **weekly surveys** that measure symptoms of depression and anxiety.
- Goal of the app-based intervention is to improve **both depression and anxiety**, which are often co-morbid.
  - Deriving insights for both outcomes separately would make it harder to identify best support strategies
  - Hence, **need to combine** multiple measures of **depression and anxiety** into ONE target outcome.

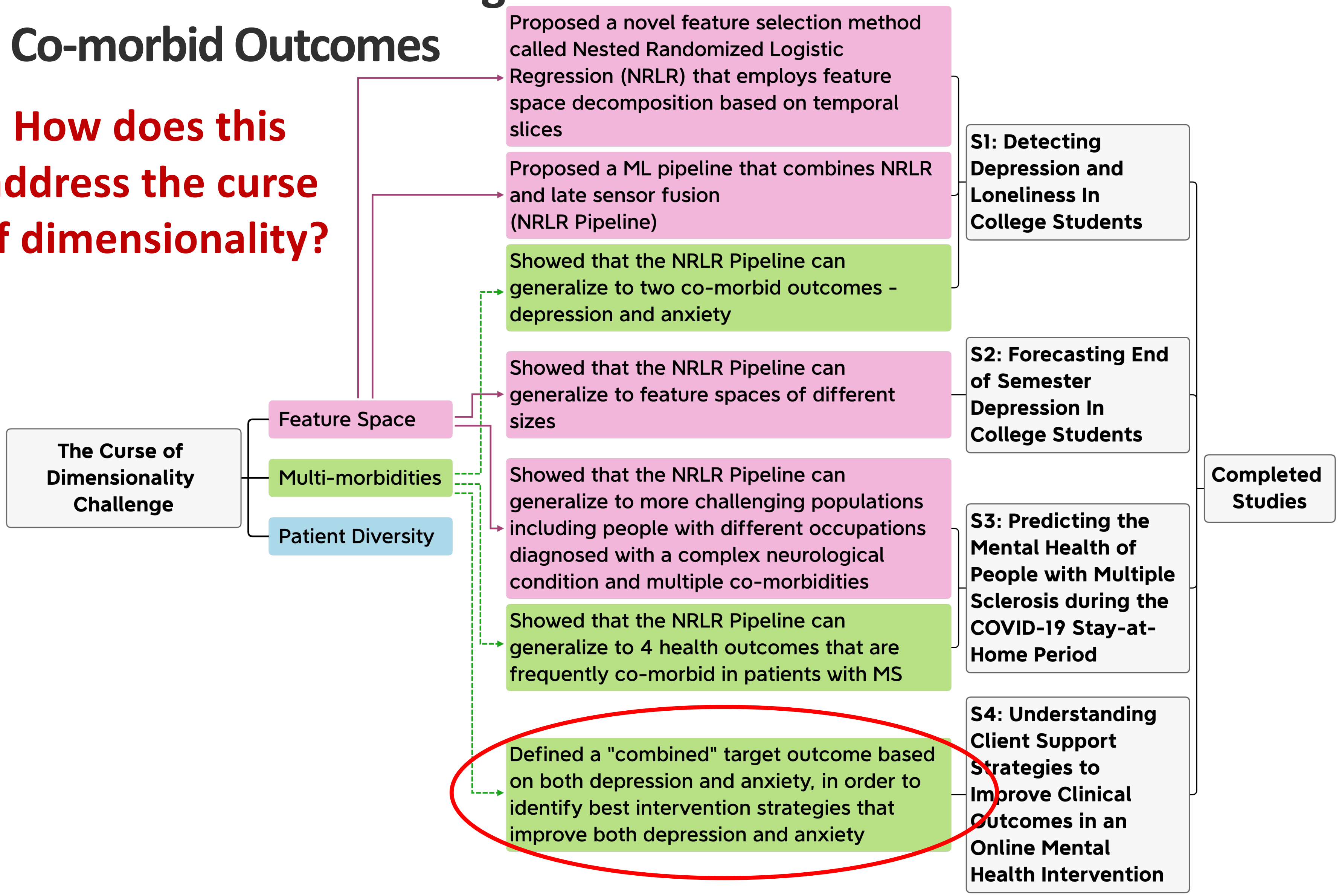
S4: Method – Combining Co-morbid Outcomes

- For each supporter, we compute 8 measures based on their patients' depression and anxiety scores → cluster

- **Combined outcome: Success of the supporter**
- High success clusters → "more successful supporters"
- Low success cluster → "less successful supporters"

