

# Patient States: Artificial Intelligence-Driven Metric Providing Comprehensive Yet Straightforward Understanding of Chronic Pain Patients

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# Disclosures

Louis Raso, MD



- Boston Scientific: Speakers Bureau
- Aurora Spine: Speakers Bureau and Stockholder
- Surgentec: Speakers Bureau, and Royalties
- FloSpine: Speakers Bureau, and Royalties

# Pain Patient Health is Multidimensional



## Pain Scores

Sources of Bias & Confound Factors

Response bias<sup>1</sup>

Memory bias/accuracy<sup>2,3</sup>

Patient comprehension

Psychosocial and  
behavioral factors<sup>1</sup>

Methodological issues

- 1) Robinson, et al. 1997      3) Schneider, et al. 2011  
2) Redelmeier and Kahneman, 1996      4) Turk et al, 2002

## Broad Outcomes

IMMPACT Recommended domains<sup>4</sup>

PAIN

PHYSICAL FUNCTION

EMOTIONAL FUNCTION

PT RATING OF IMPROVEMENT /  
SATISFACTION

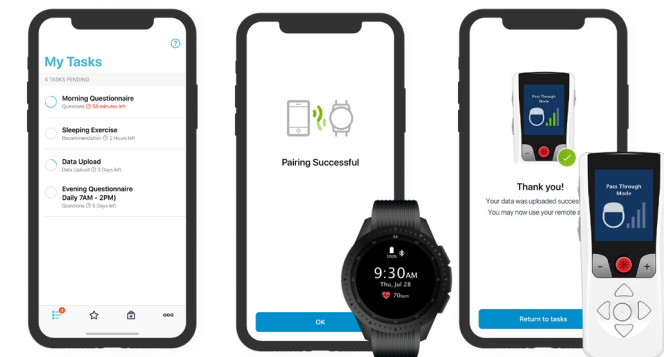
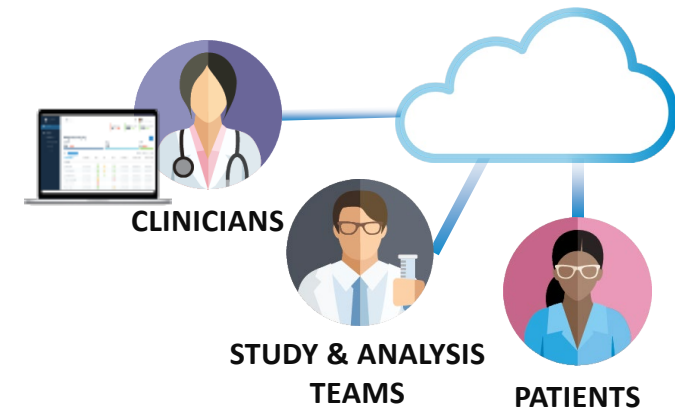
SYMPTOMS / ADVERSE EVENTS

PARTICIPANT DISPOSITION

The Initiative on Methods, Measurement, and Pain  
Assessment in Clinical Trials

## New Tools

Digital and continuous



Questionnaires,  
Text Responses,  
& Voice Recordings

Wearables

Stimulator Data

# Study Methods



<b>Study Design</b>	Two ongoing, multi-center, prospective Boston Scientific-sponsored SCS studies (NAVITAS and ENVISION), NCT03240588
<b>Key Study Methods</b>	<ul style="list-style-type: none"> <li>Ongoing Digital Health Study</li> <li>Advanced data analytic techniques and novel patient measures</li> </ul>
<b>Analysis Cohort</b>	<p>n = 116/182 patients with chronic pain treated with or candidates for SCS met the analysis inclusion criteria:</p> <ul style="list-style-type: none"> <li>Subjects wore the smartwatch &gt;10 days with overlapping daily questionnaires answered via custom-designed clinical study version of a digital health ecosystem (Boston Scientific, Valencia, CA)</li> </ul>
<b>In Clinic Assessments used in this Analysis</b>	<p>ODI Total</p> <p>EQ5D: Pain, Activities, Health VAS, Normed Score</p>

<b>Daily Questionnaires from Patient Phone Application used in this Analysis</b>	Average Pain
	Medication
	Activities of Daily Living
	Mood
	Sleep
<b>Smartwatch</b>	Alertness
	<p>Effective Mobility</p> <p>(Derived from accelerometer)</p>

