‘Segmenting’ the High-Risk, Complex Patient Population: Methods and Applications to VA Care

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ANALYTICS TEAM

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VA Primary Care High Risk Investigator Network

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Overview

Why Segment Patient Populations

How to Segment Patient Populations

High Risk Primary Care Patient Subgroups

VA Applications

Poll

What is your primary role in VA?

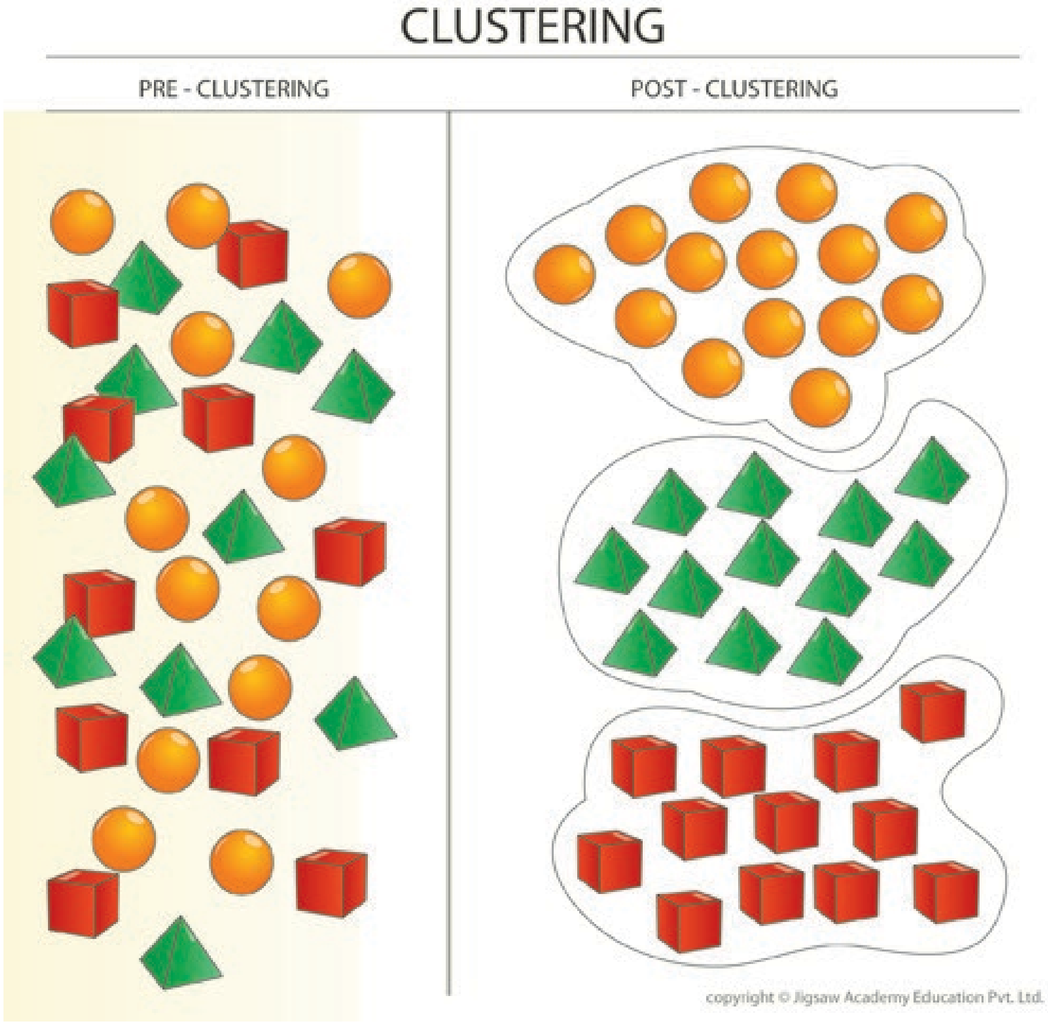
- Clinical / patient care
- Operations or administrative
- Informatics / programming
- Research
- Student/Trainee
- Other

Why Segment Patient Populations

Patient Segmentation: Balancing Population and Individual Care

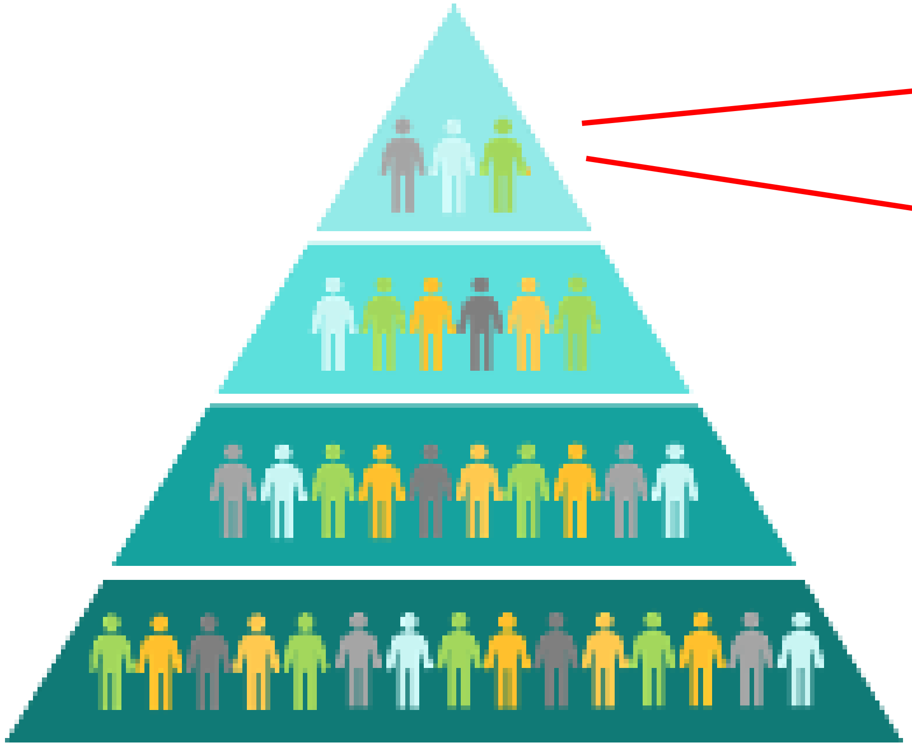
- Integrated health care systems like the VA aim to *coordinate care around the needs of the patient*
- System challenge:
  - ➢ Construct an efficient and sustainable healthcare system to care for entire patient populations…while tailoring (personalizing) care to individual Veterans
  - ➢ Build system that balances population-care and individual-level care
- Potential solution:
  - ➢ Segment populations into a small set of groups that share similar healthcare needs
  - ➢ With the goal of effectively and efficiently meeting individual Veterans' needs

