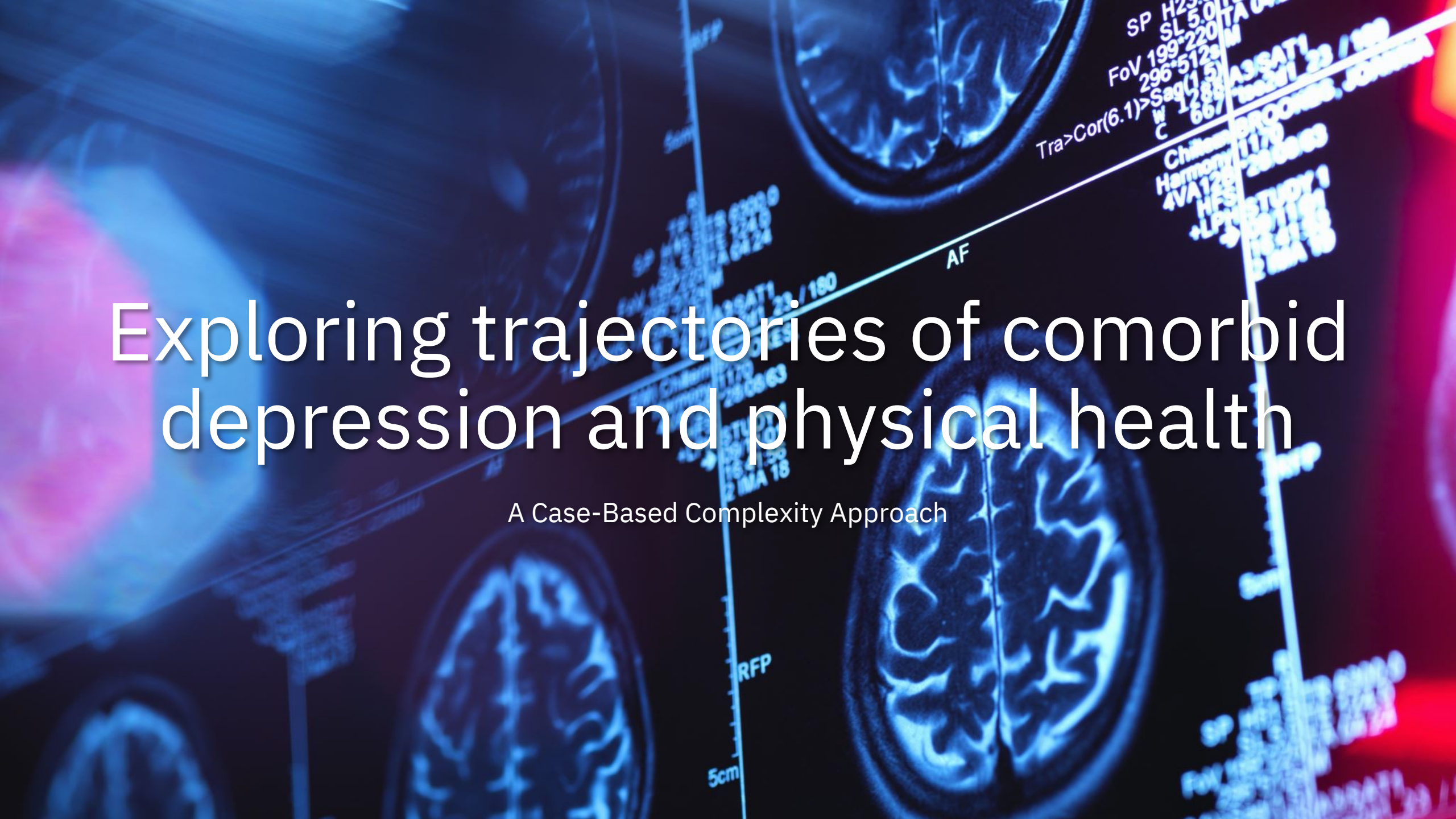


Exploring trajectories of comorbid depression and physical health

A Case-Based Complexity Approach

UNIVERSITY OF AMSTERDAM

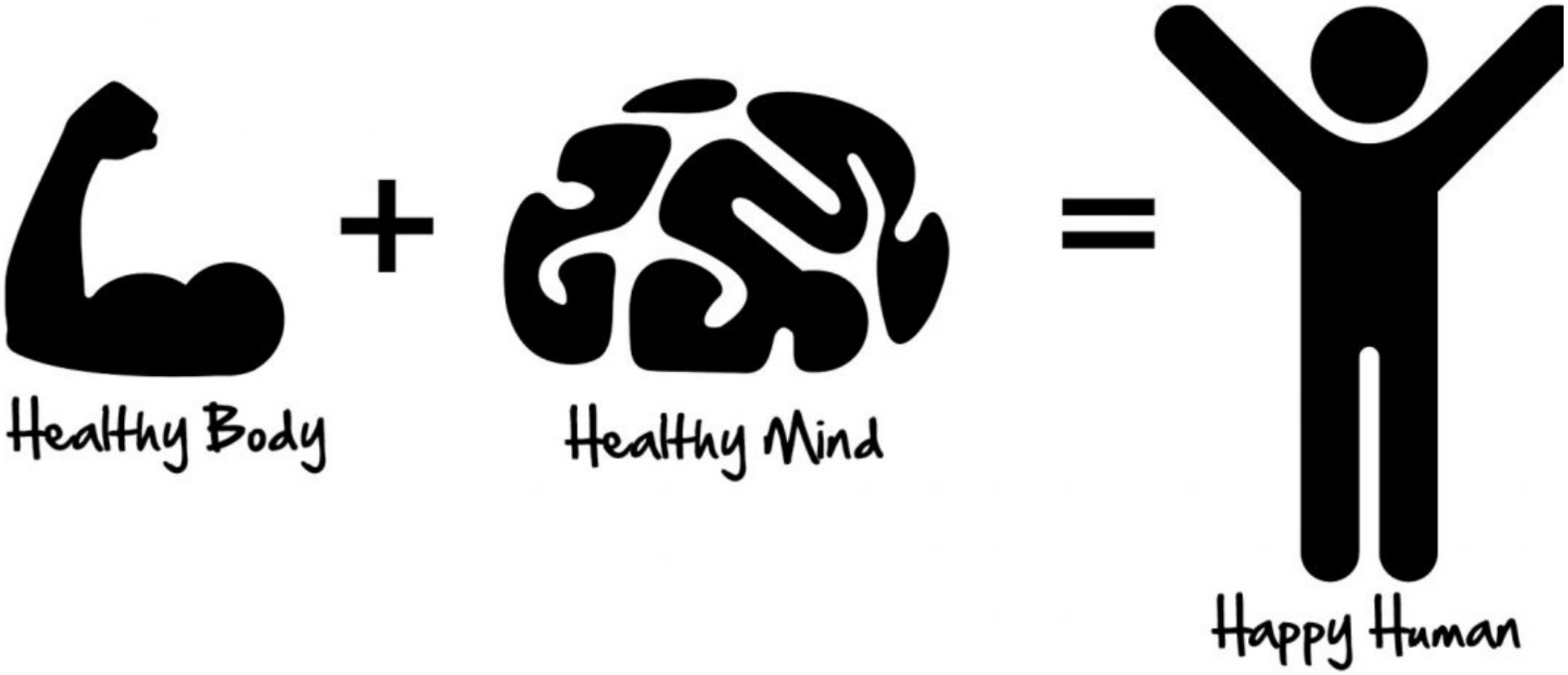
I want to thank the Centre for Urban Mental Health for the opportunity to lecture.