# IBM AI analysis discovery:

Patients move between different “States” each day



Factors  
contributing to  
Patient States

Average Pain

Medication

Activities of  
Daily Living

Mood

Sleep

Alertness

Effective  
Mobility

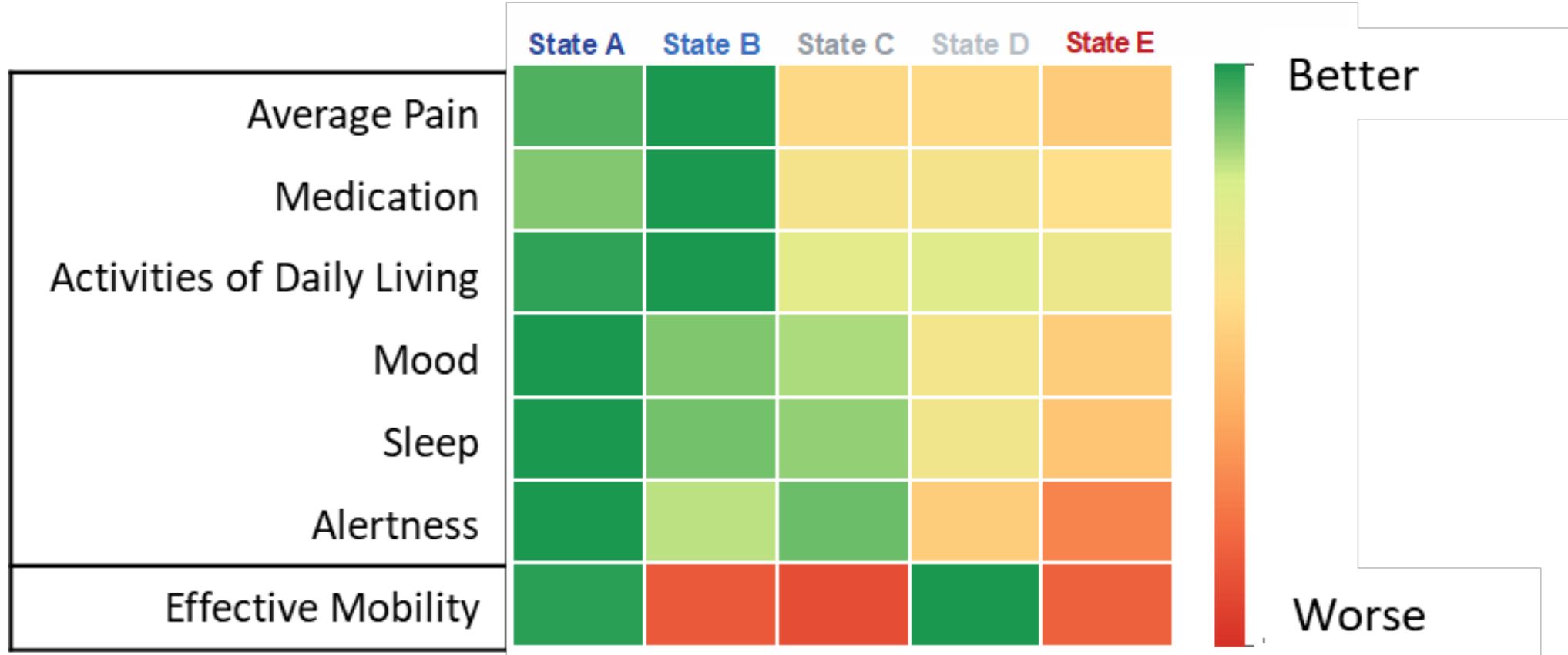
**Artificial  
Intelligence**



# States are Characterized by Differences in the Cluster Centroid Values



Factors  
contributing to  
Patient States



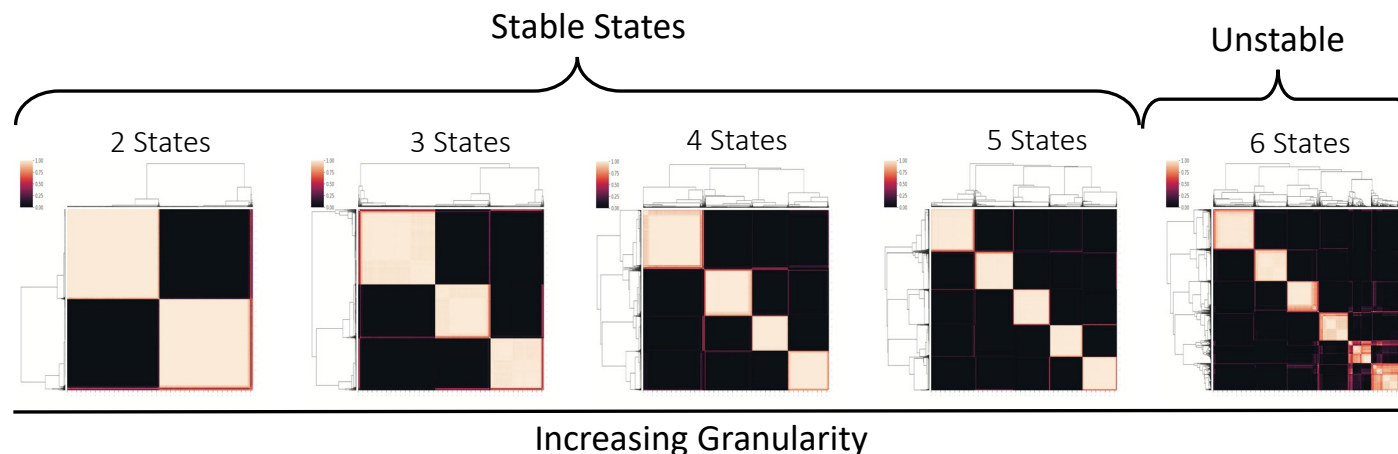
Normalized value for the centroid of each state color mapped from best to worst clinical outcome per dimension

# Advanced Analytics with Patient States



## 1 5 Stable Clusters Exist.

Stable Clusters Identified with Unsupervised Consensus Clustering methods using k-means