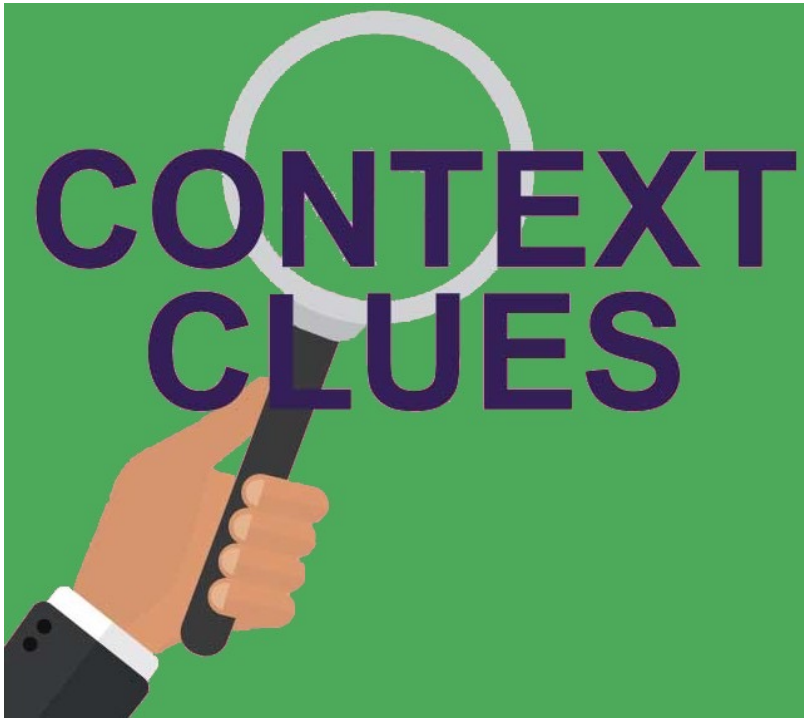
S4: Method – Combining Co-morbid Outcomes

How does this address the curse of dimensionality?



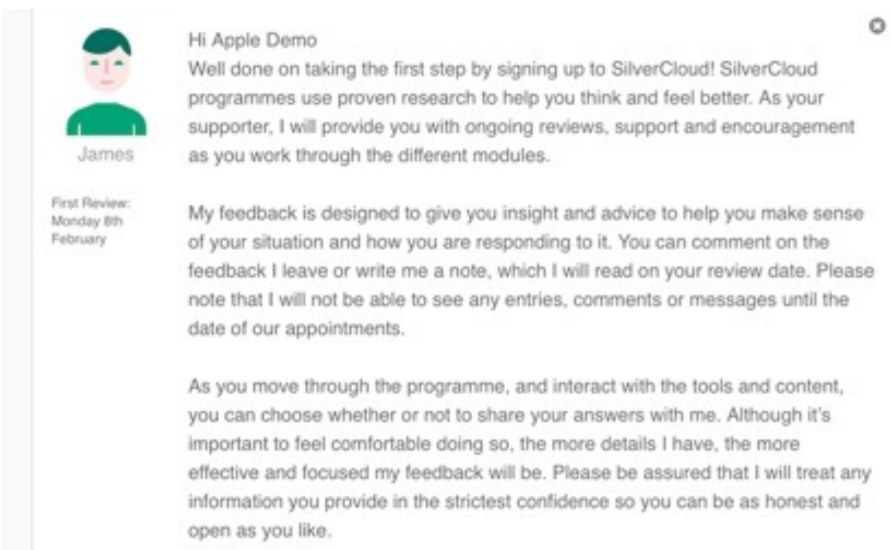
S4: Method – Feature Extraction

- Patient <Context> Variables:
  - 5 Variables:
    - ContentViews,
    - Shared,
    - MessageNumber,
    - CurrentDepression, and
    - CurrentAnxiety



S4: Method – Feature Extraction Contd.