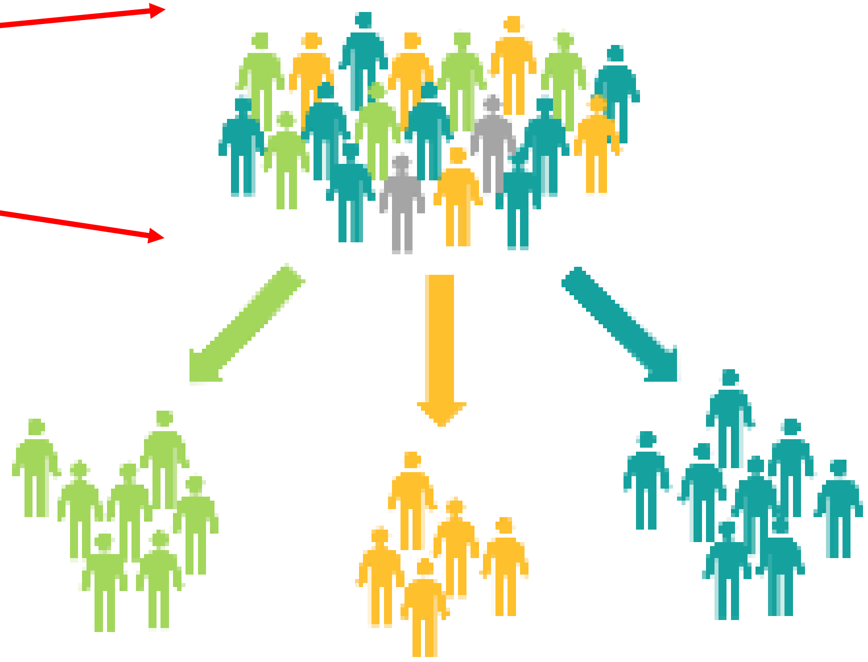
Data-Driven Subgroups



Risk Level

Segments/Groups





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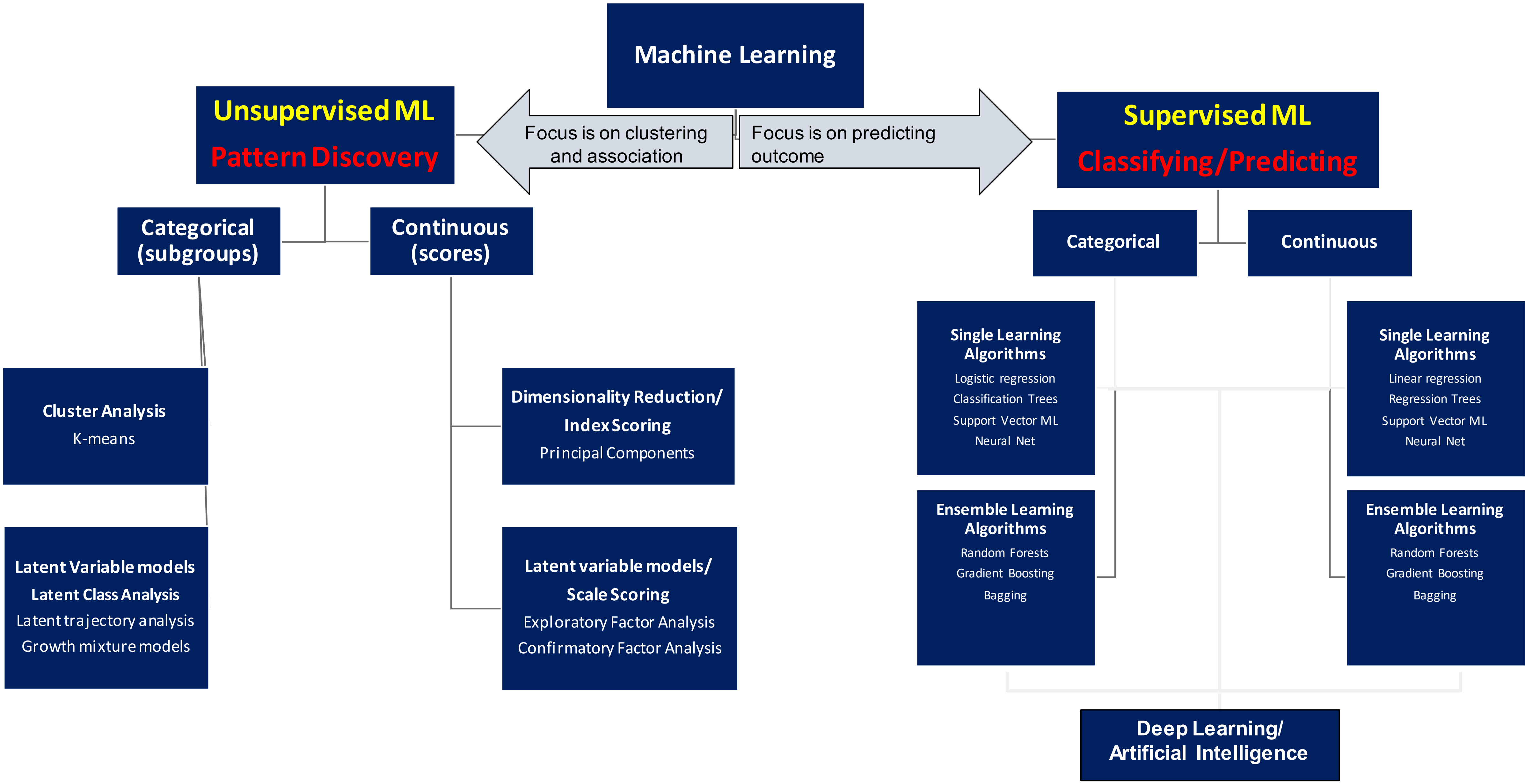
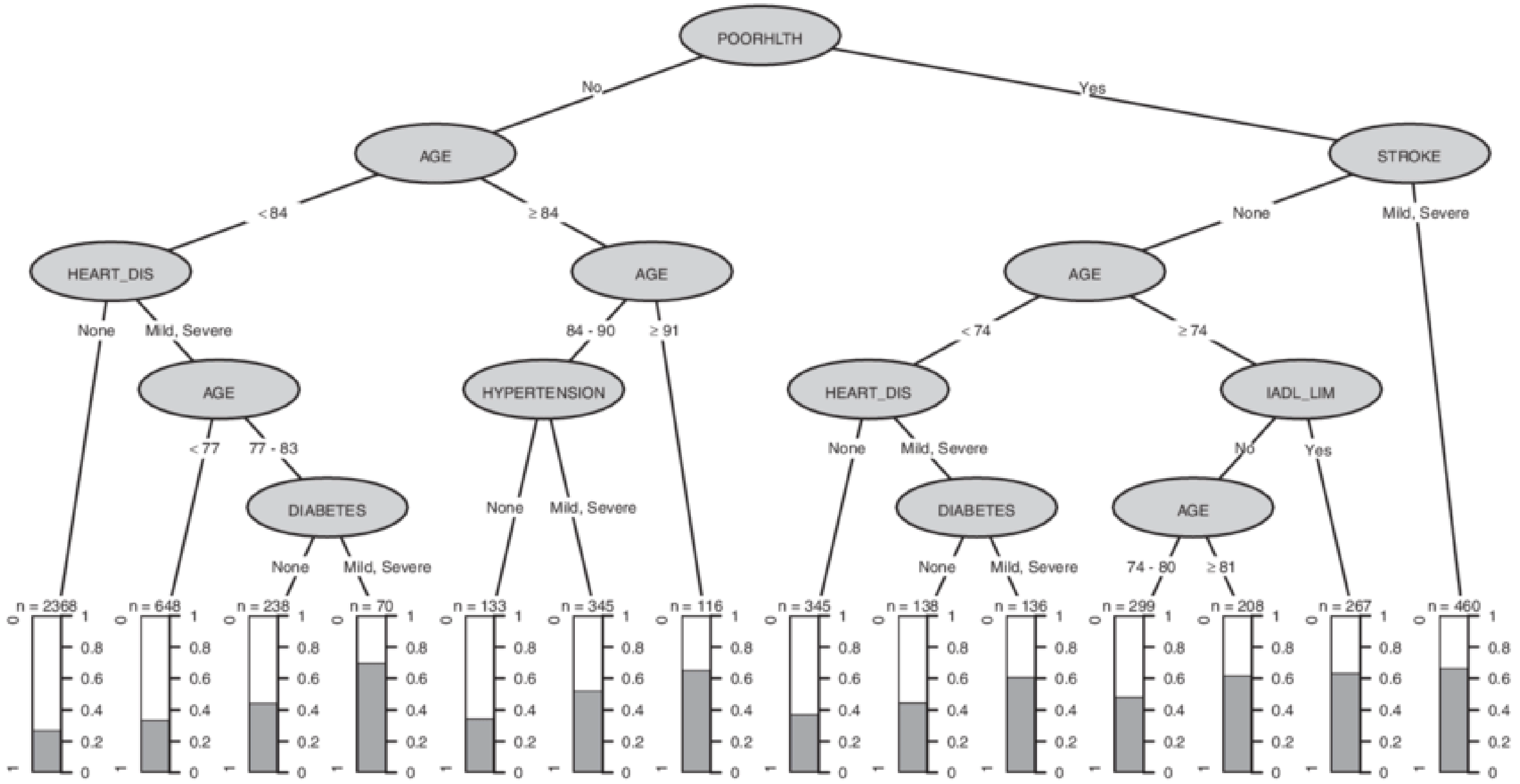
How to Segment Patient Populations

Machine-Learning Methods in Health Outcomes Research & Policy: Unsupervised vs. Supervised Machine Learning

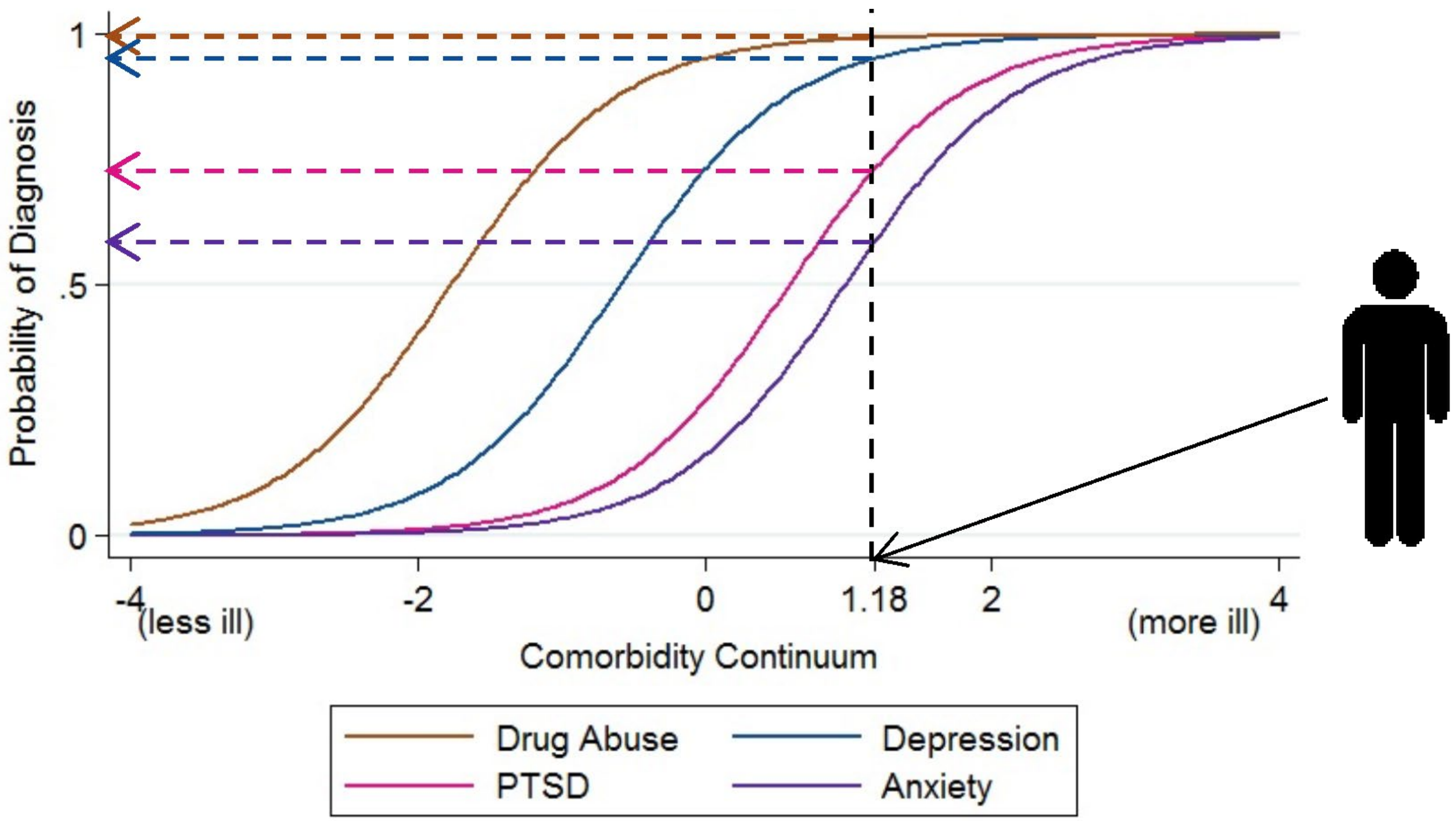


Classification and Regression Tree (CART) predicting hospitalization



Schiltz, Nicholas, et al. Identifying Specific Combinations of Multimorbidity that Contribute to Health Care Resource Utilization: An Analytic Approach. Medical care. 2016.