Consensus Cluster assignments are based on 1000 sub-sampled iterations. Strong consensus of cluster assignments indicated stability of  $\leq 5$  clusters.

## 2 States correlate with Validated In-Clinic metrics.

Correlations suggest an order from A-E.

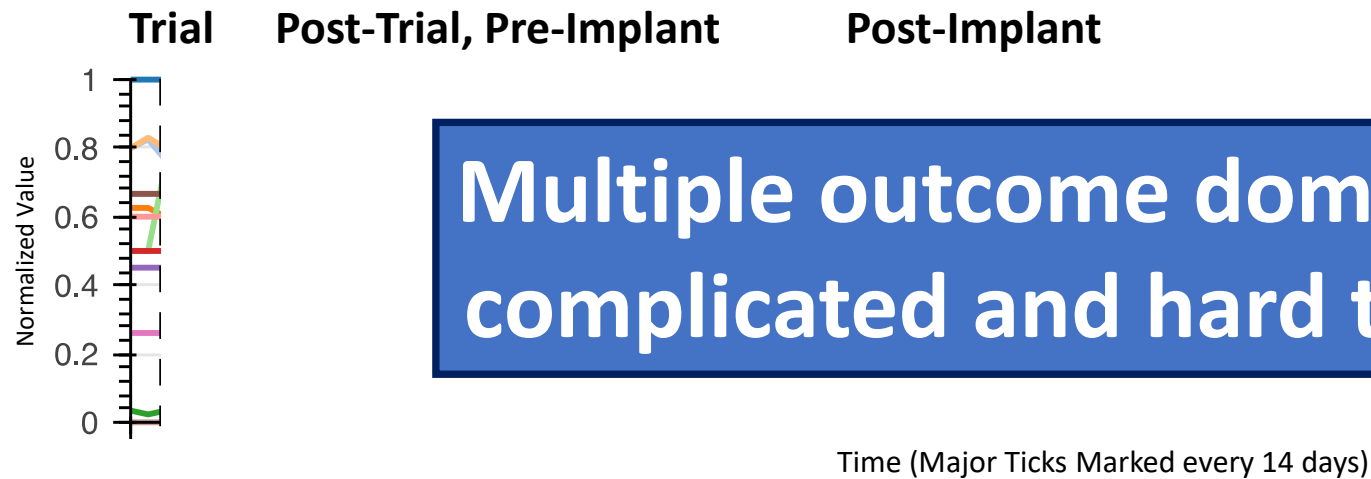
In Clinic Metric		Patients (samples)	State A	State B	State C	State D	State E
ODI Total		96 (1005)	$r = 0.48^{**}$	$r = 0.41^{**}$	$r = -0.06^*$	$r = -0.31^{**}$	$r = -0.48^{**}$
EQ5D	Activities	96 (1006)	$r = 0.28^{**}$	$r = 0.26^{**}$	$r = -0.09^{**}$	$r = -0.25^{**}$	$r = -0.32^{**}$
	Pain		$r = 0.42^{**}$	$r = 0.41^{**}$	$r = -0.09^{**}$	$r = -0.24^{**}$	$r = -0.35^{**}$
	Health VAS		$r = -0.18^{**}$	$r = -0.13^{**}$	$r = 0.04$ ns	$r = 0.19^{**}$	$r = 0.23^{**}$
	Normed Score		$r = 0.4^{**}$	$r = 0.32^{**}$	$r = -0.12^{**}$	$r = -0.2^{**}$	$r = -0.37^{**}$