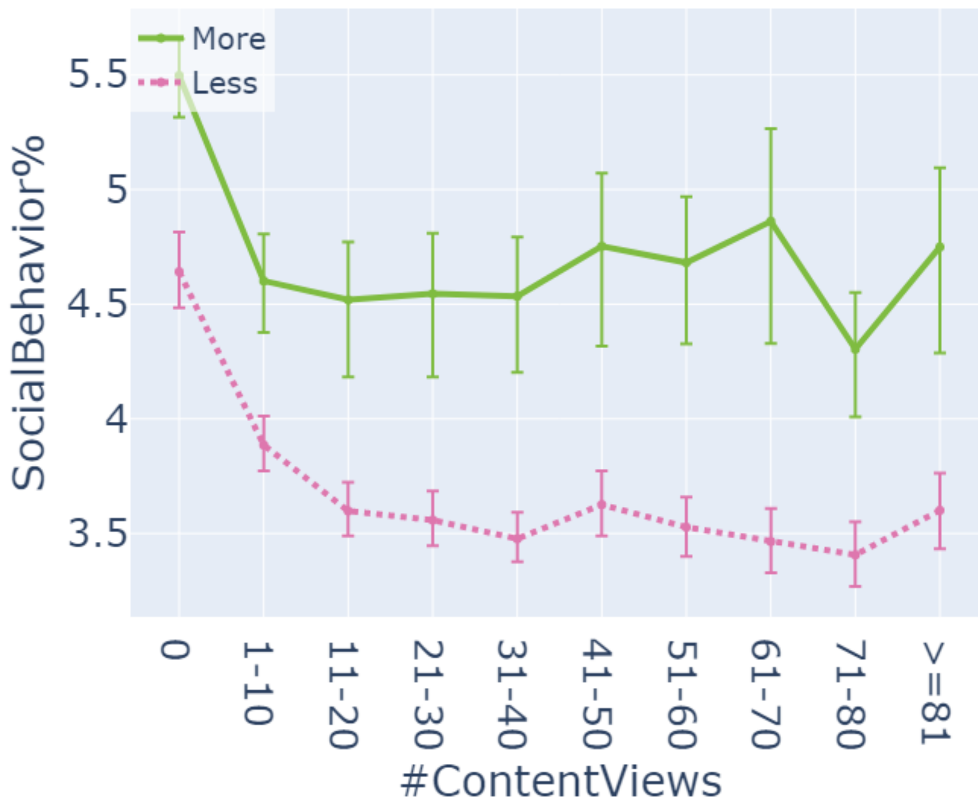
- Support <Strategy> Variables:
    - 23 variables calculated using validated lexicons and NLP techniques.



E.g., positive or negative sentiment, message length, types of words used

S4: Results – Successful Support Strategies Contd.

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



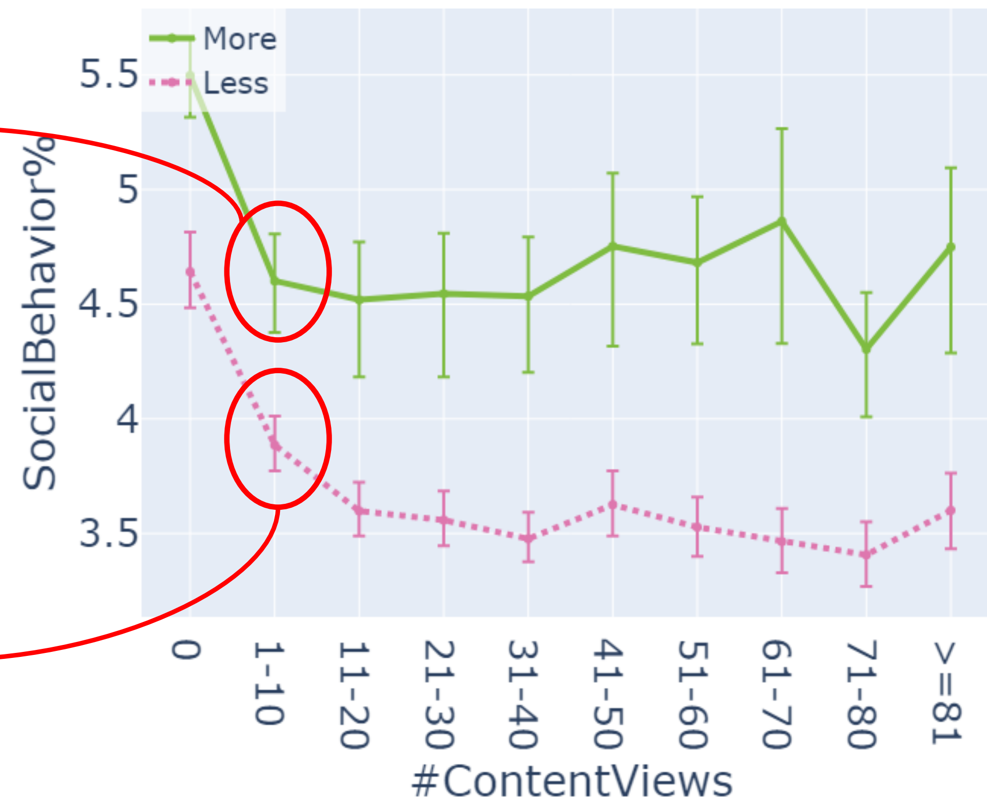
S4: Results – Successful Support Strategies Contd.