Dimensionality



Prenovost, Katherine M., et al. Using item response theory with health system data to identify latent groups of patients with multiple health conditions. *PloS one* . 2018

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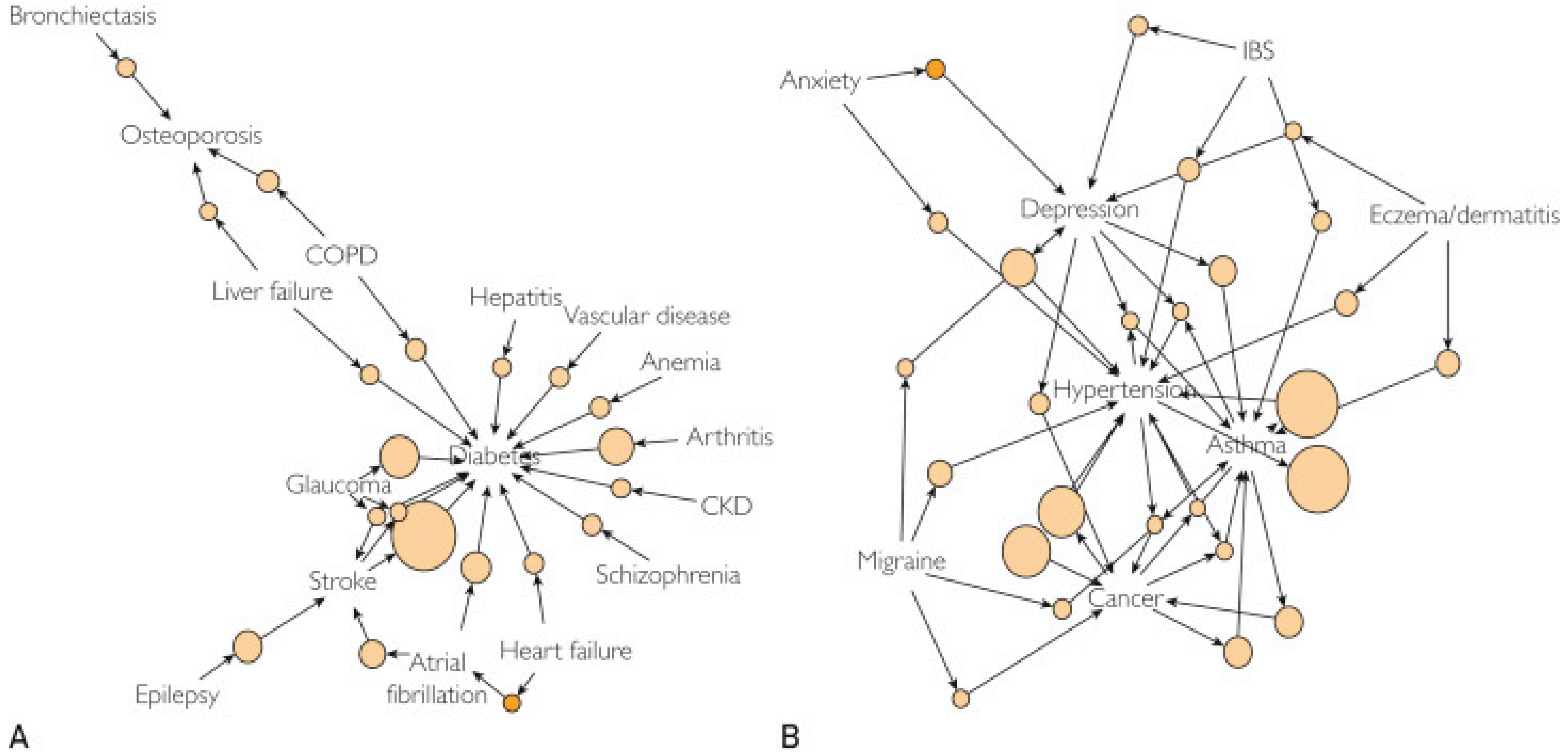
Cluster Analysis of Multimorbidity



Zemedikun, Dawit T. et al. Patterns of Multimorbidity in Middle-Aged and Older Adults: An Analysis of the UK Biobank Data. Mayo Clinic Proceedings, 2018.

Literature Review

- 12 published studies that applied data-driven segmentation methods to high-risk patient populations
- Healthcare system and governmental settings
- Lessons
  - Data inputs matter
    - Choose data that will lead to meaningful interpretation
    - Missing or biased data can lead to incomplete or misleading results
  - Rarely are next steps taken after groups are published
  - No published results of interventions based on subgroups

Arnold J, Thorpe J, Rosland AM. American Journal of Managed Care. In Press 2021.

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Prescription for Designing a Data-Driven Population Segmentation Analysis

Population

- Ensure adequate population size and heterogeneity for segmentation analysis
- Choose population based on predicted risk, cost, or multi-morbidity, depending on intended application

Situation

- Define the focus of segmentation by identifying the outcome of interest and range and domains of possible interventions

Data Inputs

- Assess which data sources are accessible for the entire population
- Map data inputs to the information needed to develop and tailor interventions
- Include limits, constraints, and biases of available information when interpreting analysis results

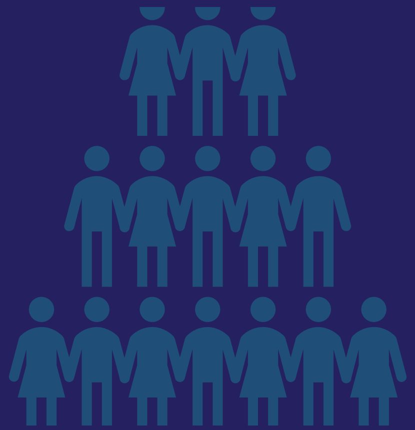
Modeling Approach

- Choose either a patient or health condition clustering approach, depending on intended application
- Develop a priori criteria (statistical and clinical) criteria for choosing the optimal model solution
- Consider adjusting inputs and re-running analyses to explore how data choices affect results