Pearson Correlation comparing: Distance from a State centroid to In-Clinic metrics.

R-values, app data w/in  $\pm 7$  days of clinic visit

$**p < 0.01$ ;  $*p < 0.05$ ; ns = not significant

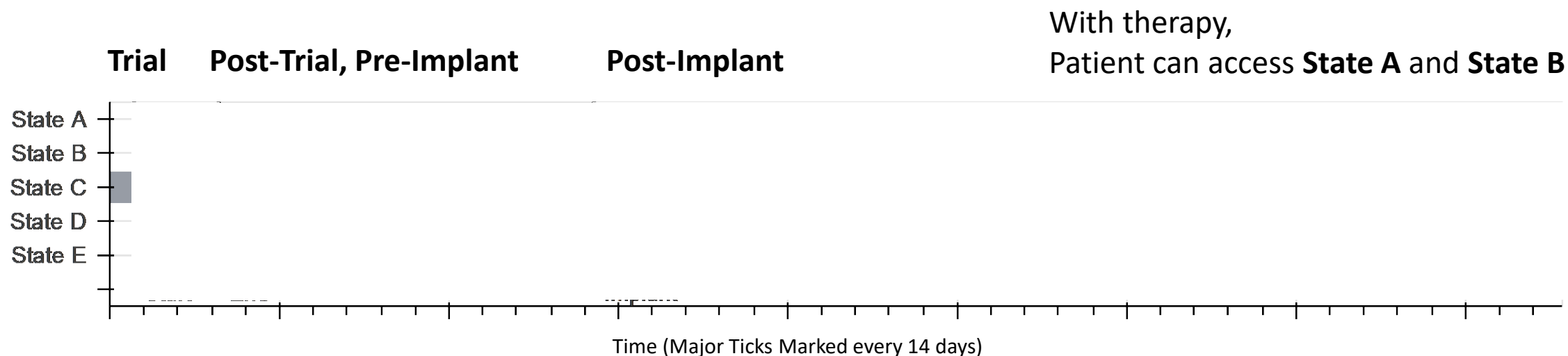
# Patient A: Monitoring Individual Domains



Domains Displayed: Pain, Sleep, Activities, Pain Interference, Medications, Alertness, Mood, Effective Mobility