- Q) What strategies are best **independent** of the patient's context?
- Only ONE context variable and ONE strategy at a time

Messages from MORE successful supporters and clients with 1-10 ContentViews

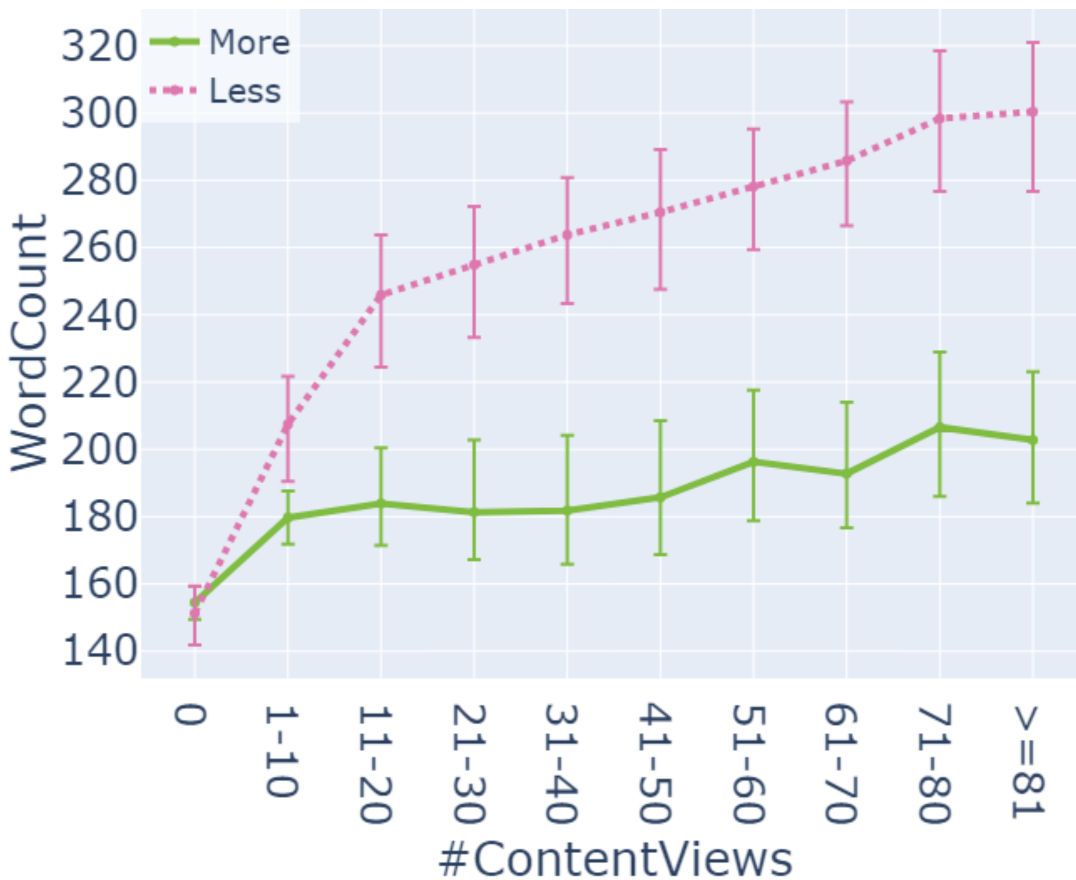
Hierarchical Bootstrapping to compare means (samples not independent)

Messages from LESS successful supporters and clients with 1-10 ContentViews



S4: Results – Successful Support Strategies Contd.

