Title
Effect of Care Coordination for Subpopulations of High-Utilizing Medicaid Patients

Author
Albertson, Elaine Michelle

Publication Date
2022

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Effect of Care Coordination for Subpopulations of High-Utilizing Medicaid Patients

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Health Policy and Management

by

Elaine Michelle Albertson

2022

ABSTRACT OF THE DISSERTATION

Effect of Care Coordination for Subpopulations

of High-Utilizing Medicaid Patients

by

Elaine Michelle Albertson

Doctor of Philosophy in Health Policy and Management

University of California, Los Angeles, 2022

Professor Nadereh Pourat, Chair

Background: Patients who use a large volume of health services, especially costly acute care, are known as high utilizers. An increasing number of programs target high utilizers, with a goal of improving health and reducing disproportionate use. These real-world programs often enroll heterogeneous populations with varying health needs and utilization histories. To appropriately evaluate programs that target high utilizers, there is a need to understand enrollee heterogeneity and how program effects vary across subpopulations. Objectives: Using data from California Whole Person Care (WPC), which provided cross-sector care coordination spanning health and social services to high-utilizing Medicaid patients, I explored: (1) what health needs characterized enrollee subpopulations, (2) what utilization trajectories prior to WPC enrollment characterized enrollee subpopulations, and (3) what were differential program effects for classes defined based on health needs and utilization. Methods: I used WPC enrollment data, and

Medicaid enrollment and claims. I used latent class analysis (LCA) to identify classes based on health needs, and group-based trajectory modeling (GBTM) to identify classes based on pre-enrollment utilization trajectories. I used difference-in-difference analysis to evaluate impacts of care coordination across classes. Results: LCA identified five classes, the largest consisting of enrollees with low overall needs (32.0%), high physical health needs (27.5%), and high behavioral health needs (26.3%). GBTM identified two classes: “Moderate-to-High” utilization (18.6%), and “Low” utilization (81.4%). High behavioral health need was associated with high utilization. Compared to program-assigned target populations, analysis classified more enrollees as having high health needs, and fewer as high utilizers. When LCA and GMM classes were cross-tabulated, all had significantly decreased adjusted rates of ED visits after WPC participation, and all but one had decreased hospitalizations. Enrollees with high behavioral health needs had significantly larger decreases in hospitalizations compared to several classes. Implications: Governments and health care organizations should consider enrollee heterogeneity when developing cross-sector care coordination or other interventions to reduce utilization. Classification methods including LCA and GBTM can inform intervention tailoring and evaluation. Though care coordination is promising for enrollees with many backgrounds, programs should anticipate larger impacts for some subpopulations, and provide additional resources or innovative strategies accordingly.

The dissertation of Elaine Michelle Albertson is approved.

Mitchell David Wong

Beth Ann Glenn-Mallouk

Warren S. Comulada

Emily Parmenter

Nadereh Pourat, Committee Chair

University of California, Los Angeles

2022

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ACS	Ambulatory Care-Sensitive Conditions
AIAN	American Indian or Alaska Native
AIC	Akaike Information Criterion
API	Asian or Pacific Islander
AR-HM	At-Risk-of-Homelessness
BIC	Bayesian Information Criterion
CPC	Chronic Physical Conditions
ED	Emergency Department
GBTM	Group-Based Trajectory Modeling
GMM	Growth Mixture Modeling
HM	Homeless
HO	High Overall Health Needs
HPH	High Physical Health Needs
HU	High Utilizers
IP	Inpatient Admissions/Hospitalizations
JI	Justice-Involved
LCA	Latent Class Analysis
LO	Low Overall Health Needs
SD	Standard Deviation
SMI	Serious Mental Illness
SUD	Substance Use Disorder
WPC	Whole Person Care

ACKNOWLEDGEMENTS

This dissertation was completed with the support of the dedicated team at the UCLA Center for Health Policy Research Health Economics & Evaluation Research program.

Funding was provided by a UCLA CTSI TL1 Translational Science Fellowship, NIH/NCATS UCLA CTSI Grant Number TL1TR001883.