I want to also thank the Institute of Advanced Study for the opportunity to be a fellow during the 2021-2022 year.

Presentation Overview

- Challenge of modelling co-morbid depression and physical health.
- Utility of case-based complexity.
- Overview of study and key novel results.
- Demonstration of COMPLEX-IT for doing similar research.

Comorbid Depression and Physical Health




But that is not the whole story

Where and how people live matters

- People live in complex systems
  - Environmental Determinants
  - Socio-Economic Determinants
  - Psychological Determinants
  - Family and Social Networks

Methodological Challenge

The temporal evolution of depression and physical health is often comorbid, this relationship is not singular in its aetiological pattern, but is multiple and aetiologically complex.

METHODOLOGICAL CHALLENGES:

- Cataloguing multiple trends
- Developing multiple complex aetiological explanations
- Creating rich profiles from these different aetiologies
- Modelling the collective large-scale dynamics of these trends

Received: 5 March 2018 | Revised: 27 July 2018 | Accepted: 20 August 2018

DOI: 10.1111/jep.13042

ORIGINAL PAPER

WILEY Journal of Evaluation in Clinical Practice
International Journal of Public Health Policy and Health Services Research

Exploring comorbid depression and physical health trajectories: A case-based computational modelling approach

Brian Castellani PhD, Professor of Sociology[1,6] |
Frances Griffiths MD PhD, Professor of Medicine[2,3] |
Rajeev Rajaram PhD, Associate Professor[4] | Jane Gunn MD PhD, Professor of Medicine[5]

What we did and what we found

- N = 259 people were subsampled from the Diamond database, one of the largest primary care depression cohort studies worldwide.
- A global measure of depressive symptoms (PHQ-9) and physical health (PCS-12) were assessed at 3, 6, 9, and 12 months and then annually for a total of 7 years.
- Eleven trajectories and 2 large-scale collective dynamics were identified, revealing that while depression is comorbid with poor physical health, chronic illness is often low dynamic and not always linked to depression.
- Also, some of the cases in the unhealthy and oscillator trends remained ill without much chance of improvement.
- Finally, childhood abuse, partner violence, and negative life events are greater amongst unhealthy trends.

Case-Based Complexity

Case-based complexity

- My colleagues and I have spent the past several years developing a new approach to modeling complex systems, called based case-based complexity.
- It integrates Ragin and Byrne's case-comparative method with the latest developments in computational modeling.
- The argument is that complex systems are the methodological equivalent of cases; and, therefore, complex systems are best modeled from a case-based perspective.

Case-based complexity

So, what makes case-based so different?

First, we can talk what this approach does not do:

1. Not focused on variables.
2. Not focused on simple aggregate averages.
3. Not reductionist
4. Not static
5. Not focused on one-size-fits-all models, interventions or services.
6. Does not fit data to curves.

Case-based complexity

- Convert databases into sets of cases (k dimensional row vectors; i.e., rows containing k elements).
- Compute the trajectory (velocity vector) for each case based on a set of bio-social variables called traces.
- Construct a theoretical map to explain these traces.
- Use vector quantization (i.e., k-means, topographical neural nets) to longitudinally cluster case trajectories into major/minor trends.

Case-based complexity

- Employ genetic algorithms and ordinary differential equations to create a microscopic (vector field) model (the inverse problem) of these trajectories.
- Look for complex steady-state behaviours (e.g., spiralling sources, etc) in the microscopic model.
- Use the macroscopic model to simulate known and novel case-based scenarios (the forward problem).
- Construct multiple thick descriptions (clinical cases, urban studies, etc) similar to qualitative or ethnographic research.