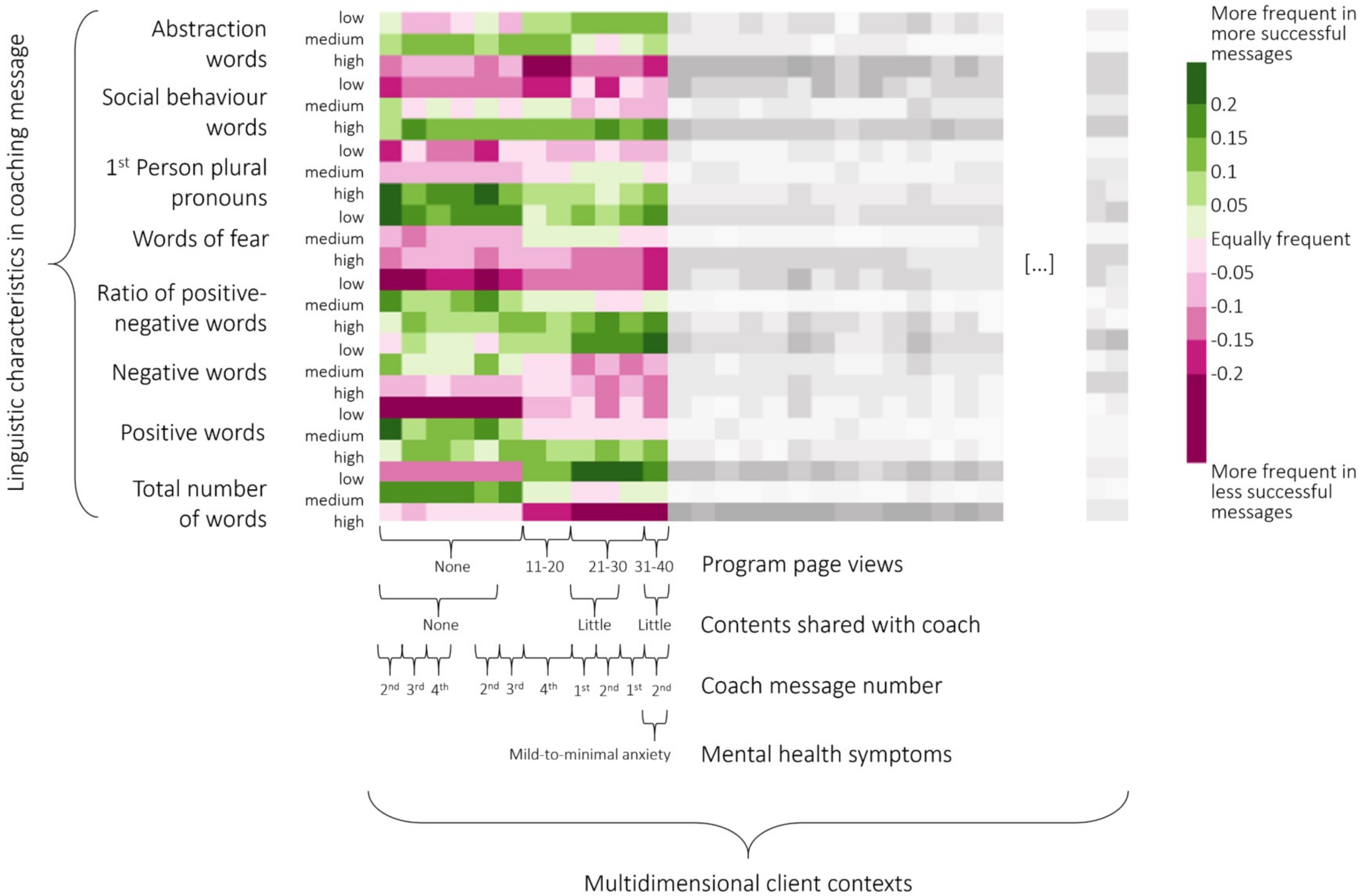
- More successful messages were shorter!



S4: Methods – Context-Specific Support Strategies

- So far, we've found strategies that work well independent of context or across all contexts → "general" strategies
- Q) Can we find strategies that work better in specific narrow contexts? → "specific" strategies
  - Do general strategies "flip" in specific narrow contexts?
  - Has interesting implications for personalization!
- So far, we've only considered ONE context and ONE strategy variable at a time.
  - For this, we will consider multiple context variables *i.e.*, multidimensional client contexts