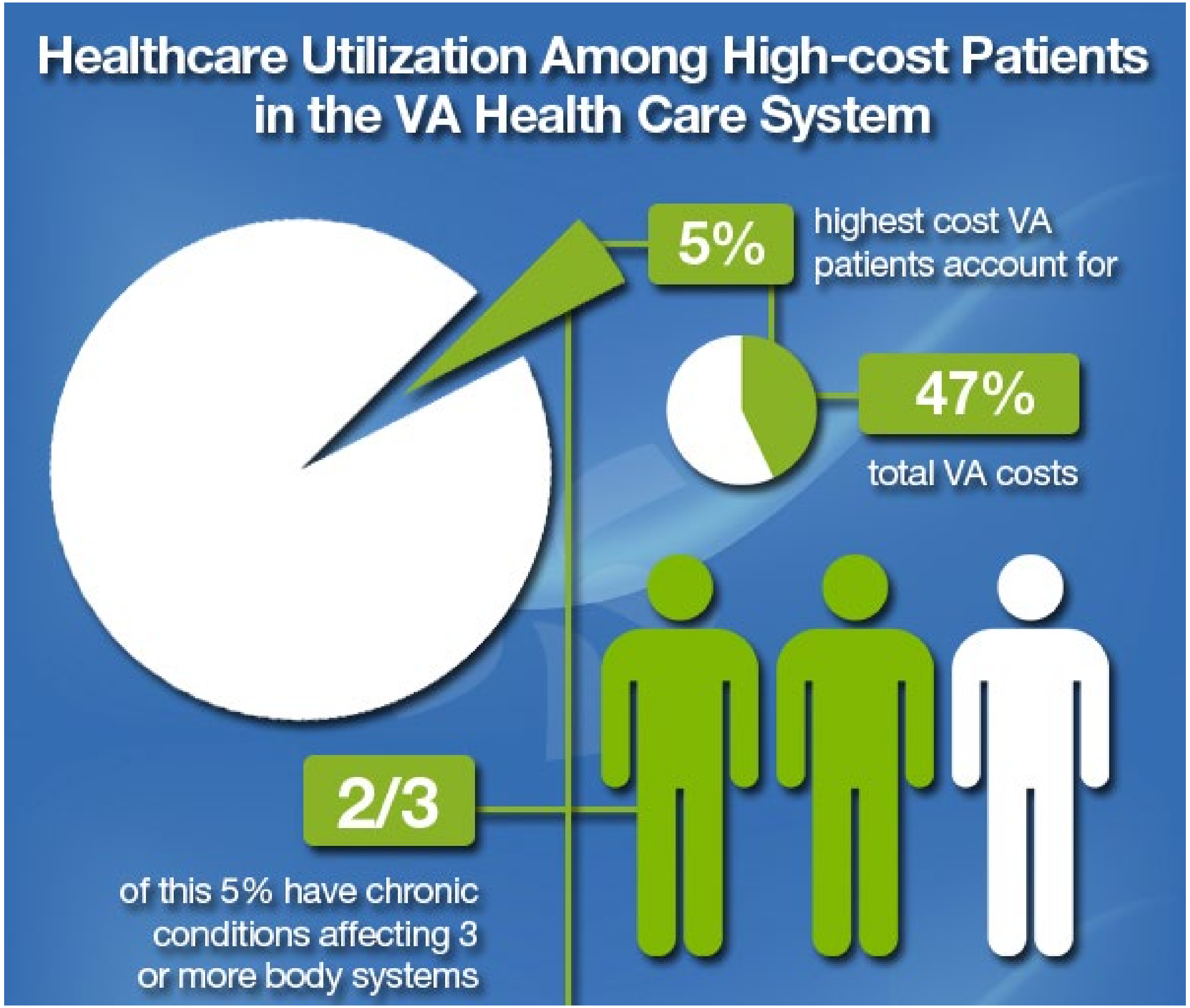
Next Steps

- Validate groupings based on prospective health outcomes
- Profile each groups' sociodemographics, utilization, and modifiable health risks/needs
- Design and test interventions tailored to each groups' profile

Arnold J, Thorpe J, Rosland AM. American Journal of Managed Care. In Press 2021.



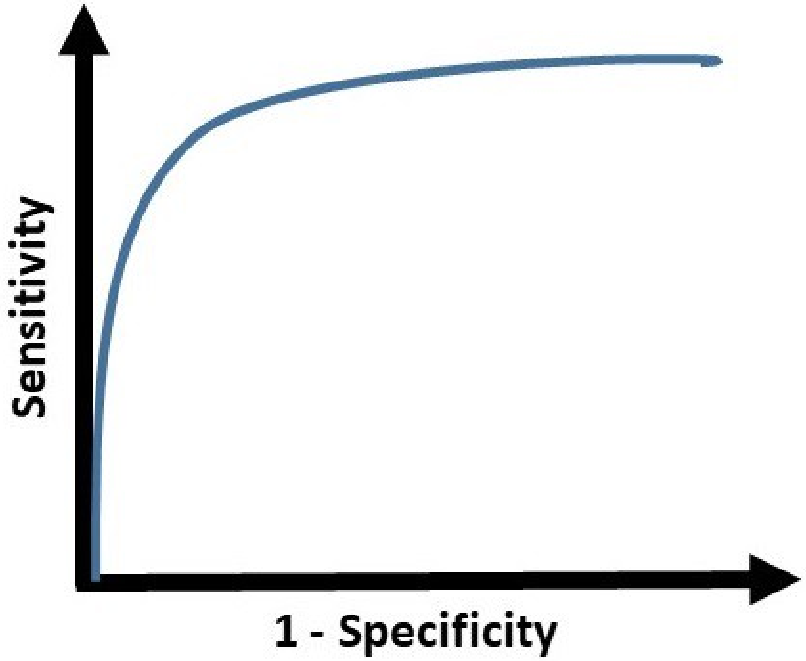
High Risk Primary Care Patient Subgroups



Zulman DM, *et al.*, *BMJ Open.* 2015

We can identify WHO is at high risk for hospitalization

- VA Risk Prediction scores have high predictive accuracy
  - Care Assessment Needs (CAN) score for mortality, hospitalization
  - Risk 3M for ambulatory care sensitive hospitalizations
  - And others



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Two Patients with High CAN Scores:

- Elderly woman with severe congestive heart failure, diabetes, and frailty
- Young man with substance use disorder, housing instability and high blood pressure

Typical Approaches:

- Comprehensive individual assessment or
- One intervention applied to all

Challenges:

- Individualized assessment is time and resource consuming
- One-size-fits-all interventions have not been effective

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High Risk Veteran Subgroups

Solution:
Use VA data to uncover latent, data-driven groups among high risk patients

- Sort high CAN patients into common groups based on diagnosis profile
- Address common 'care steps' for all members of a group at the same time
- Support proactive, efficient management of patients at high risk of hospitalization

Latent Class Analysis Models

- **For the population,** how many meaningful classes exist
- **For each group**, how many patients are matched (class prevalence)
- **For each chronic condition**, how likely it is to be present in each group (item response probability)
- **For each patient**, how closely do their diagnoses align with the profile of each group (predicted probability)

Latent Class Analysis 2018 & 2020

High-Risk Patient Sample

- PACT Patients with probability of 1-year hospitalization ≥ 90^{th} percentile (based on VA Care Assessment Needs prediction score) at any time during 2018 or 2020

Data Entered Into Models

- 26 chronic diagnoses commonly managed in primary care
- Coded "yes" if any ICD-10 for the condition in the 24 months prior to cohort entry in 2 outpatient or 1 inpatient encounters

Number of Classes

- Tested 1 to 7

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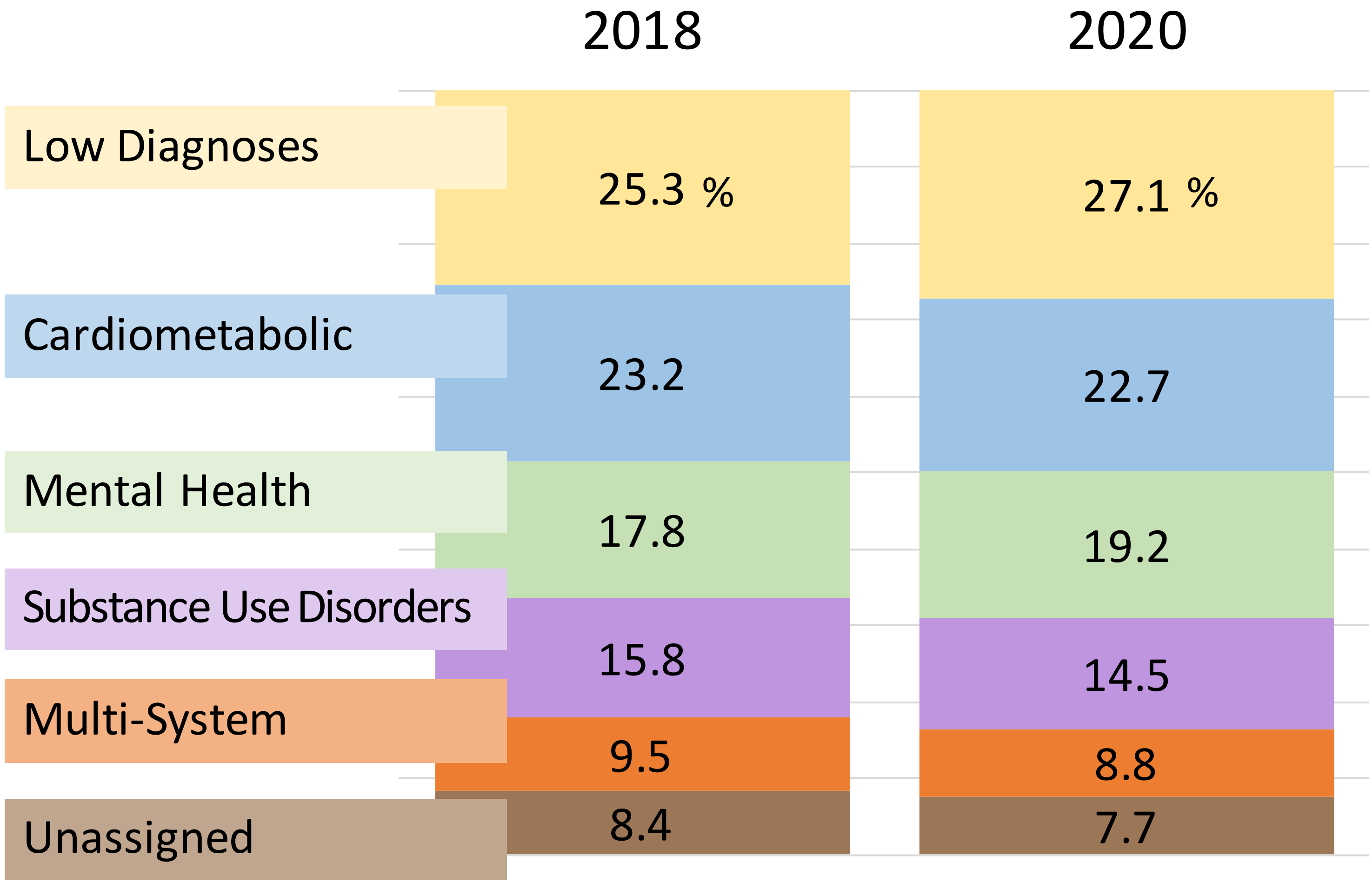
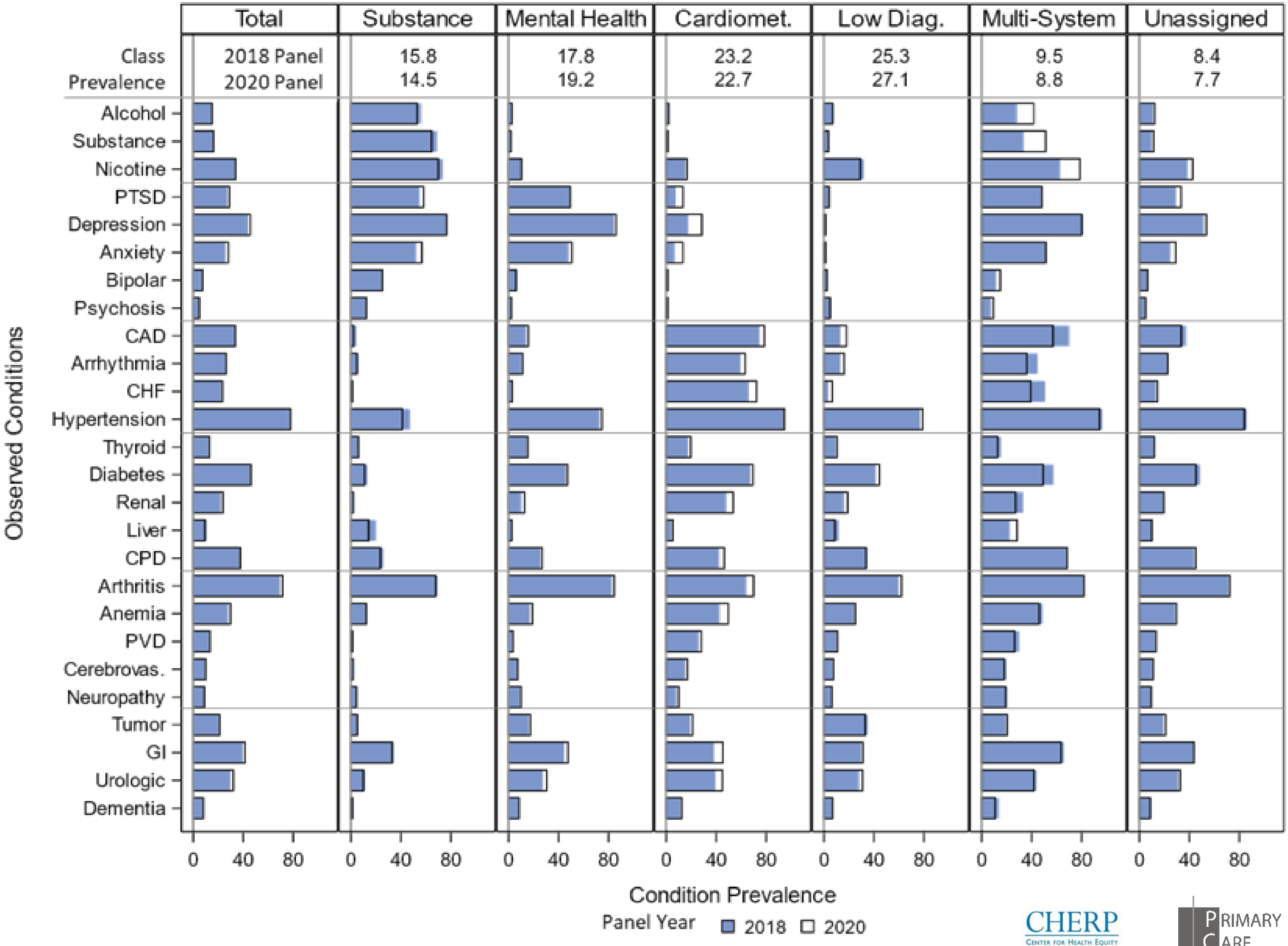
Prevalence of Latent Classes Identified in 2018 (n=951,771) & 2020 (n=978,771)