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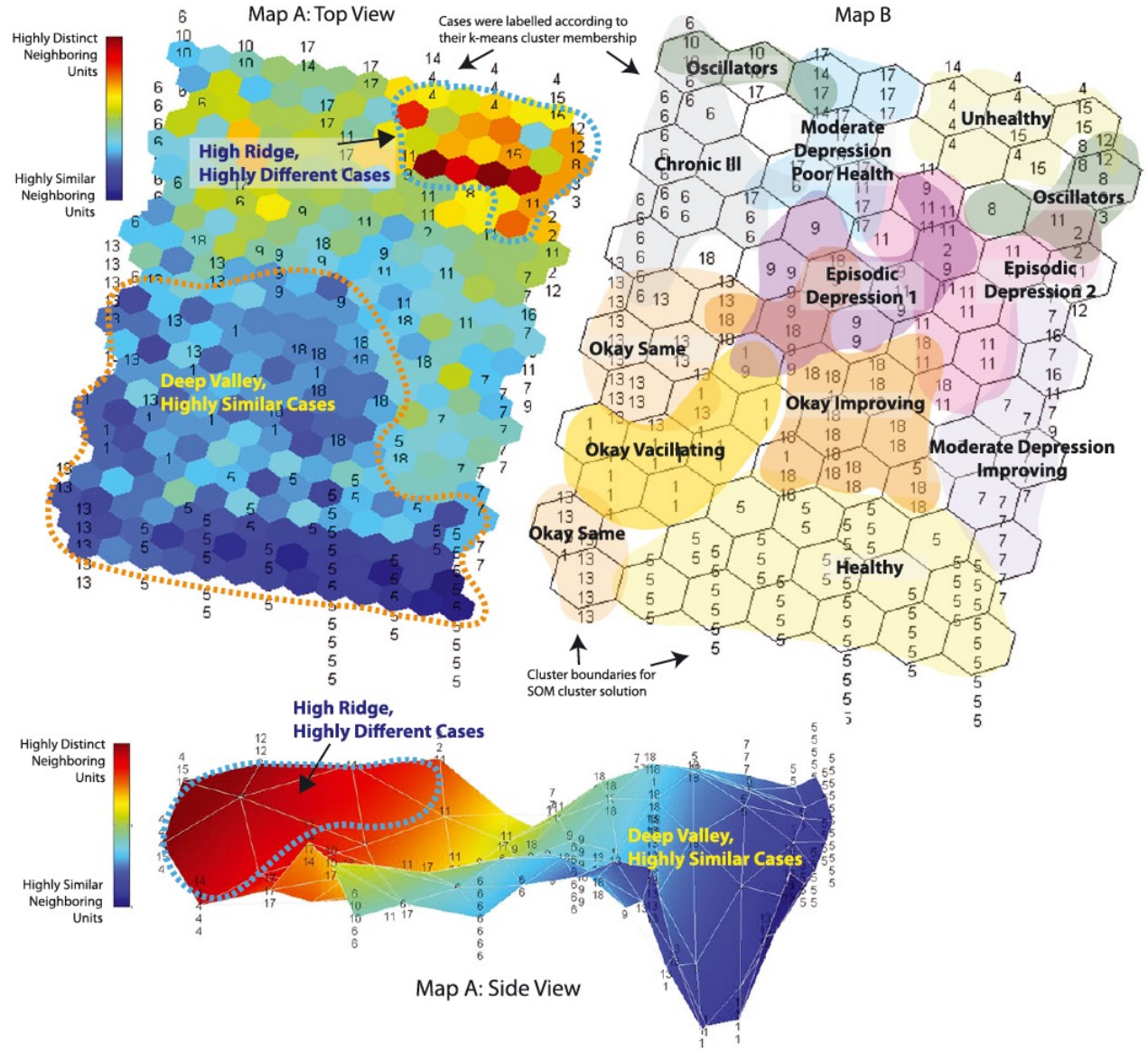
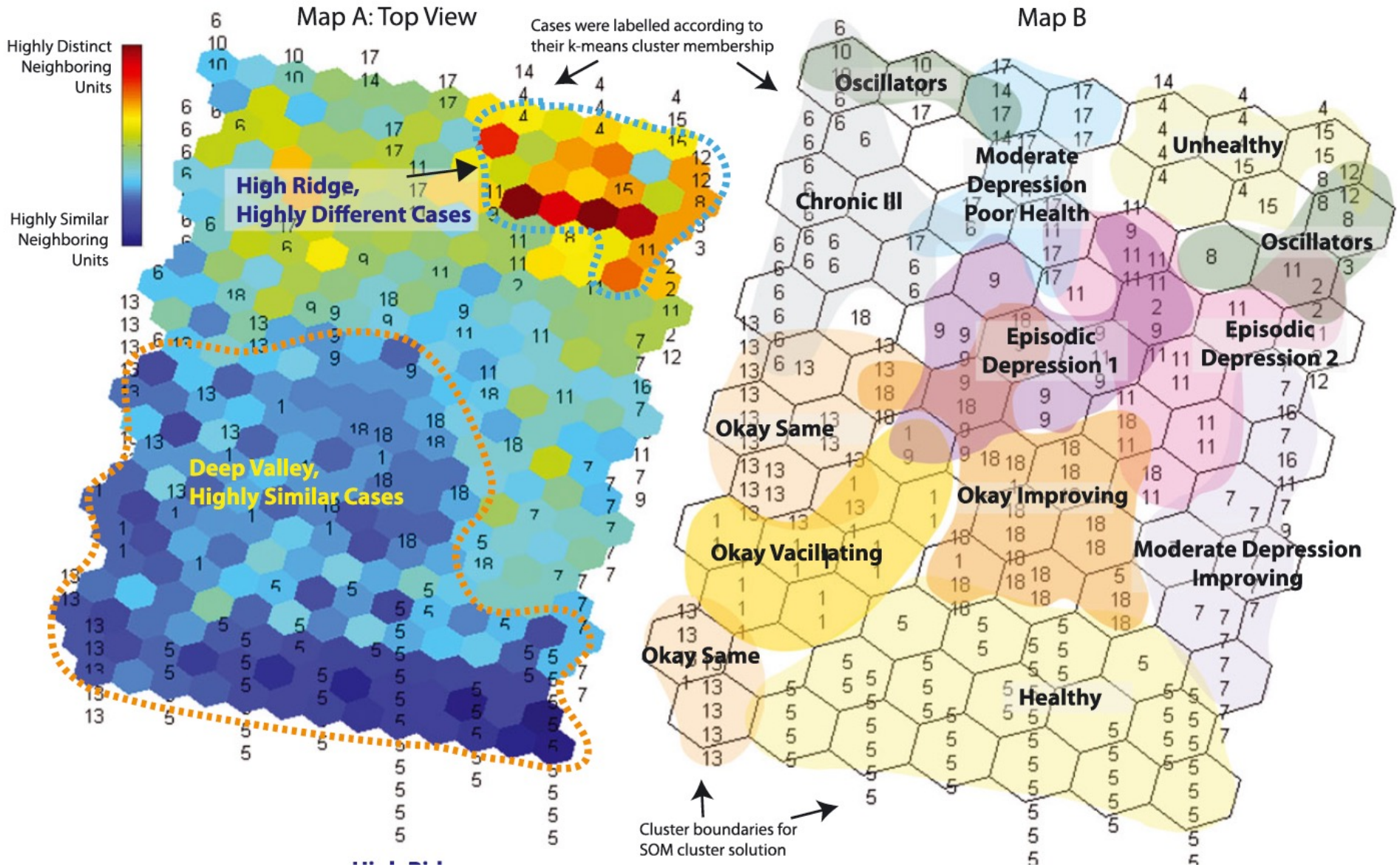
We found 11 cluster trends

Longitudinal Trend					
	Healthy (N = 58)	Okay Vacillate (N = 20)	Okay Same (N = 27)	Okay Improving (N = 26)	Moderate Depression Improving (N = 18)

Episodic Depression 1 (N = 16)	Episodic Depression 2 (N = 22)	Moderate Depression Poor Health (N = 14)	Unhealthy (N = 9)	Chronic Ill (N = 23)	Oscillators (N = 17)