S4: Results – Context-Specific Support Strategies



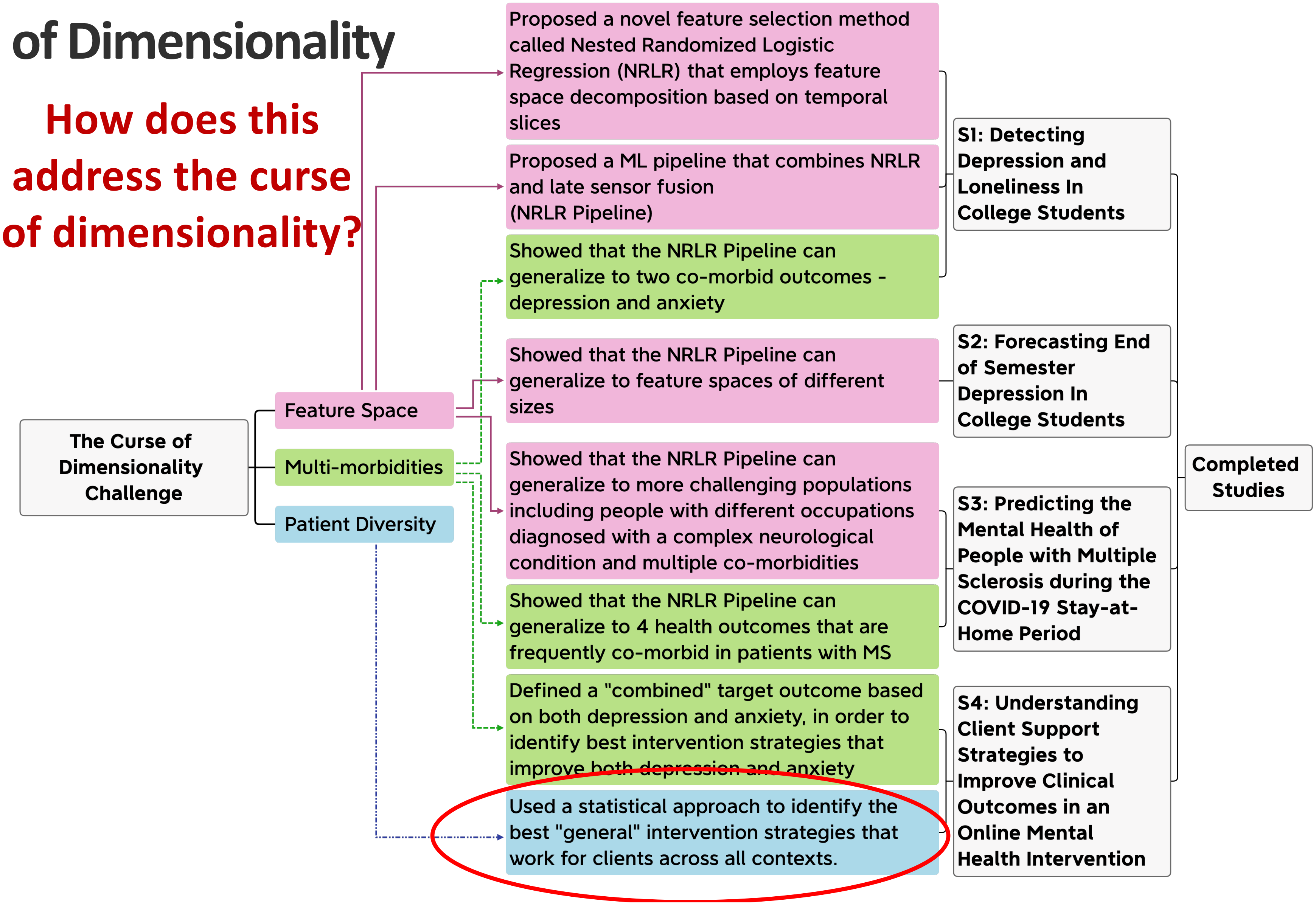
S4: Results – Context-Specific Support Strategies Contd.

S4: Results – Context-Specific Support Strategies Contd.

- For less engaged clients, writing longer, more positive and more supportive messages 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.

S4: Addressing the Curse of Dimensionality

How does this address the curse of dimensionality?