VITA/BIOGRAPHICAL SKETCH

Previous Degrees

MPH, Health Services, June 2018, University of Washington School of Public Health

BS, Earth Systems, June 2011, Stanford School of Earth, Energy, & Environmental Sciences

Academic Employment

Graduate Student Researcher, Center for Health Policy Research, UCLA (09/2018 - 06/2022)

Graduate Student Researcher, Department of Health Services, University of Washington (01/2017 - 08/2018)

Publications

Albertson, E. M., Chuang, E., O'Masta, C., Miake-Lye, I., Haley, L. A., & Pourat, N. (2021). Systematic review of care coordination interventions linking health and social services for high-utilizing patient populations. *Population Health Management*, *25*(1), 73-85.

Coe, N.B., Ingraham, B., **Albertson, E.**, Zhou, L., Wood, S., Grembowski, D., & Conrad, D. (2021) The one-year impact of accountable care networks among Washington State employees. *Health Services Research*, *56*(4), 604-614.

Albertson, E. M., Wood, S. J., Coe, N. B., & Conrad, D. (2020). Health care leader perspectives on state government-sponsored accountable care for public employees. *American Journal of Accountable Care*, *8*(3), 4-11.

Albertson, E. M., Chen, R., Matheson, A., Ursua, M. G., Fliss, M. D., & Farquhar, S. (2020). Effect of public housing redevelopment on reported and perceived crime in a Seattle neighborhood. *Crime Prevention and Community Safety*, *22*, 381-398.

Kwan-Gett, T. S., **Albertson, E. M.**, Banks, J., Revere, D., Rogers, M., Baseman, J., Andris, L., & Conrad, D. (2020). Mixed methods evaluation of the Washington State Practice Transformation Support Hub. *Journal of Public Health Management and Practice*, *27*(5), 484-491.

Chuang, E., Pourat, N., Haley, L. A., O'Masta, B., **Albertson, E.**, & Lu, C. (2020). Integrating health and human services in California's Whole Person Care Medicaid 1115 Waiver Demonstration. *Health Affairs*, *39*(4), 639-648.

Albertson, E. M., Scannell, C., Ashtari, N., & Barnert, E. (2020). Eliminating gaps in Medicaid coverage during reentry after incarceration. *American Journal of Public Health*, *110*(3), 317-321.

Wood, S. J., **Albertson, E. M.**, & Conrad, D. A. (2019). Accountable care program implementation and effects on participating health care systems in Washington State: A conceptual model. *Journal of Ambulatory Care Management*, *42*(4), 321-336.

I. INTRODUCTION

Motivation for this Dissertation, Main Analyses, and Significance

My research objective was to evaluate the effect of care coordination on subpopulations of enrollees who had varying health needs and utilization trajectories prior to program enrollment, using data from Whole Person Care (WPC), a Section 1115(a) Medicaid waiver program in California. I extended beyond core WPC evaluation activities, which followed program-defined target populations and did not include the analyses in this dissertation. I identified distinct subpopulations of enrollees based on their health and utilization history prior to WPC enrollment, described their characteristics, and evaluated the overall impact of care coordination on utilization outcomes for different subpopulations.

Individuals who use a disproportionately high amount of health care services have become the focus of efforts to reduce avoidable health spending and improve population health in the United States (U.S.). Many health care systems have developed interventions to reduce unnecessary utilization. However, unlike randomized controlled studies, most of these programs are based on enrollment criteria selected by the program (e.g., a recent emergency department visit, or homelessness) without randomization to intervention and control groups, and offer providers discretion over who to enroll. These approaches to enrollment result in unknown heterogeneity in health needs and utilization trajectories of enrolled patients, which poses challenges to evaluating program impact. For example, program effects may be different for multi-morbid enrollees with a single episode of hospitalization, compared to those with serious mental health conditions and multiple episodes of high utilization prior to enrollment, underscoring the importance of subgroup analysis stratified by enrollee subpopulation.

I identified distinct subpopulations among current and potential high utilizers enrolled in WPC, which aimed to reduce inappropriate acute care use, and I explored whether care coordination effects differed across subpopulations of high utilizers with different utilization trajectories. Analysis consisted of mixture models, specifically latent class analysis (LCA) and group-based trajectory modeling (GBTM), to classify enrollees into subpopulations based on their health needs, and on their utilization history prior to enrolling in the program. Classification of enrollees into subpopulations was followed by a difference-in-difference analysis to evaluate the effect of care coordination on acute care utilization (emergency and inpatient care) for different subpopulations of enrollees. This analysis was conducted using the example of WPC, a Medicaid care coordination program that aimed to reduce inappropriate utilization of emergency and inpatient services. My study was significant because I demonstrated the importance of considering how program enrollment goals may differ from the reality of who is enrolled, and because I provided much-needed quantitative evidence regarding the effect of care coordination on service use for current and potential high utilizers.