Map A: Top View
Cases were labelled according to their k-means cluster membership
Map B
Highly Distinct Neighboring Units
Highly Similar Neighboring Units
High Ridge, Highly Different Cases
Deep Valley, Highly Similar Cases
Oscillators
Moderate Depression Poor Health
Chronic Ill
Unhealthy
Oscillators
Episodic Depression 1
Episodic Depression 2
Okay Same
Okay Improving
Okay Vacillating
Moderate Depression Improving
Okay Same
Healthy
Cluster boundaries for SOM cluster solution
High Ridge, Highly Different Cases
Highly Distinct Neighboring Units
Highly Similar Neighboring Units
Deep Valley, Highly Similar Cases
Map A: Side View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High Ridge, Highly Different Cases
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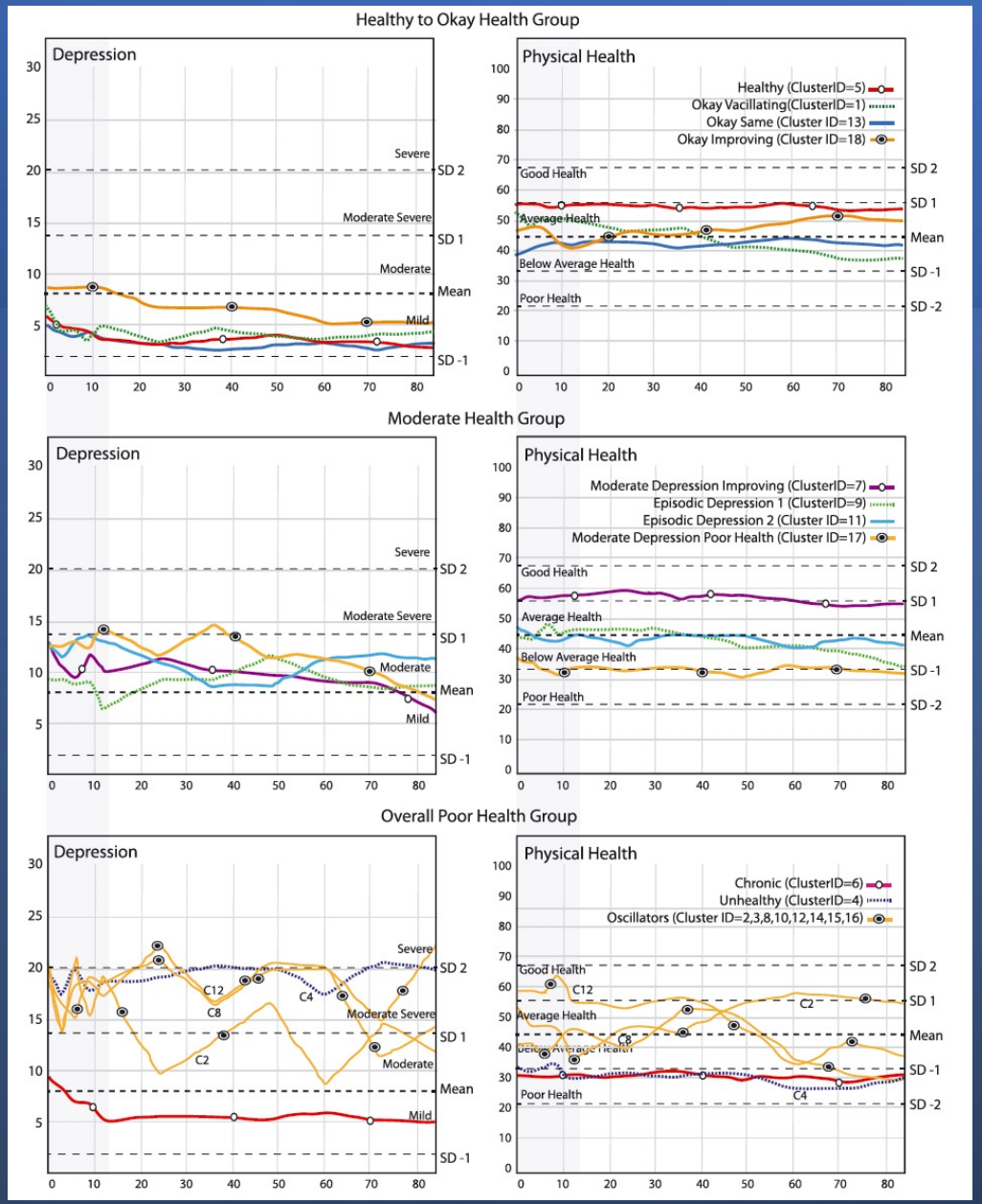
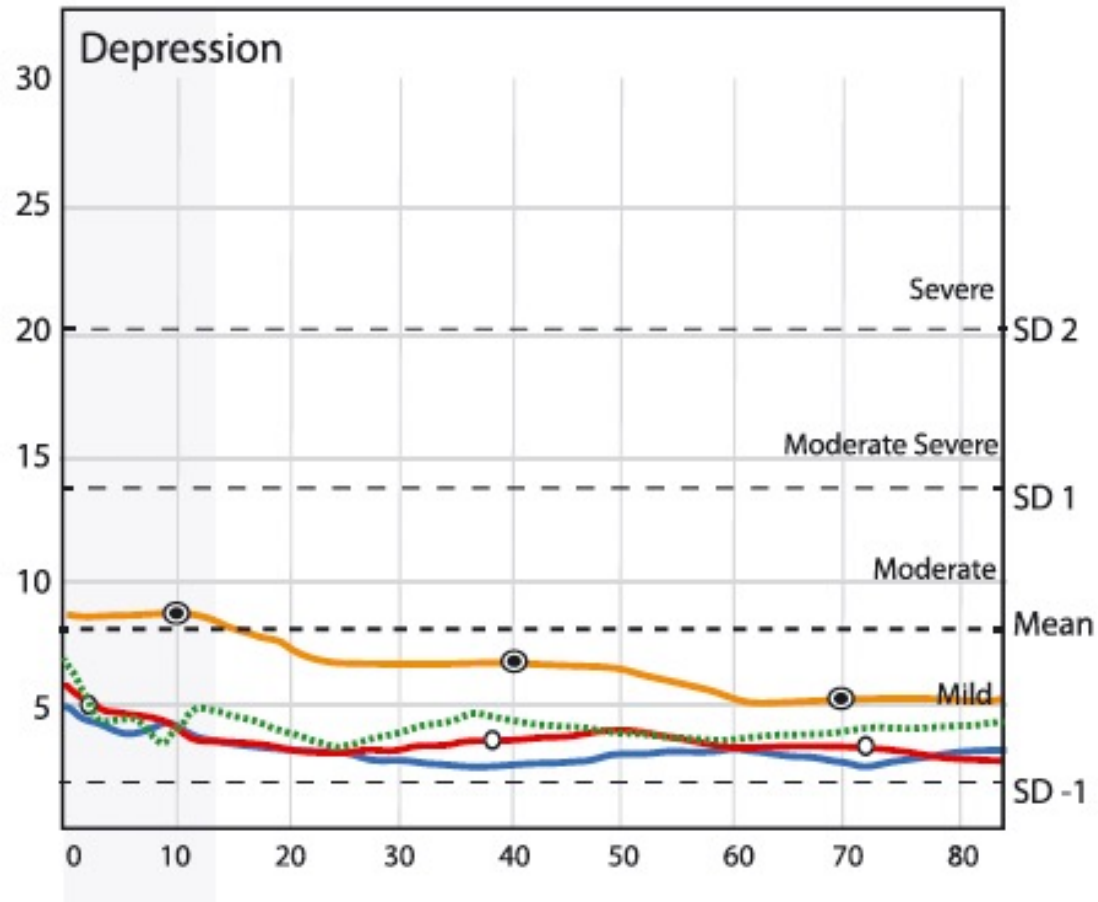
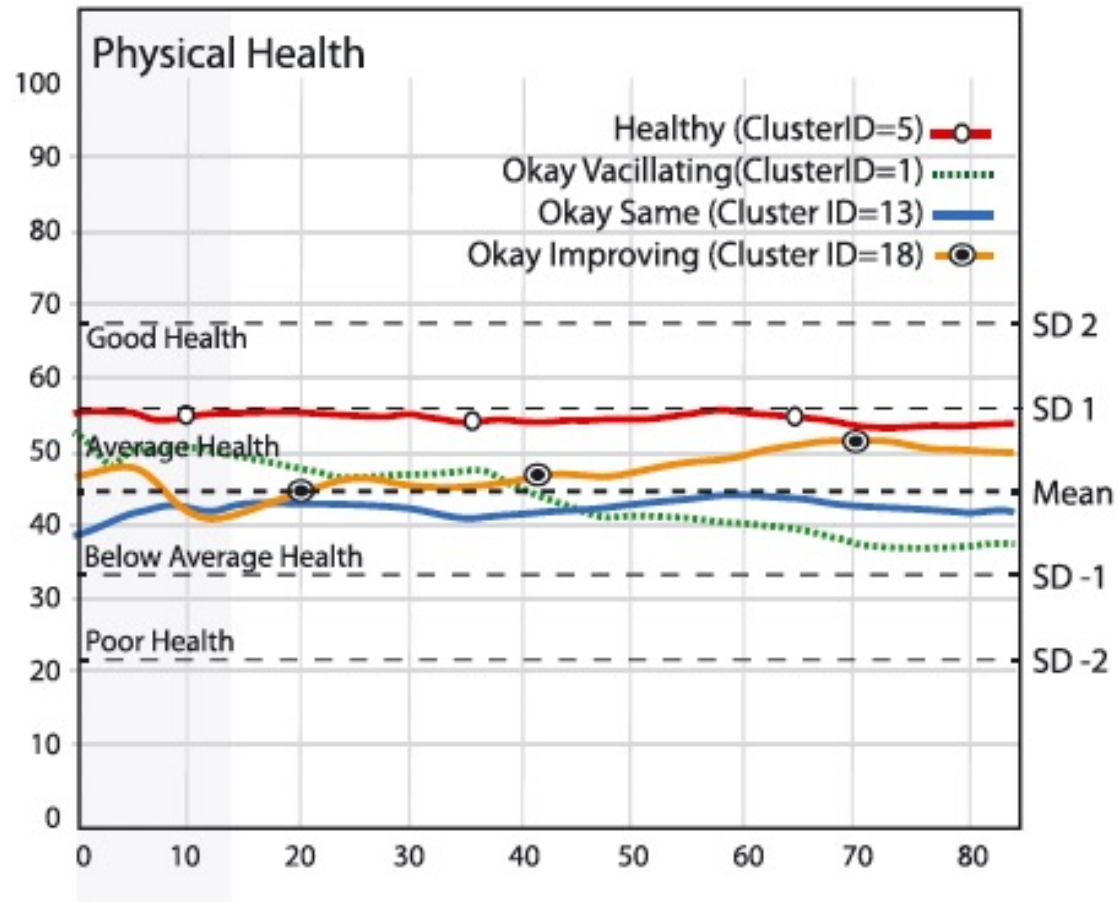
Oscillators
Chronic Ill
Moderate Depression Poor Health
Unhealthy
Oscillators
Episodic Depression 1
Episodic Depression 2
Okay Same
Okay Improving
Okay Vacillating
Moderate Depression Improving
Okay Same
Healthy
Cluster boundaries for SOM cluster solution