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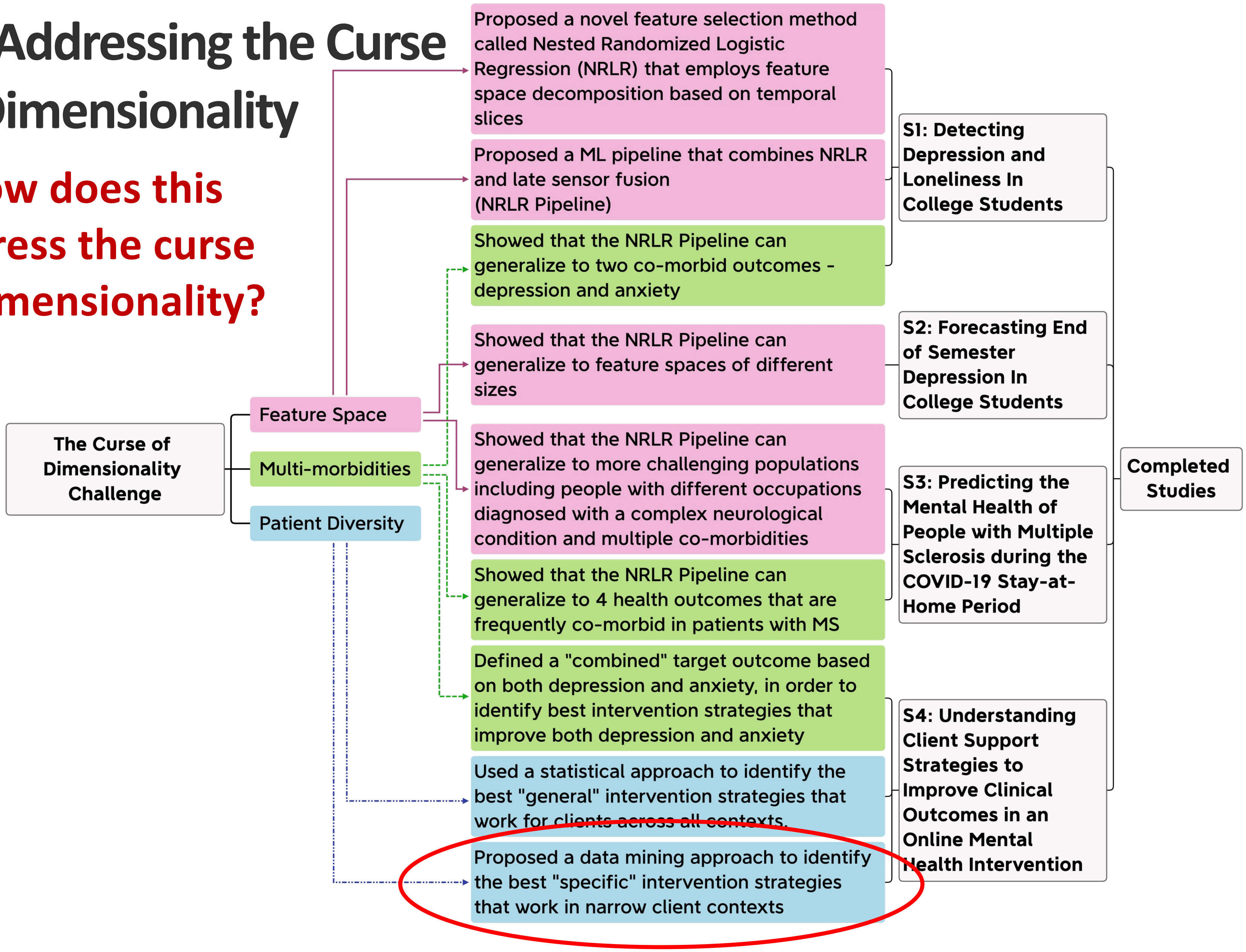
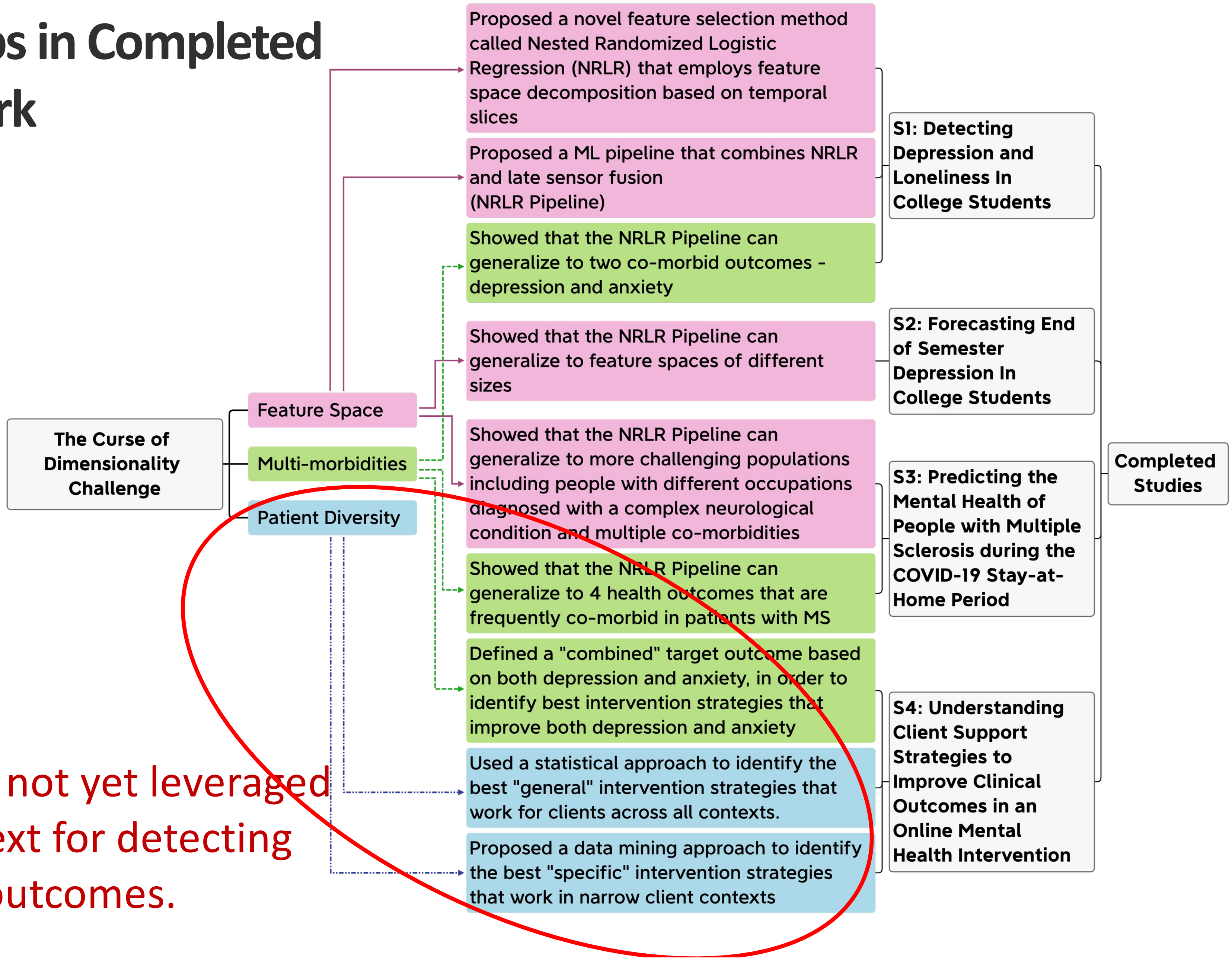