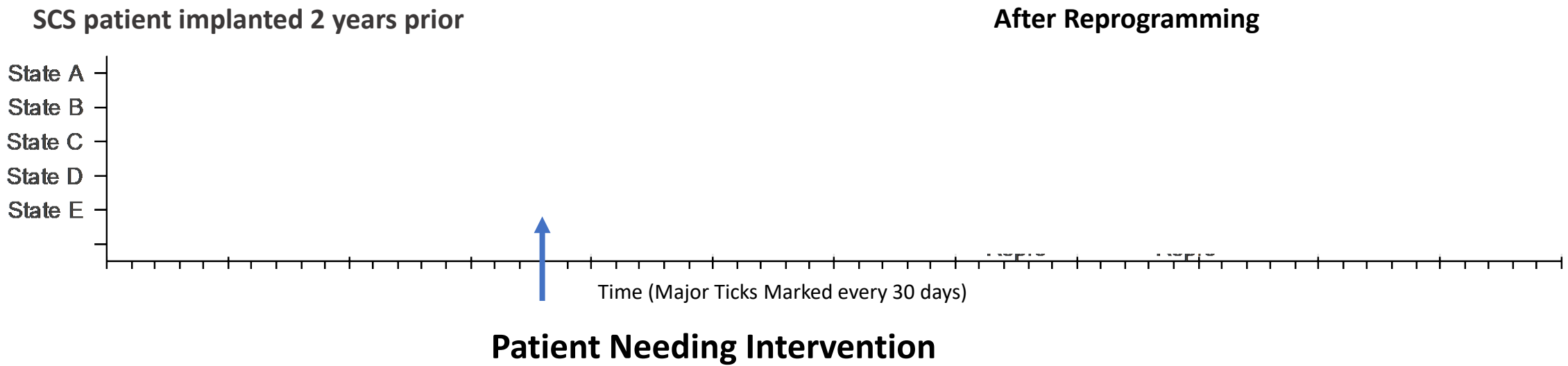


# Patient A: Simplified Monitoring Using Patient States



**Patient States →  
Comprehensive Yet Straightforward  
Understanding of the Patient**

# Patient B: Patient States Can Empower Clinicians

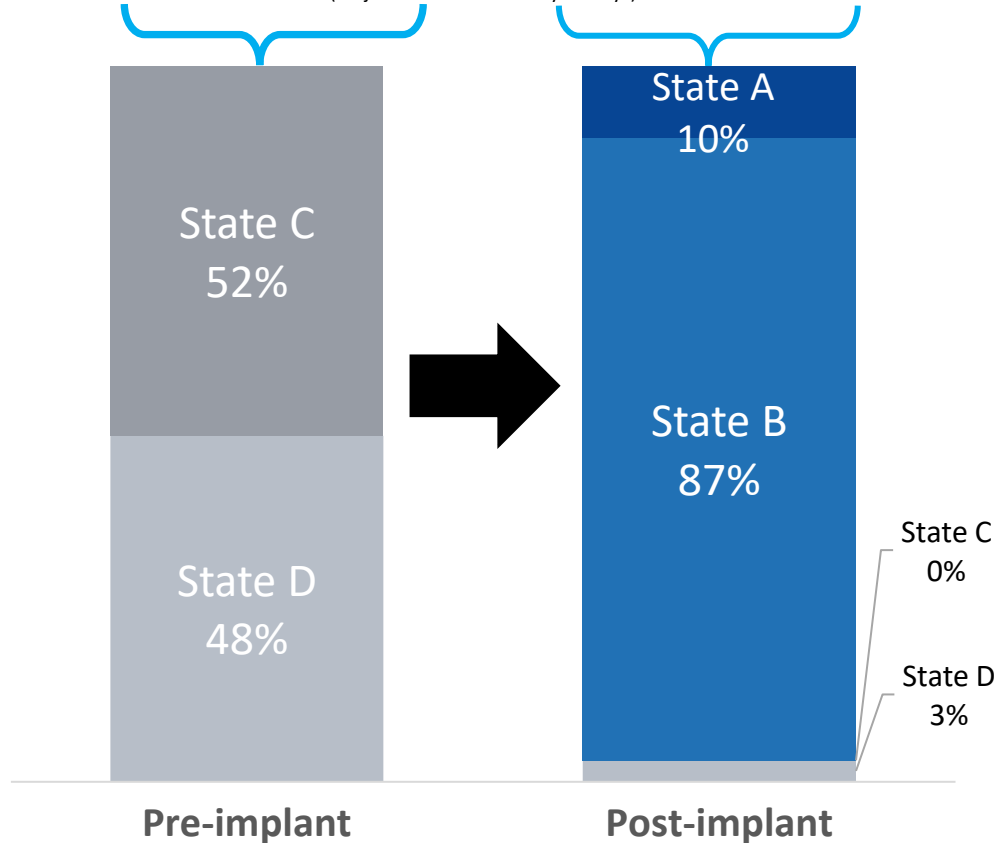
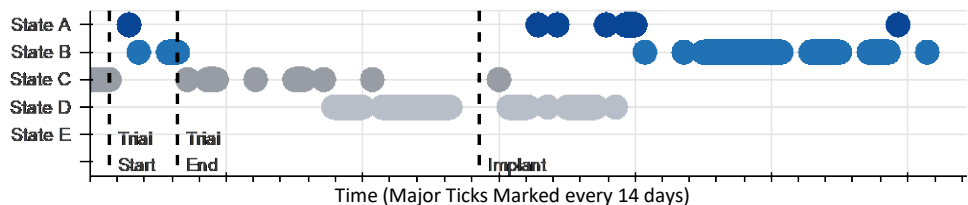