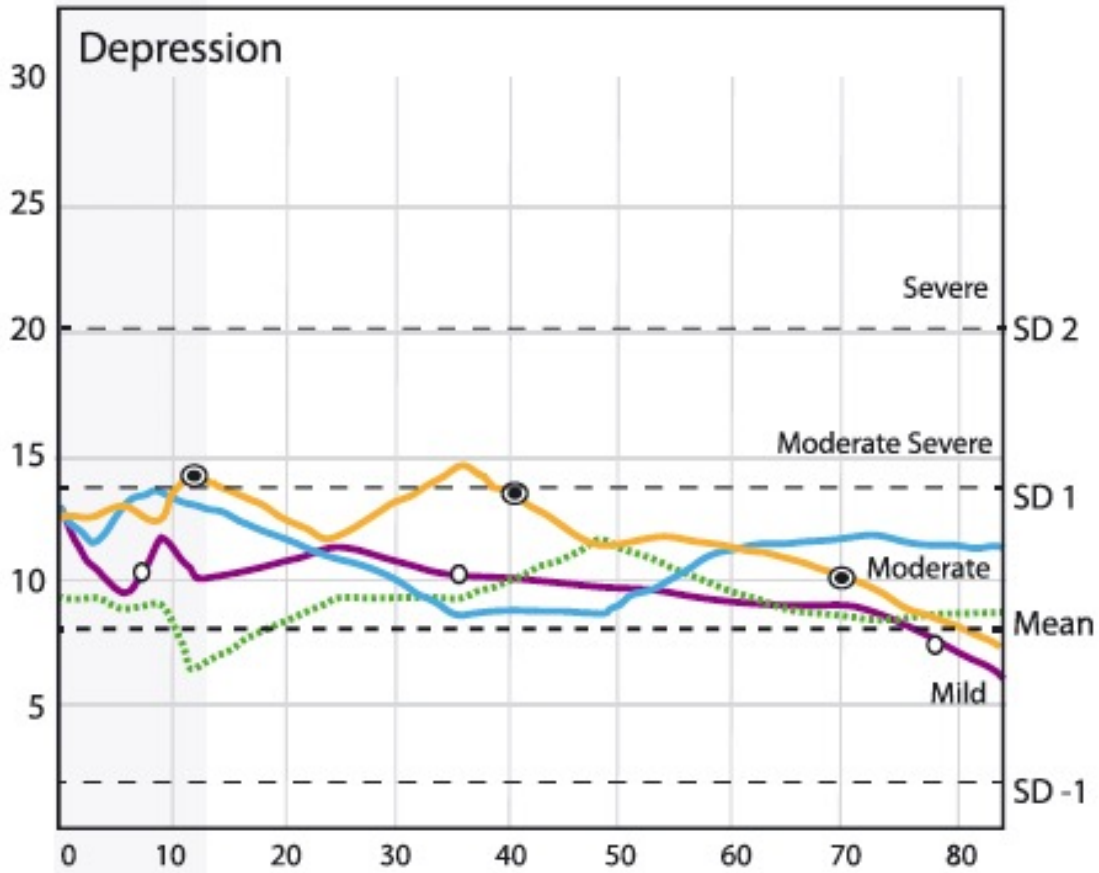

Healthy to Okay Health Group
Depression
Severe
Moderate Severe
Moderate
Mild
SD 2
SD 1
Mean
SD -1
Physical Health
Healthy (ClusterID=5)
Okay Vacillating(ClusterID=1)
Okay Same (Cluster ID=13)
Okay Improving (Cluster ID=18)
Good Health
Average Health
Below Average Health
Poor Health
SD 2
SD 1
Mean
SD -1
SD -2
Moderate Health Group
Depression
Severe
Moderate Severe
Moderate
Mild
SD 2
SD 1
Mean
SD -1
Physical Health
Moderate Depression Improving (ClusterID=7)
Episodic Depression 1 (ClusterID=9)
Episodic Depression 2 (Cluster ID=11)
Moderate Depression Poor Health (Cluster ID=17)
Good Health
Average Health
Below Average Health
Poor Health
SD 2
SD 1
Mean
SD -1
SD -2
Overall Poor Health Group
Depression
Severe
Moderate Severe
Moderate
Mild
C12
C8
C4
C2
SD 2
SD 1
Mean
SD -1
Physical Health
Chronic (ClusterID=6)
Unhealthy (ClusterID=4)
Oscillators (Cluster ID=2,3,8,10,12,14,15,16)
Good Health
Average Health
Poor Health
C12
C2
C8
C4
SD 2
SD 1
Mean
SD -1
SD -2