Diagnoses by Group

2018 *blue*
2020 *outline*



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Individual Change in Status, Among Patients Observed in 2018 and 2020 (n=563,725)

563,725 (59%) of the patients in the 2018 cohort were also in the 2020 high risk cohort

	Group in 2020, Row Percent					
Group and Prevalence in 2018	Substance Use Disord.	Mental Health	Cardio-met.	Low Diagnoses	Multi-System	Unassigned
Substance Use Disorders (16%)	64	8	0	5	16	6
Mental Health (18%)	6	61	9	8	7	9
Cardiometabolic (23%)	0	3	76	13	3	4
Low Diagnosis (25%)	3	9	15	60	6	7
Multi-System (10%)	3	11	26	6	45	9
Unassigned (8%)	6	19	22	18	16	18

*Data are **row percent**: patient status in 2020 by group assignment in 2018*

Model Equity

Algorithms can perpetuate health disparities

- Machine learning algorithms find patterns in data
- Social disparity is embedded in our health services data
  - Different actual rates of exposures and illness
  - Different access to medical care and likelihood of official diagnosis
  - Differences in medical record documentation once diagnosed
- Algorithms built on health services data will reflect and can perpetuate those disparities
- Most methods of assessing equity focus on evaluating algorithms that predict an observed outcome

Model Equity for latent class analysis

How to check

Do models perform well for subpopulations of patients?

- Compare predicted probabilities by subpopulation
- Compare profiles of conditions by subpopulation

Investigate missing data:

- Are there conditions that are systematically underdiagnosed or underdocumented in certain subpopulations?

Modeling Options

Covariates: Adding subpopulation characteristic as a model covariate may increase predicted probabilities of group membership

Stratification: Analyze separate models if evidence of meaningfully different subpopulations is found

Address the impact of missing data: External data sources, multiple imputation, sensitivity analyses

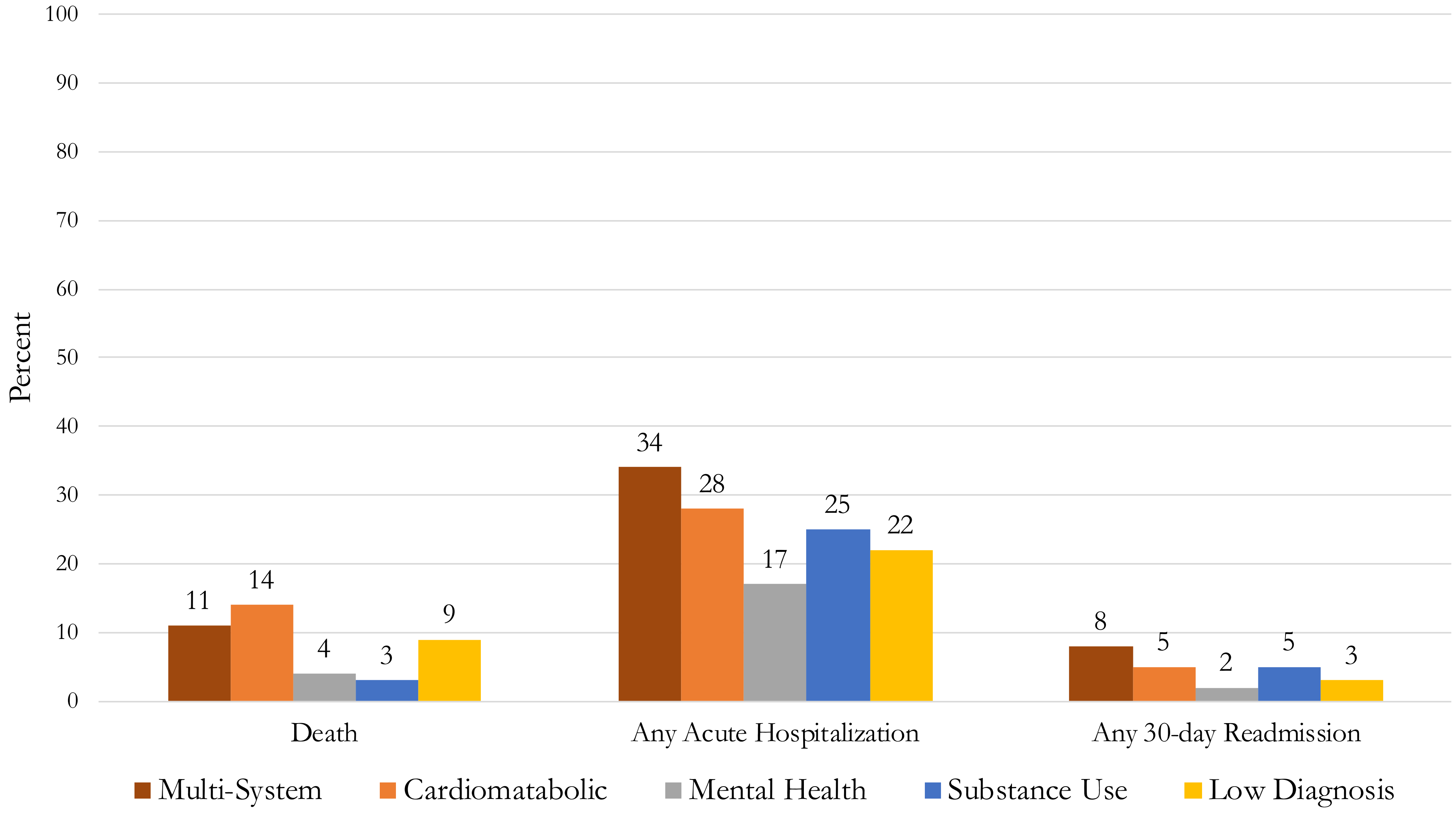
Applications

Linking Segments to Action

Use healthcare system data to examine:

- Distinct outcome patterns by group
- Diagnosis and utilization patterns by group
- Unique care needs or care gaps by group

Mortality and Hospitalizations Over 1 Year, 2018 Cohort



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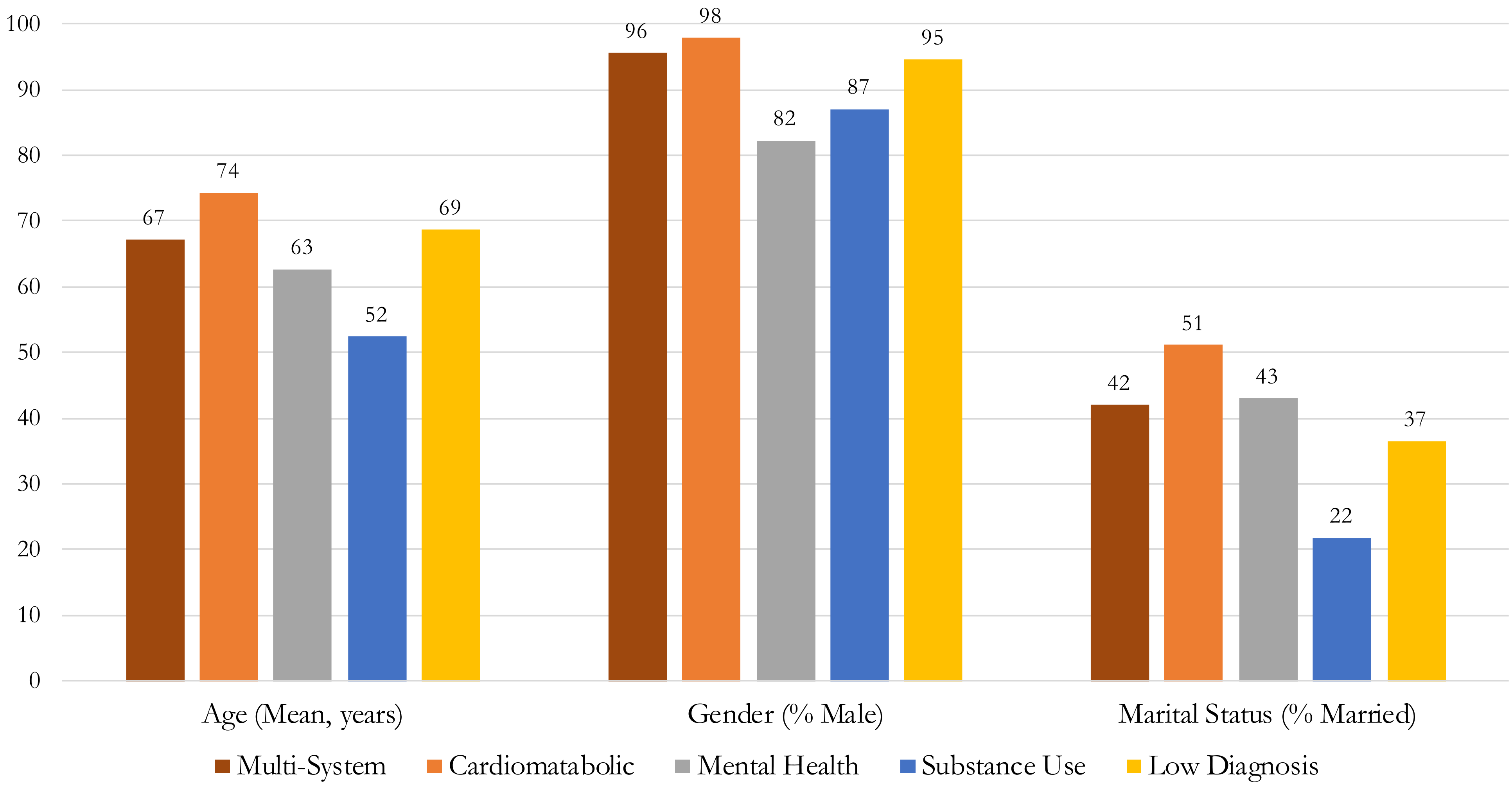
Patient Characteristics, 2018 Cohort



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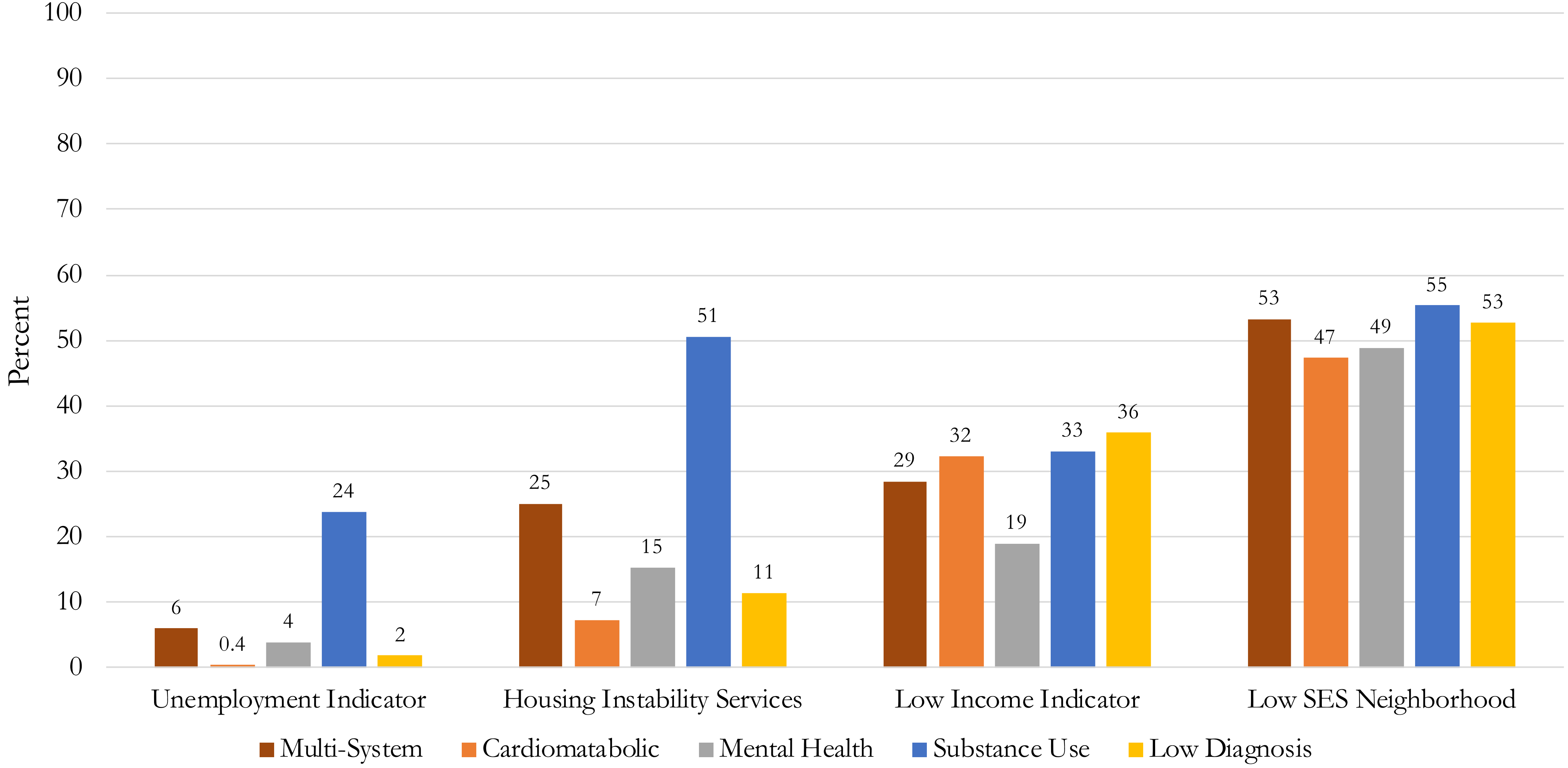
Socioeconomic EHR/Administrative Variables, 2018 Cohort