Proposal Outline

- Introduction
- The Curse of Dimensionality Challenge
- Completed Work
- **Gaps in Completed Work**
- Proposed Work
- Proposed Timeline
- Thesis Contributions

Gaps in Completed Work



Have not yet leveraged context for detecting MH outcomes.

Gaps in Completed Work Contd.

- Leverage patient contexts for detection and understanding can:
  - Increase model performance
  - Lead to more interpretable insights for ML-based detection or clinician diagnosis and related treatment.

Proposal Outline

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Proposed Work

- Study 5:
  - Detect biweekly/ monthly mental health outcomes for patients with multiple sclerosis (baseline).
  - Can we leverage the patient's context (past outcomes or behaviors) to extract interpretable data-driven insights about mental health?
  - Can we leverage the patient's context to improve the model performance for predicting biweekly/ monthly mental health outcomes?

Note: Study 6 has been removed

- Study 6 in the proposal document was about combining multiple outcomes into ONE outcome for detection tasks.
- However:
    - We do not have enough data to pursue this.
    - Combined outcomes may not make sense for detection.
- Hence, study 6 has been removed.

Proposal Outline

- Introduction
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- Gaps in Completed Work
- Proposed Work
- **Proposed Timeline**
- Thesis Contributions

Proposed Timeline

Time	To Do
May 2022	Study 5 baseline
Jun-Aug 2022	Study 5 analysis and results
Sep-Dec 2022	Internship, Job Search
Jan-Feb 2023	Write Study 5 Paper
Mar-Apr 2023	Thesis writing Job Search
May 2023	Thesis Defense

Proposal Outline

- Introduction
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- Completed Work
- Gaps in Completed Work
- Proposed Work
- Proposed Timeline
- **Thesis Contributions**

Thesis Contributions

1. Contributed a feature selection approach (NRLR) that mitigates the curse of dimensionality in the feature space by decomposing the feature space during feature selection. Enables detection and early prediction with limited ground truth, thus reducing survey burden on the user.
2. Presented a ML pipeline (the NRLR Pipeline) that can be used to detect multiple co-morbid health outcomes in homogenous and complex populations.
3. Presented an approach that combines multiple outcomes into one final outcome, that can then be used to understand or personalize an intervention.

Thesis Contributions

4. Presented an approach that leverages the patient's context to analyze and identify "general" intervention strategies that work across multiple contexts, and "specific" intervention strategies that work in certain contexts.
5. [Expected] Will use the NRLR pipeline to detect biweekly/ monthly health outcomes in a complex population (pwMS).
6. [Expected] Will present an approach that leverages the patient's context to improve our understanding of the patient's health and/or improve the model performance for detecting biweekly/ monthly health outcomes.

Q&A?

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