**Patient States holds promise to  
allow timely intervention**

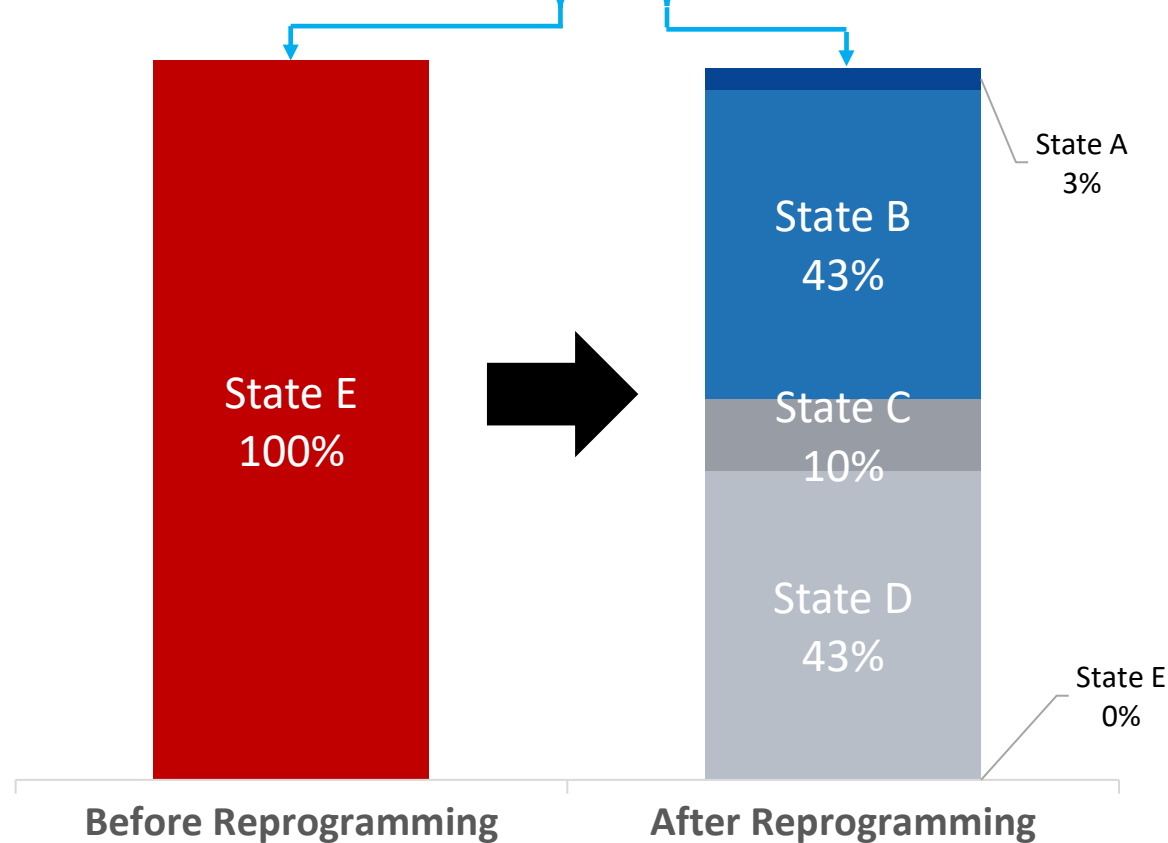
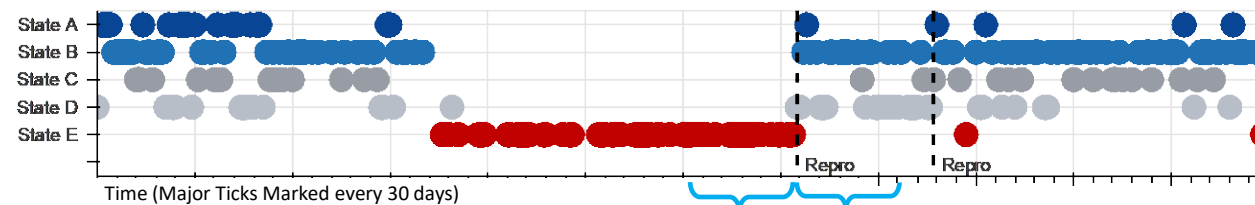
# Patient State Dwell Time: Simplified Comparisons



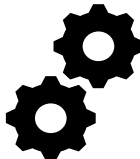
**Patient A**



**Patient B**



## Patient States...

 Harness artificial intelligence to provide novel understanding chronic pain patients in a simple and easy manner

 Could enable clinicians to prioritize and deliver timely interventions to improve patient outcomes

 Holds promise for the efficient management of care for large groups of chronic pain patients