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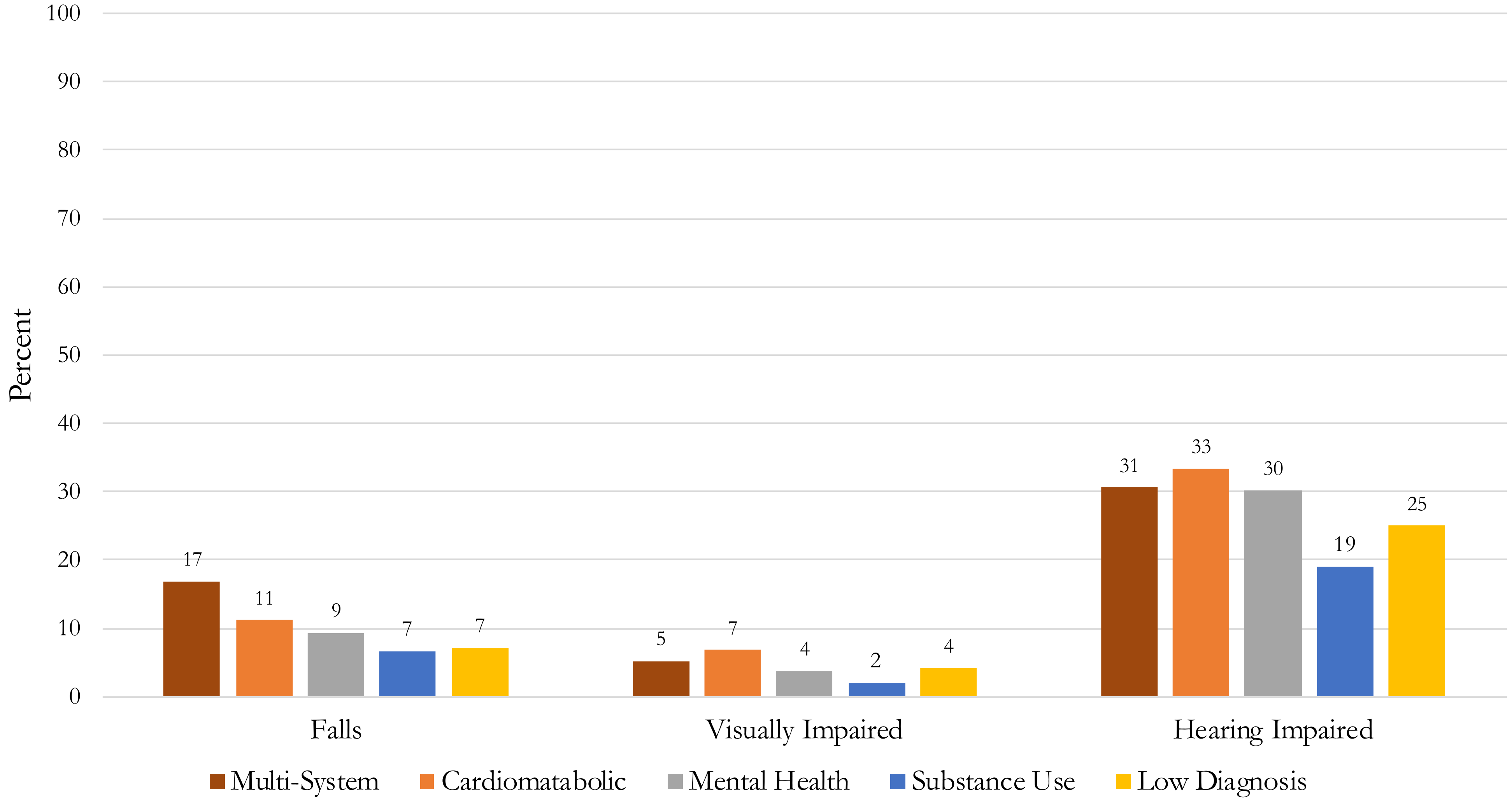
Functional Status, 2018 Cohort



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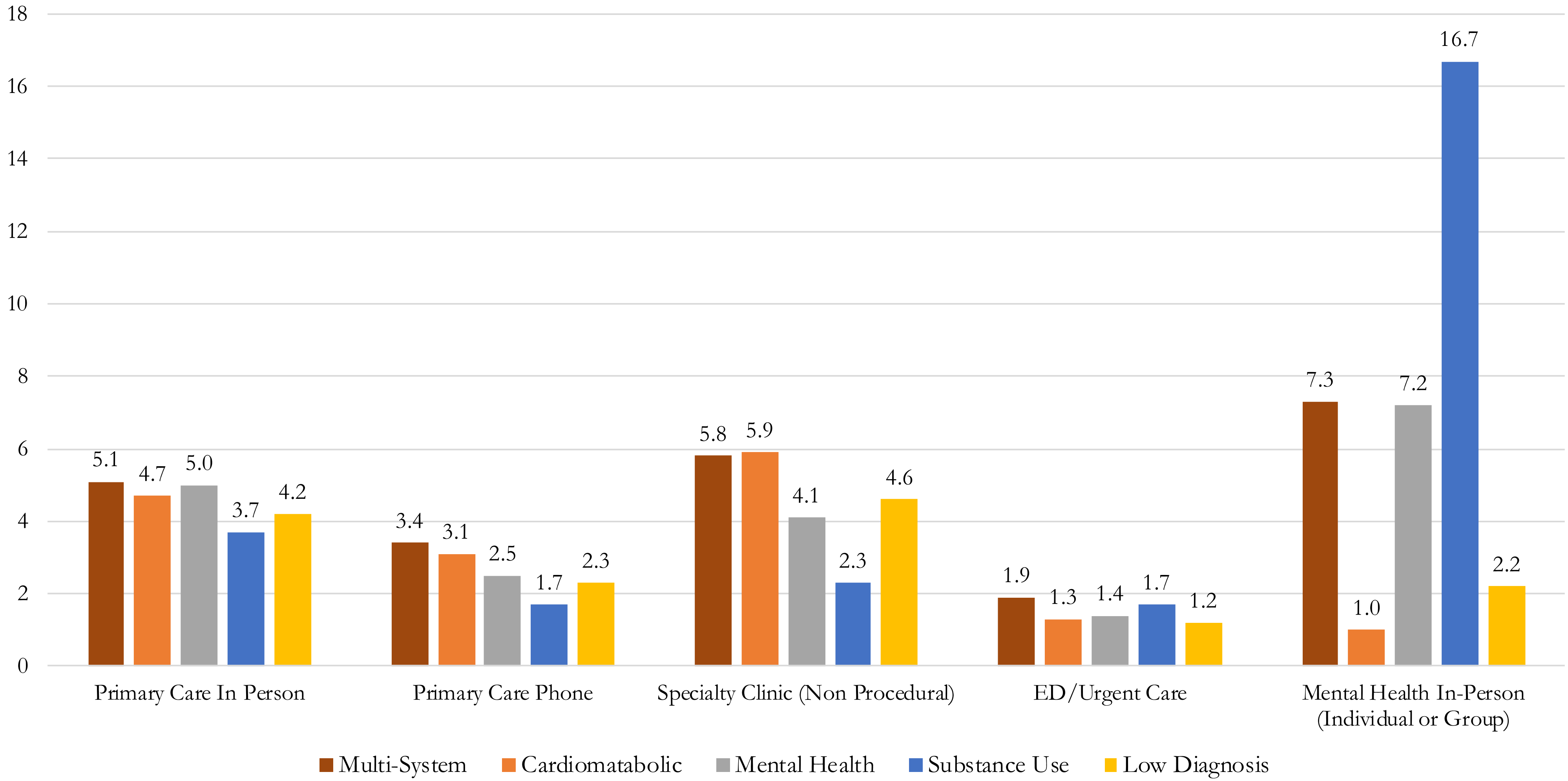
VA Outpatient Encounters Per Year, 2018 Cohort



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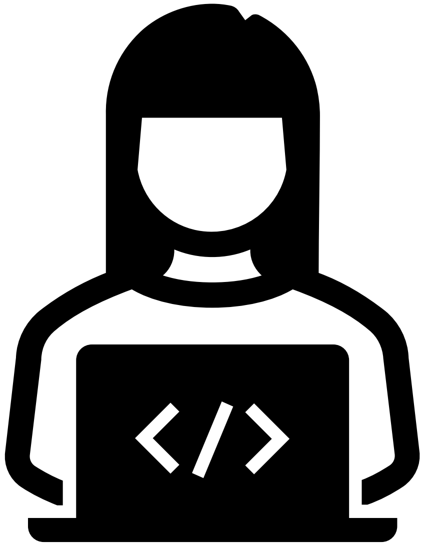
High Risk Subgroups Management PCAS Tool: Development



- High Risk Veteran Subgroups models
- Link subgroups to outcome and utilization patterns
- Input from two VA-wide expert panels (2016, 2018)

- Tool programming (CSDE, Spark Seed Spread Innovation Program)
- Two rounds of user-testing from PCPs and RNs at multiple PACT sites

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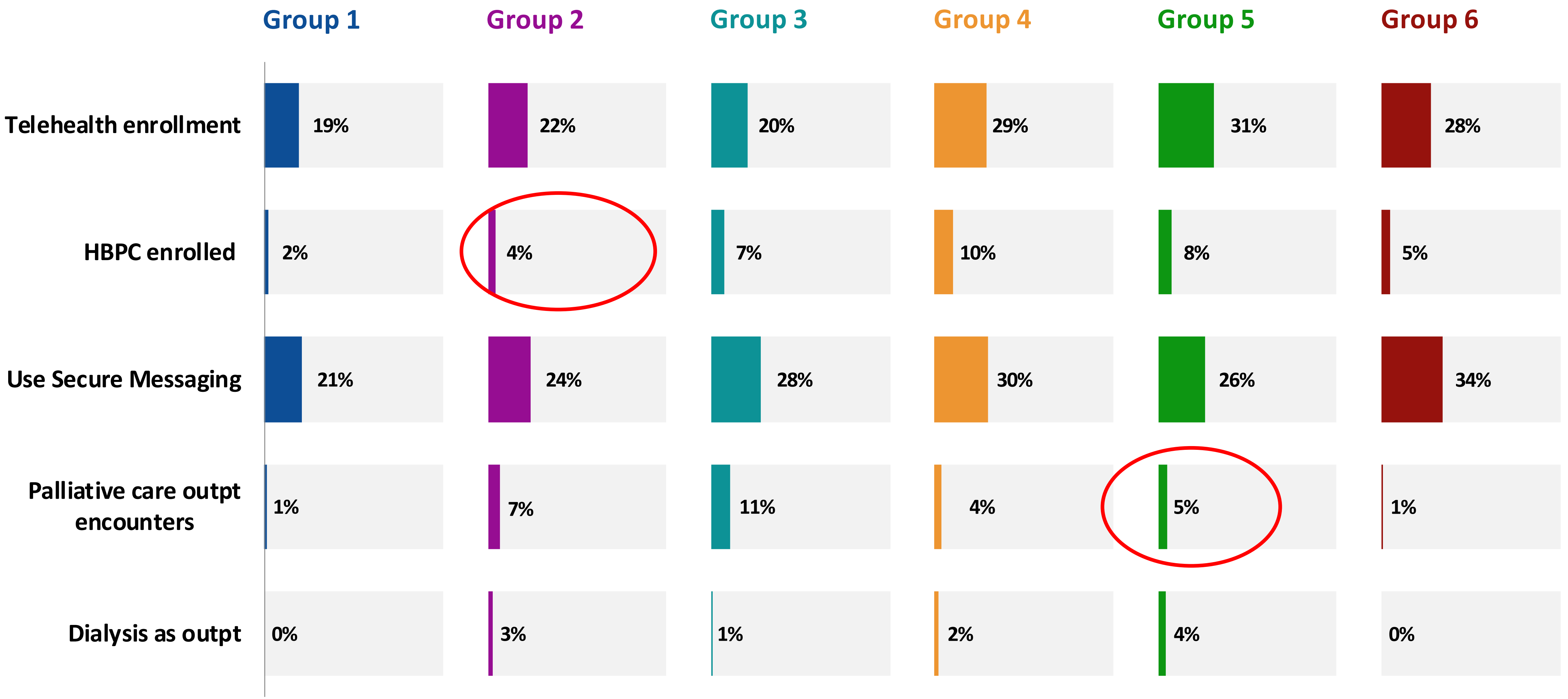
VA Program Use by Subgroup