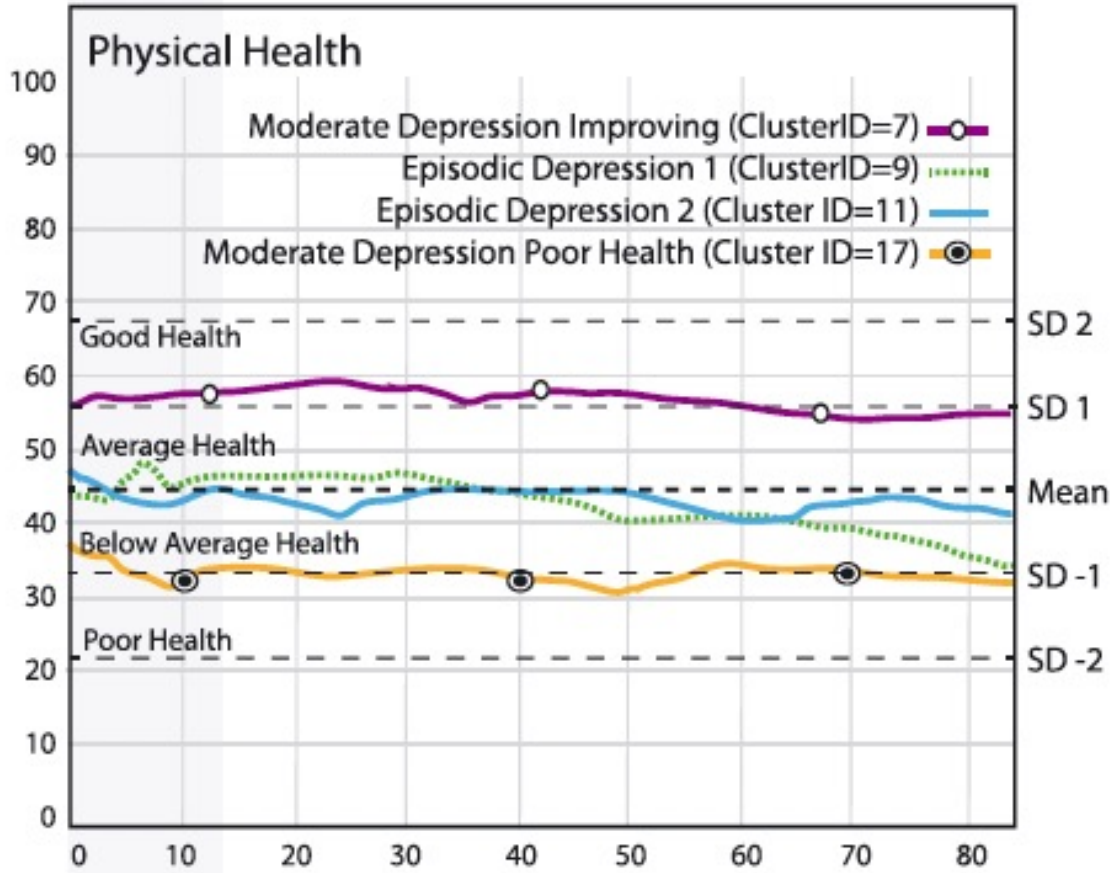
Healthy to Okay Health Group

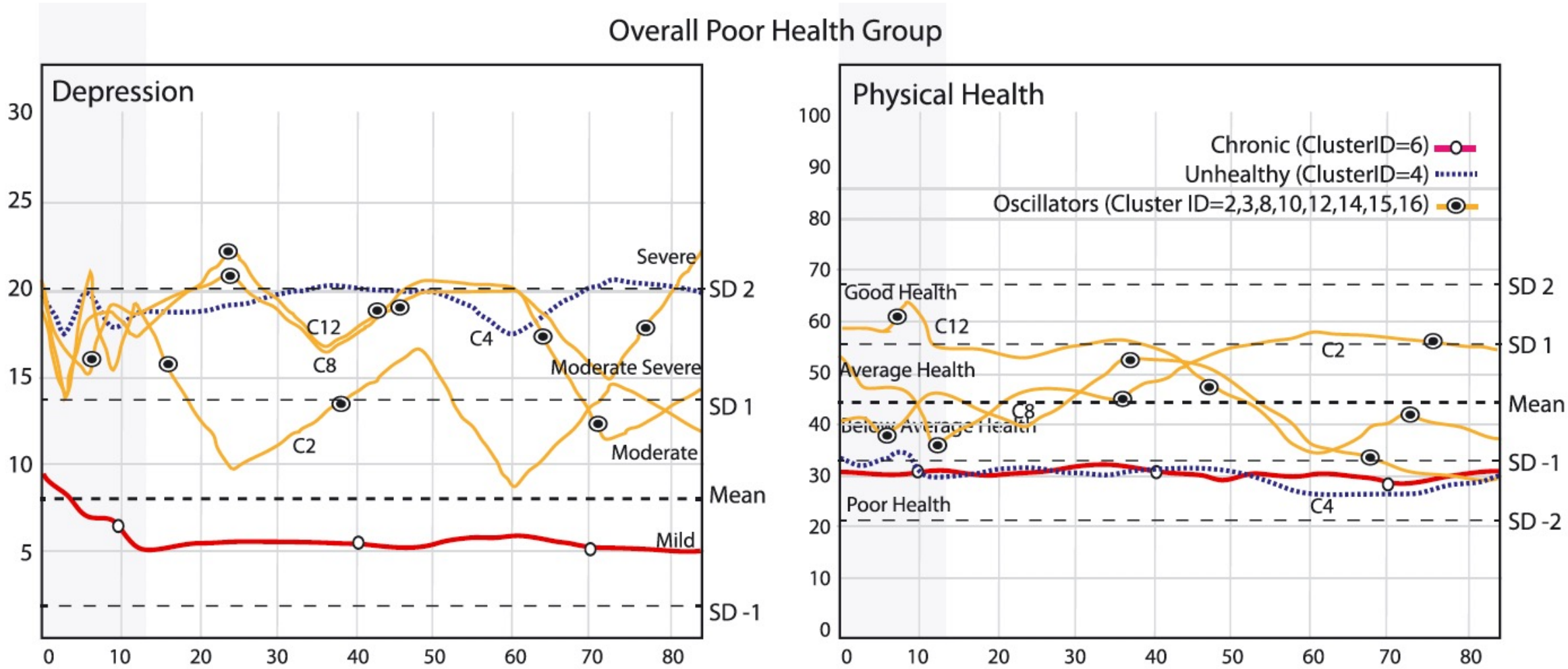




Moderate Health Group






Overall Poor Health Group
Depression
30
25
20
15
10
5
0
10
20
30
40
50
60
70
80
Severe
Moderate Severe
Moderate
Mild
SD 2
SD 1
Mean
SD -1
C12
C8
C4
C2
Physical Health
100
90
80
70
60
50
40
30
20
10
0
Chronic (ClusterID=6)
Unhealthy (ClusterID=4)
Oscillators (Cluster ID=2,3,8,10,12,14,15,16)
Good Health
Average Health
Poor Health
SD 2
SD 1
Mean
SD -1
SD -2
C12
C8
C4
C2

Psychological
Days out of role due to emotional problems***
Hazardous drinking in last 12 months**
Any substance abuse[a]
Never smoked
Currently smoke
Depression a current problem[a]
Ever told by doctor had depression[a]
Ever told by doctor had anxiety[a]
Dysthymia[ba]
Currently taking depression meds[a]
Currently taking antianxiety meds
Currently taking antipsychotic meds[a]
Currently taking sedative meds[a]
Partner abuse, severe[ca]
Childhood sexual abuse[da]