High Utilizers

Definition and Characteristics

Though definitions vary, high utilizers can be broadly described as patients with a history of high use of health services. Most research on high utilizers defines high utilization as disproportionate use of acute care services, such as emergency department and inpatient care, during a given period. For example, analyses have used thresholds such as having three or more hospitalizations in a year,[1,2] three or more hospitalizations in a six-month period,[3] or at least one hospital admission or at least two emergency department visits in a quarter.[4] Other analyses have used more subjective thresholds specific to their study population, such as defining high utilizers as those with a rate of emergency department use within the top 10% of all study enrollees.[5] Less commonly, some have treated high utilization as equivalent to having high health spending, using thresholds such as exceeding $10,000 in annual health spending to identify "high utilizers."[6]

High utilizers are not always at high risk of adverse health outcomes, but there is a large amount of overlap between high utilizing and high-risk populations. For example, compared to the general patient population, high utilizers often have greater health needs including medical comorbidities and chronic disease,[1,6,7] and behavioral health conditions including serious mental illness and substance use disorder[1,7] Additionally, compared to the general population high utilizers often experience more social and economic challenges such as food insecurity,[8] homelessness or unstable housing,[1,7,8] limited education,[6,8] low income level or lack of employment,[1,6,8] childhood trauma,[9] and a history of criminal justice system involvement.[7]

Interventions to Address High Use

In the United States, high utilizers have become a focus of many health care improvement initiatives due to rising health care costs and incentives for quality improvement such as alternative payment models. Improving care for high utilizing patients has been described as an "urgent priority" for humanitarian and financial reasons,[10] and reducing unnecessary acute care utilization has been described as "pivotal."[11] As a result, provider organizations and insurers have developed myriad interventions that target high utilizers to reduce avoidable utilization and improve health outcomes.[12]

One systematic review of interventions to decrease use of acute care by high utilizers identified care coordination as a key approach for addressing high use.[12] Though many definitions exist,[13–15] care coordination can be broadly defined as team-based linkage and management of care across providers or settings, including information sharing and accountability structures. care coordination has been implemented in a variety of settings to link patients to medical care, behavioral health care, and social services.[16–28] Notably, because profiles of high utilizers indicate that many have complex health and social needs, cross-sector care coordination programs have emerged that link patients to social services that are not usually provided in health care, such as housing, employment assistance, and other supports. Prior research has evaluated the effect of coordinating health care and social services on utilization outcomes, with mixed results.[21,22,24,25,28] However, these evaluations have typically reported effects for all enrollees together, rather than disaggregating by enrollee subpopulation. Lack of subpopulation analysis may be due to relatively small enrollment in many of these programs, which often consist of a few hundred enrollees or less. One study of care coordination across health care and social services with a larger enrollee pool of over 19,000 patients included a subgroup analysis focused on those with a history of high utilization, but provided limited resolution on trajectories of utilization over time.[29] There remains a need to understand how care coordination interventions affect subpopulations of enrollees.

The Whole Person Care Program: Coordinating Health Care and Social Services for High Utilizers

Services and Implementation

The California Whole Person Care (WPC) program, administered by the state's Medicaid program known as "Medi-Cal," provided an opportunity for a more granular understanding of the effect of care coordination on subpopulations of high utilizers. Established in 2016, WPC is a $3 billion statewide project supported by a Medicaid Section 1115(a) waiver from the Centers for Medicare and Medicaid Services (CMS).[30] As of March 2021, WPC had served 222,102 unique individuals.[31] The program is administered as a collection of twenty-five county-based pilot programs run by "lead entities," typically city or county agencies. Each lead entity facilitates collaboration between local governmental and community-based partner organizations to strengthen and coordinate medical, behavioral health, and social services for enrollees.[30] Though all pilots are required to coordinate care across sectors, some provide additional supportive services such as medical respite for enrollees who needed a place to recover after care, employment assistance for enrollees with economic instability, and sobering centers to divert enrollees experiencing an acute substance abuse episode from the emergency department.[30]