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PATIENT CARE ASSESSMENT SYSTEM
PCAS
5.0

a product of
Analytics & Performance Integration

Manage Patients | Consults | Administration | PCMM Tasks | News

Manage Patients

Or Filter Panel Based on Risk Characteristics:	
High Risk:	**Focused Care Management:**
ACSC Risk Score (3 months) [?]	Case Management Activity [?]
CAN	GOCC(Goals of Care Conversation) [?]
CAN by Comorbidity Group [?] OR Select	HBPC enrolled
COVID-19 Positive [?]	Homeless Services Use
HF Admission (recent)	Hospice Use
PCAS High Risk Flag	Medication Renewal [?]
Suicide Risk	Opioid Use [?]
	Palliative Care Use
	Telehealth Enrolled
PCAS Assigned Risk:	**Utilization:**
PCAS Clinical Priority OR Se	Bed Days
	MCA

- OR Select
- Cancer
- Cardiometabolic
- Liver
- Low Comorbidity
- Mental Health
- Substance Use

Clear Filter

Patient Report

Last 4 SSN	Patient Name	ACSC	CAN	Covid19 Status	PCAS Clinical Priority	PCAS High Risk Flag	VA Last Appointment	VA Next Appointment	Personal Health Inventory	Med Renewal	Tasks	GOCC [?]	Comorbidity Group	Team	Active or Pending Consults	BDOC	MCA Cost
		97	INPT									YES	Mental Health			21	$250,003.29
		94	90									YES	Cardiometabolic		3	2	$12,423.98
		81	70									NO	Low Comorbidity			0	$8,175.67

https://secure.vssc.med.va.gov/PCAS

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Cardiometabolic Comorbidity High-Risk Group Non-PCMM User

Patient Name: **SSN:** **DOB:**

Diagnoses Reported for this Patient

Diagnosis	Reported
Alcohol Use	☐
Drug Use	☐
Nicotine Use	☐
PTSD	☐
Depression	☑
Anxiety Disorder	☐
Bipolar Disorder	☐
Psychosis	☐
CAD	☑
Arrhythmia	☐
CHF	☐
Diabetes	☑
CKD	☐
Liver Disease	☐
Chronic Pulm	☑
Pain & Arthritis	☐
Cerebrovascular	☐
Cancer	☐

Cardiometabolic Group Care Steps

Suggested Care Steps are based on factors that drive risk for hospitalization for patients in this group. Care Steps are meant to prompt you to consider care that may avoid hospitalization, but is not already reflected in quality metric reminders.

Patients in the Cardiometabolic Group who also have kidney disease or active mental health conditions are at highest risk for hospitalization and poor health outcomes.

Care steps listed come from computer algorithms and are appropriate for many, but not all, patients in this group. Clinical judgement and shared decision making with the patient is required.

CARE STEP TO CONSIDER	RECEIVED*
1. For patients with CKD Stage III-V, has the patient had a nephrology visit in the last 14 months?	Not Applicable
2. Patients in this group with active mental health conditions are at higher risk for hospitalization. If the patient shows signs of a mental health condition, consider consulting PMCHI or Mental Health for a thorough assessment, even if the patient does not have a current mental health condition diagnosis. Has the patient had an assessment for mental health concerns (PCMHI or Mental Health Clinic) in the last 14 months?”	Yes (1/20/2021)
3. For patients with a high predicted one-year risk for death, has the patient had a palliative or hospice care encounter in the last 14 months?	No – Add a Task

*Data are refreshed nightly

About the Cardiometabolic Group

Patients in this group:
1)Have VA Care Assessment Needs (CAN) hospitalization score ≥ 90th percentile within the last year.
2) Match the Cardiometabolic Group diagnosis profile at 80% likelihood or higher.

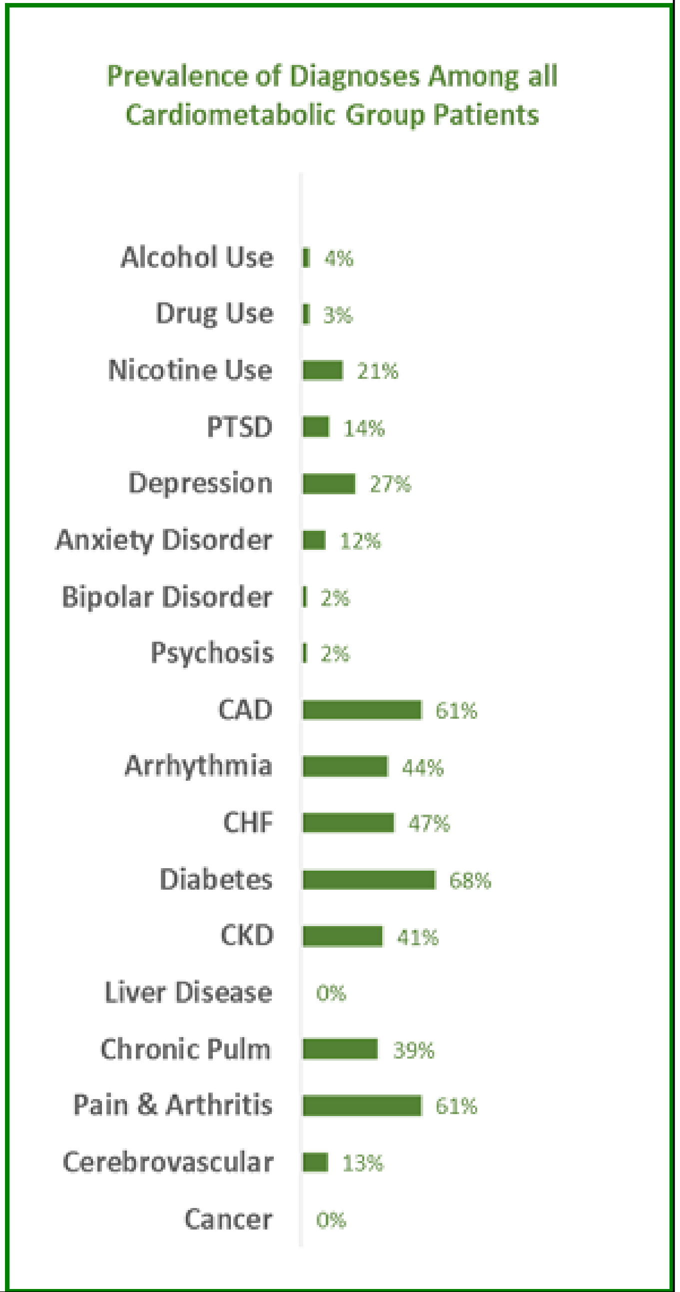
This patient's pattern of diagnoses over the last year best align with the Cardiometabolic Group.

Patients in Cardiometabolic Group often have CAD, CHF, and diabetes. Reference the checkmarks above to identify which diagnoses this patient has that align them with this group.

Everyone in this group is at high risk of being hospitalized over the next 12 months (CAN score ≥ 90).

Patients in the Cardiometabolic Group with diagnoses of **kidney disease** or **mental health conditions** tend to have particularly high numbers of comorbid diagnoses and high clinical complexity compared to others in this group.

As compared to other High CAN patients, patients in the Cardiometabolic Group have these characteristics:
- Highest rate of 30-day hospital readmissions
- High rate of visits to subspecialists
- Low rate of referral to palliative care even when they may qualify



Click Here for Methodology

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Possible Applications for High Risk Patient Subgroups

- Tailor bundled interventions to each group's common diagnoses
- Monitor patients for signs of conditions that are most common group reasons for hospital admission
- Meet patients 'where they are' (e.g. intervene with Substance Use group in ED, Multisystem over the phone)
- Assign main case manager / care coordinator to appropriate specialist
- Track facility quality metrics / outcomes by group
- Programs target groups that have apparent gaps in services (e.g. Home Based Primary Care, Palliative Care)

Additional Information

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PCAS Tool SharePoint

VA Office of Primary Care Analytic Team

VA Primary Care High Risk Investigator Network

https://www.complexcaring.pitt.edu/va-primary-care-high-risk-investigator-network