Childhood sexual abuse, severe[da]
Childhood physical abuse[da]
Childhood physical abuse, severe[d]**

Physical
Chronic illness or disability[ea]
Chronic condition last 12 months[f]
Self-health rating[g]***
Days out of role for physical health***

Physical Factors

Psychological Factors

Sociological Factors

Income[a]***
Socioeconomic advantage[b]†
Highest level of education[c]***
Visits to health professional[d]***
Age***
Negative life events score (0 to 13)***
SSQ number of supporters[e]***
Social participation score[f]***
Unable to work[g]*
Employed[g]*
General practice location (rural)
Private health insurance
Per cent female (N = 185)[h]
Per cent male (N = 74)[h]
Lives alone
Married
Satisfied with support[i]**

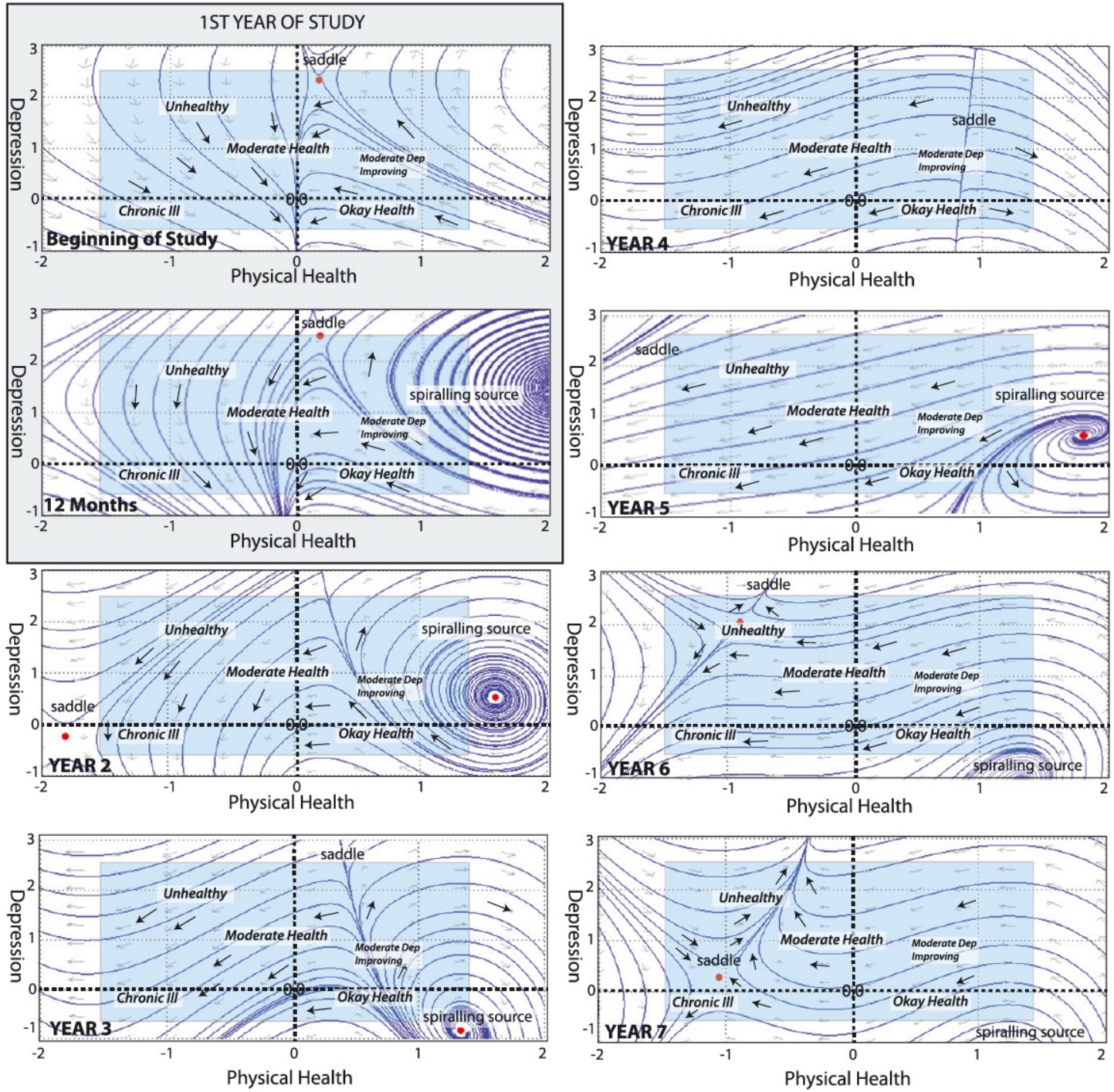
Our first clinical narrative is for the healthiest cluster trend. Healthy (N = 58), with high across-the-board rates of health and sociodemographic wellbeing, this trend is doing well. It is also the youngest.