Target Populations and Enrollment

WPC aimed to reduce avoidable acute care utilization by enrolling "high-risk, high-utilizing" Medi-Cal beneficiaries.[32] However, the twenty-five county-based pilots had a high degree of latitude in identifying and enrolling patients. Approaches varied in two main ways (Introduction Table 1). First, pilots used different enrollment strategies. These included referrals from partner and non-partner organizations (80% of pilots), and use of administrative data to identify prospective enrollees (44% of pilots).[33] Of those that used administrative data, one primarily used predictive modeling to identify people who were at risk of future adverse events. Second, pilots elected to focus enrollment on different WPC target populations, and were permitted flexibility in how they defined these target populations. Per the requirements for participating in WPC, pilots classified enrollees into six target populations that were defined by the state: high utilizers, people experiencing homelessness, people at-risk of homelessness, people with serious mental illness or substance use disorder, people with chronic physical conditions, and people with a history of criminal justice system involvement. Thus, some pilots enrolled people based on high utilization, either documented prior to enrollment or expected in the future based on predictions, while other pilots enrolled people based on health or social conditions such as experiences of homeless, criminal justice system involvement, or behavioral health or medical diagnoses. Pilot definitions of who was a "high utilizer" were especially variable, and an interim evaluation report found that enrollees in this WPC target population actually had lower average acute care utilization prior to enrollment compared to enrollees targeted for behavioral health conditions or experiencing homelessness.[33] Though flexible enrollment rules supported the implementation frameworks and needs of each pilot, they did not systematically classify enrollee medical and social complexity or utilization patterns prior to enrollment, creating unknown heterogeneity in the enrollee population.

Introduction Table 1. Enrollment strategy and target population by WPC Pilot county.

WPC Pilot County	Enrollment Strategy	WPC Target Population(s)					
		HU	**CPC**	**SMI-SUD**	**HM**	**AR-HM**	**JI**
Alameda	– Administratively Enrolled	•			•		
Contra Costa	– Predictive Risk Modeling with Two Risk Levels	•					
Kern	– Health Plan Administrative Data – Referrals	•			•	•	•
Kings	– Referrals-Based System		•	•			
Los Angeles	– Referrals	•	•	•	•	•	•
Marin	– Administrative Data – Referrals	•			•	•	
Mendocino	– Referrals			•			
Monterey	– Referrals – Direct Outreach				•		
Napa	– Referrals				•	•	
Orange	– Administrative Managed Care Data – Referrals			•	•		
Placer	– Referrals	•	•	•	•	•	•
Riverside	– Screening at Probation						•
Sacramento	– Direct Referrals – Outreach	•			•		
San Bernardino	– Identified Via Administrative Data (Medical Record, Health Department)	•					
San Diego	– Referrals from Direct Service Partners	•			•	•	
San Francisco	– Administrative Data				•		
San Joaquin	– Referrals – Health Plan Lists	•		•	•	•	
San Mateo	– Administrative Data – Referrals	•					
Santa Clara	– Referrals – Administrative Lists	•					
Santa Cruz	– Open Referral Process		•	•			
Shasta	– Referrals	•	•	•	•	•	
Small Counties	– Referrals – Targeted and Active Outreach	•		•	•	•	
Solano	– Referrals – Administrative Data	•		•			
Sonoma	– Referrals			•	•	•	
Ventura	– Referrals – Administrative Data	•					

Tabulated from interim evaluation report (Exhibit 15: Selection of Primary Target Population by WPC Pilot; Appendix M: Care Coordination Case Studies).[33]

Abbreviations refer to High Utilizers (HU); Chronic Physical Conditions (CPC); Serious Mental Illness/Substance Use Disorder (SMI-SUD); Homeless (HM); At-Risk-of-Homelessness (AR-HM); Justice-Involved (JI).

• indicates inclusion of specific target population.

Evaluation

The California Department of Health Care Services (DHCS) contracted the state-level evaluation of WPC to the UCLA Center for Health Policy Research (UCLA). This in-depth evaluation was designed to address eleven questions related to program implementation and sustainability, and impacts on quality of care, enrollee health, and cost of care.[33] UCLA collected information from multiple sources to inform the evaluation. Available data included: (1) claims data for WPC enrollees and a control group spanning pre- and post-enrollment periods; (2) qualitative interviews with program leadership and staff; (3) surveys of representatives of lead entities and their partner organizations; and (4) documentation and reports created by the program.

The interim WPC evaluation published in 2019 used a quasi-experimental approach to examine the program's effect on utilization across the six program-defined target populations (Introduction Table 1).[33] However, the evaluation did not include an empirical classification of WPC enrollees based on health needs or utilization trajectories prior to enrollment, leaving a gap in assessing how the program impacted different enrollee subpopulations.

Research Objective and Specific Aims

Aim 1. Understanding Characteristics of High Utilizers and Their Utilization Trajectories

First, I explored the health needs of current and potential high utilizers targeted by WPC, and their trajectories of acute care utilization prior to WPC enrollment. The research questions and hypotheses were:

- Research question 1: Are there distinct subpopulations of WPC enrollees who can be identified based on medical and behavioral health conditions?

Hypothesis 1: There will be distinct subpopulations with different combinations of medical and behavioral health conditions, because counties with WPC pilot programs each had flexibility in modifying or adding enrollment criteria, and in classifying enrollees into the program-defined WPC target populations. This flexibility led to unknown heterogeneity in health conditions among those enrolled in WPC.

- Research question 2: Are there distinct longitudinal trajectories of acute care utilization before WPC enrollment?

  Hypothesis 2a: There will be distinct subpopulations who had different utilization trajectories, including intermittent or persistent high utilization, prior to WPC enrollment. This is because counties with WPC pilot programs did not always select enrollees based on longitudinal utilization patterns, and may have focused more broadly on predicted high use, or high use at certain time points prior to enrollment.

  Hypothesis 2b: Subpopulations of high utilizers with high health needs will have higher and more persistent levels of utilization prior to enrollment compared to subpopulations with lower health needs. This is because those with more complex needs may have had difficulty navigating the system on their own and required more care coordination services to address root causes of utilization.

Aim 2. Effect of Care Coordination for High Utilizers with Varying Utilization Trajectories

For this aim, I evaluated the effect of care coordination on acute care utilization for enrollees with different health needs and utilization trajectories prior to enrollment. This aim addressed the following research question:

- Research question 3: How will care coordination impact acute care utilization of WPC enrollees with different health needs and utilization trajectories prior to enrollment?

  Hypothesis 3a: Care coordination will have a smaller effect on the acute care utilization of enrollees with high physical health needs, high behavioral health needs, or both. This is because they may have conditions had that are difficult to resolve, and need more intensive services beyond care coordination alone.

  Hypothesis 3b: Care coordination will have a smaller effect on enrollees with persistent high utilization prior to enrollment compared to enrollees with low utilization. This is because they may have more severe conditions leading to frequent acute care utilization, or have low health needs but more entrenched acute care utilization behaviors that made it difficult to reduce service use through care coordination alone.

II. IDENTIFYING SUBPOPULATIONS OF MEDICAID PATIENTS IN A CARE COORDINATION INTERVENTION TARGETING HIGH UTILIZERS: A LATENT CLASS ANALYSIS

Abstract

Background: Patients who use a large volume of health services, especially costly acute care, are known as high utilizers. An increasing number of health care programs target current and potential high utilizers to improve health and reduce disproportionate service use. However, especially in large or statewide programs, enrollment criteria can be applied differently by implementing organizations, leading to heterogeneity in the participating population, and creating problems when interventions and evaluations do not address the experiences of important subgroups. Identifying subpopulations can improve understanding of high utilizers and facilitate valuable subgroup analysis. **Objective:** To understand the combination of health indicators that characterize subpopulations of a large sample of Medicaid patients enrolled in a complex, large-scale care coordination program that targeted current and potential high utilizers. **Methods:** Adult patients who enrolled during the first two years of the program and who were continuously enrolled in Medicaid for at least two years prior to program initiation were included in a latent class analysis (LCA) (n = 73,186). Health indicators were constructed from claims data, and consisted of pre-program chronic condition diagnoses categorized into nine clinically relevant variables. A final model was selected based on goodness-of-fit statistics and interpretability. Classes were described in terms of demographics, program target populations, health conditions, and utilization. **Results:** An assessment of LCA output indicated a five-class solution. The biggest class consisted of patients with low physical and behavioral health need

(32%), who were enrolled because the intervention targeted both current and potential high utilizers based on social and health factors beyond utilization history. Additional large classes were high physical but low behavioral health need (28%), and low physical but high behavioral need (26%). **Implications:** Interventions designed to reduce high utilization should focus on those with different levels and types of need since those at lower levels of need may still be at risk of high utilization. Understanding the health profiles of enrollees can clarify how enrollment criteria are applied in practice, and has implications for how to treat and manage different subpopulations.