Okay Vacillating (N = 20): As the specific indicators in Tables 3 and 4 show, this trend is struggling a bit, including declining physical health, but otherwise okay. Note: By "okay", we mean that the scores on PHQ9 and PCS12 for this trend (as well as others below that use the same term) are in the satisfactory range, but are not exceptionally or especially good. This trend is also middle aged, and at baseline, 85% reported a chronic condition in last 12 months. Ten per cent also report currently taking antipsychotics, the second highest rate among the trends, and 45% have a rural GP, the highest rate (along with the unhealthy group) among the trends.

Unhealthy (N = 9): This middle-aged trend has sustained poor physical and mental health. It also has, overall, the most disadvantaged sociodemographic profile. Psychological distress is also pronounced, with 100% being told by provider, at baseline; they have depression and anxiety. Childhood abuse exposure is second highest of all groups, and severe partner abuse is more than double the rate in any other group. In terms of physical health, they have the third highest rate of chronic illness, they have the worst self-health rating, and the highest rate of days missed for physical and emotional disorders.

Chronically Ill (N = 23): This older trend is struggling with chronic illness, but only mild depression. However, in terms of physical illness, 73.9% reported a past chronic illness or disability, 73.9% reported a current chronic condition, 21.7% cannot work, and only 47.8% are currently employed. This trend also had the third worst self-health rating and the third highest number of days missed for a physical condition.

Oscillators (N = 17): As a reminder, our study did not seek to remove or ignore small-n trends in order to explore trajectories where the comorbid relationship between depression and physical health was high dynamic. Such was the case with the oscillator trend. Each of these 8 minor trajectories—with the largest cluster added to this trend being N = 4 cases—fluctuates between moderate to severe levels of unhealthiness. As a group, the socioeconomic well-being of the Oscillators is average to below average. They also have (along with Okay Improving) the highest rates of substance abuse; very high rates of depression, anxiety, and dysthymia; and the highest rate of antipsychotic medication usage. Abuse history is also significant, with 69.2% reporting childhood physical abuse and 46.2% reporting severe childhood sexual abuse. They also have 1 of the worst baseline self-health ratings, missing a significant number of days due to emotional or physical issues.


1ST YEAR OF STUDY
Beginning of Study
12 Months
YEAR 2
YEAR 3
YEAR 4
YEAR 5
YEAR 6
YEAR 7
Unhealthy
Moderate Health
Moderate Dep Improving
Chronic Ill
Okay Health
saddle
spiralling source
Depression
Physical Health

- Looking at the results, this stage of the analysis suggests that depression is more dynamic than typically portrayed by conventional modelling.

- The identification of saddle points also suggests that there may be limits to what treatment can achieve for some people—particularly among the Unhealthy and Oscillator trends.

- However, it also suggests that saddle points are dynamic, so health care experts and public institutions (potentially through effective preventive policy) can potentially change them by, for example, reducing the physical and sexual abuse people (particularly women) experience.

- Again, these insights are exploratory and, therefore, further analysis and replication is necessary.

COMPLEX-IT

What is COMPLEX-IT?

COMPLEX-IT

Exploring complex data from a case-based perspective

Build the Model

1. Build Database and Import Cases
2. Cluster Cases

Test the Model

3. The Computer's turn
4. Compare and Visualise Results

Extend the Model

5. Simulate Interventions
6. Predict New Cases

Export Results

7. Generate Report

beta version release 2019

COMPLEX-IT is a web-based and downloadable software tool designed to increase your access to the tools of computational social science (i.e., artificial intelligence, micro-simulation, predictive analytics). It does this through a user friendly interface, with quick access to introductions on concepts and methods; and with directions to richer detail and information for those who want it.

The result is a seamless and visually intuitive learning environment for exploring your complex data -- from data classification and visualisation to exploring simulated interventions and policy changes to data forecasting.

You don't need any technical expertise to start using COMPLEX-IT, all that is required is a data set you want to explore, and a curious mind!

COMPLEX-IT

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Centre for the Evaluation of Complexity Across the Nexus

KENT STATE UNIVERSITY
ASHTABULA

COMPLEX-IT 1.0.0 Beta - exploring complex data from a case-based perspective

Build Your Model

1. Build database and import your cases

2. Cluster your cases

Confirm & Explore Your Model

3. Use AI to confirm your cluster solution

4. Compare and visualize your results

Run Scenario Simulations

5. Simulate your scenarios, policies, and interventions

Run Data-forecasting/classification

6. Use AI to predict the cluster membership of new cases

Export Your Results

7. Generate your report

STEP 1: IMPORTING YOUR DATABASE

For TUTORIALS on preparing and importing your data for COMPLEX-IT CLICK HERE

To start an analysis session, import your data set using the BROWSE button below.

Your data must be in the form of a csv file. For more on creating csv files CLICK HERE

Choose CSV File

Browse | No file selected

☑ Header?

Separator:

Comma

Number of rows in the preview:

20

Number of columns in the preview:

10

Note: Even if the preview only shows a restricted number of observations, the map will be based on the full dataset.

https://www.art-sciencefactory.com/complexit.html

Thank You