Background

For decades, the United States has spent markedly more per capita on health care compared to every other wealthy country, without achieving parity in population health outcomes such as life expectancy.[34] Though high prices are an important driver of high costs,[35] high utilization including the amount and intensity of services accounts for a notable portion of health expenditure growth.[36] With a goal of improving health, resulting in lower utilization and therefore lower costs,[10] health systems and insurers have developed interventions for patients who use a disproportionate amount of costly care.[12] These programs are most effective when they first classify patients into types, so that program developers can create the best intervention given the unique mix of conditions in the patient population, and can better evaluate program impacts for different subpopulations.[37–39]

Prior studies that classified high utilizers provided valuable insights to inform the development and provision of services. For example, one study identified five classes of patients who had high inpatient admission rates in a safety net health system, and recommended specific types of services to support each class (e.g., homeless-oriented, gender-oriented, and substance use-oriented services).[40] Another identified seven classes of medically complex patients in a large integrated health system, and suggested management strategies for each (e.g., coordinated mental health and social services for patients in the "Psychiatric Illness" class).[41] Additional studies have provided similar examples of interventions that targeted patients based on identified subpopulations.[4,42–47]

The analytic approach used to classify high utilizers can influence whether the resulting classifications are useful for informing interventions. For example, one study used a machine learning algorithm to identify 25 classes of high utilizing Medicaid patients, but provided no clinical recommendations related to each class.[48] Another classified a nationally representative sample of Medicare beneficiaries, but concluded that heterogeneity of the population prevented the resulting classifications from being clinically meaningful.[49] These studies highlight the importance of having a well-defined study aim for classification analysis, and identifying a useful number of classes to interpret and translate findings into practice.[41,47,50]

Additionally, studies that focus on cost, rather than health conditions, to define high utilizers may miss important aspects of this population such as what health factors drive the high cost, and what classes emerge among lower-cost high utilizers. For example, one study classified frequent users of a hospital's emergency department into four classes (short-term, cardiac, long-term, and minor care) with the aim of identifying opportunities for cost savings, but did not deeply discuss the underlying health-related reasons for visits.[51] In another cost-focused analysis, one study selected patients with the top 1% of expenditures in a health system, and classified them based on their clinical conditions.[50] Because of the high cost of care for elderly and end-of-life patients, the resulting sample was significantly older than the general health system population (mean age of 62 vs. 49 years old), and the analysis thus provided little insight into younger subpopulations.

My study provided new insight into classes of current and potential high utilizers and their potential intervention needs by classifying, based on their health status, Medicaid patients enrolled in a large-scale care coordination program. The statewide California Whole Person Care (WPC) program was established in 2016 under a Medicaid Section 1115(a) waiver from the Centers for Medicare and Medicaid Services (CMS).[30] As of March 2021, the program had enrolled 222,102 unique individuals across 25 "lead entities" (typically led by county agencies).[31] Through a mix of strategies and services, the program coordinated medical, behavioral health, and social services for Medicaid patients with complex needs.[30] Key program goals included reducing emergency department and inpatient use.[33]

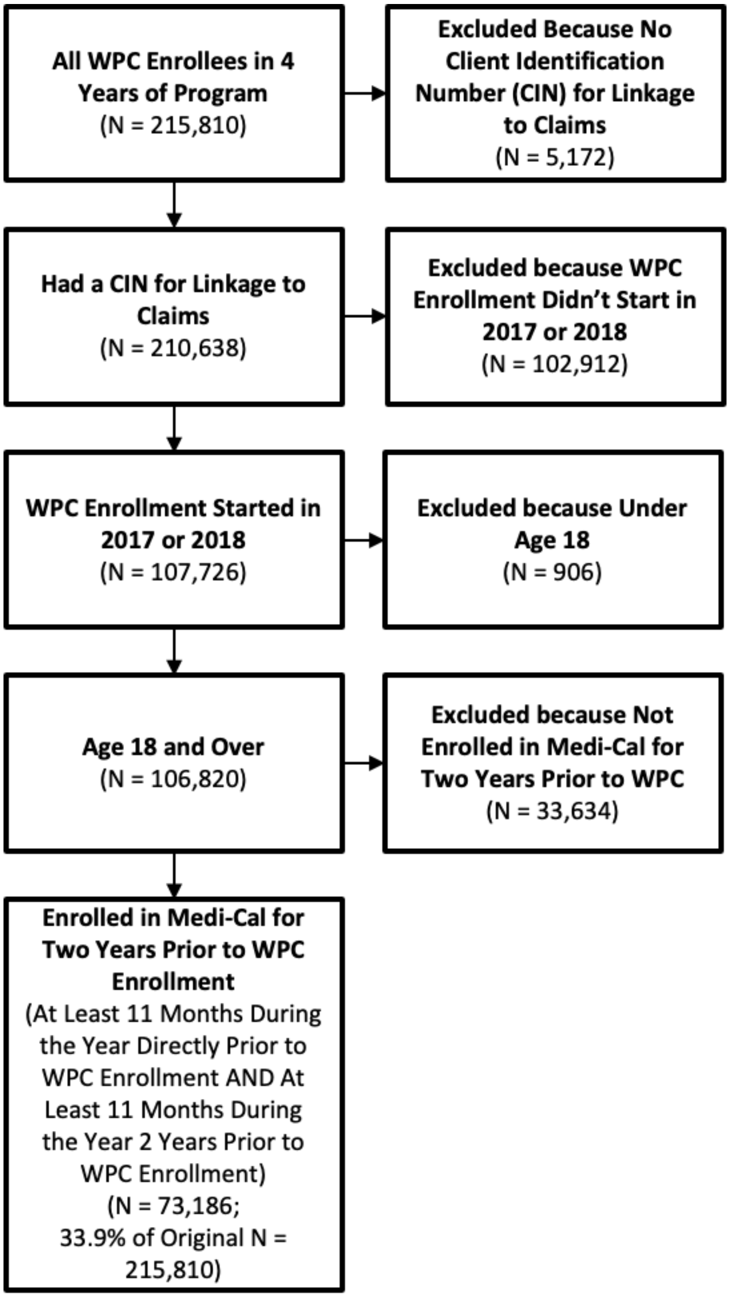
Based on guidance from the state agency that administered WPC, lead entities focused on enrolling people who met the criteria of six target populations: high utilizers, people experiencing homeless, people at-risk of homelessness, people with serious mental illness or substance use disorder, people with chronic physical conditions, and people with a history of criminal justice system involvement.[30] Some lead entities targeted only one of these groups, while others targeted several or all of them. To accommodate regional differences, the state also granted lead entities a high degree of flexibility in patient recruitment strategies and enrollment criteria, resulting in heterogeneity within target populations. For example, though the Contra Costa County WPC Pilot focused only on the "High Utilizers" WPC target population, they used an algorithm to enroll patients based on risk of future high utilization, rather than prior utilization alone, leading to potential discrepancies between the target population label and actual utilization histories.[33] In the context of this complex real-world intervention, I used an empirical, data-driven classification method to explore whether there were distinct subgroups of WPC enrollees who could be identified based on health conditions.

Methods

Study Sample

The study sample consisted of adults who enrolled in WPC in 2017 or 2018, and who had been enrolled in the state's Medicaid program for at least two years prior to enrollment in WPC (Figure 1.1). When patients enrolled in WPC multiple times (e.g., with interim periods of disenrollment) I used the first WPC enrollment date. To allow for small breaks in Medicaid enrollment, I defined two years of prior Medicaid enrollment as consisting of 11 or more months enrolled in Medicaid during the first year prior to WPC enrollment, and 11 or more months enrolled in Medicaid during the second year prior to WPC enrollment. I excluded a small percent of enrollees (<3%) because they lacked a Client Identification Number (CIN) and could not be linked to Medicaid claims. Of the 106,820 adults who enrolled in 2017 or 2018 and had a CIN, 73,186 were enrolled in Medicaid for at least two years prior to enrollment (allowing for 1 month disenrolled per year) and constituted the final analytic sample. The study sample contained 67.9% of the people who enrolled in WPC in 2017 or 2018 (n = 107,726), and 33.9% of the overall WPC population who enrolled during the first four years of the program from 2017 through 2020 (n = 215,810).

Figure 1.1 Flowchart of included and excluded enrollees.



Latent Class Analysis

I used latent class analysis (LCA) to identify classes of WPC enrollees. Studies have used both LCA and machine learning clustering algorithms such as *k*-means to identify enrollee classes based on clinical and diagnostic indicators of health status.[40,41,47–50] Though machine learning clustering algorithms have gained popularity, LCA remains a prevalent method of patient classification.[52] LCA offers benefits including goodness-of-fit statistics that are widely used in frequentist statistics, such as the Akaike and Bayesian Information Criteria (AIC and BIC), to aid in identification of the optimal number of classes (machine learning cluster analyses often use data visualization or other iterative methods[53,54]); class membership probabilities to understand the certainty of class assignment; and freedom from needing to standardize variables prior to analysis.[52,55] I cleaned data and conducted descriptive analysis in RStudio Version 1.2.5003,[56] and conducted LCA in Mplus Version 7.[57]

I identified enrollee classes based on the presence of chronic medical and behavioral health conditions during the two years prior two WPC enrollment. For the WPC evaluation, 70 health condition indicators were constructed from Medicaid claims using code lists from the Chronic Conditions Data Warehouse (CCW).[58] Using literature review and expert input, I collapsed the indicators into nine clinically meaningful and mutually exclusive categories relevant to the context of the WPC program (Table 1.1). For each category, I classified each enrollee as "1" if they had any condition in that category at any point during the two years prior to WPC enrollment, and as "0" if they never had any of the conditions in that category during the two years prior to WPC enrollment. I conducted sensitivity analysis to check robustness of results to inclusion and exclusion of selected variables from the categories.

I implemented the LCA for two to nine classes, progressively increasing the number of random starting values to ensure that the best log likelihood value was replicated and the results were stable.[59] I obtained posterior probabilities of membership in each class, and assigned class membership based on highest probability. I selected the final number of classes based on goodness-of-fit statistics (AIC, BIC, and entropy), a threshold of at least 5% of the sample being in the smallest class, and clinical relevance of the results.

Table 1.1. Mutually exclusive indicators used in LCA.

Indicator	Included Conditions
1. Ambulatory Care-Sensitive Conditions	Diabetes; Hyperlipidemia; Hypertension; Obesity
2. Moderate-to-Severe Cardiovascular Disease	Acute myocardial infarction; Atrial fibrillation; Heart failure; Ischemic heart disease; Peripheral vascular disease; Stroke
3. Kidney or Liver Disease	Liver disease; Chronic kidney disease (CKD); Viral hepatitis (A through E)
4. Respiratory Disease	Asthma; Chronic obstructive pulmonary disease (COPD)
5. Anxiety or Depression	Anxiety disorders; Depression
6. Serious Mental Illness	Bipolar disorder; Personality disorders; Schizophrenia and psychotic disorders
7. Substance Use Disorder	Alcohol use disorder; Drug use disorder
8. Other Complicating Conditions - High Acuity	Cancer (colorectal, endometrial, breast, lung, and prostate); Leukemia and lymphoma, HIV/AIDS; Traumatic brain injury; Spinal cord injury; Spina bifida; Alzheimer's disease and dementia; Cerebral palsy; Cystic fibrosis; Multiple sclerosis; Muscular dystrophy; Hip/pelvic fracture
9. Other Complicating Conditions - Moderate-to-Low Acuity	Acquired hypothyroidism; Benign prostatic hyperplasia; Osteoporosis; Arthritis; Fibromyalgia, chronic pain, and fatigue; Pressure and chronic ulcers; Anemia; PTSD; ADHD; Epilepsy; Migraine and chronic headache; Autism spectrum disorders; Intellectual disabilities; Learning disabilities; Other developmental delays; Cataract; Glaucoma; Blindness and visual impairment; Deafness and hearing impairment; Mobility impairment; Tobacco use

Kidney and liver disease were combined into one category because they had notable overlap in the sample (29% of those with liver disease or viral hepatitis also had CKD), and because these diseases both can result from substance use disorder (SUD),[60,61] which was prevalent in this sample. Prevalence of conditions are provided in Appendix 1.5.

Characterization of Latent Health Needs Classes

I linked class membership to enrollee demographics and acute care utilization prior to WPC enrollment to further characterize the resulting classes. I obtained enrollee demographics from Medicaid enrollment data. These consisted of gender (female vs. male), age (17 and under, 18 to 34, 35 to 49, 50 to 64, or 65 and over), race and ethnicity (White, Black, Latinx, Asian or Pacific Islander, American Indian or Alaska Native, or Other/Unknown), and preferred language for communication (English, Spanish, or Other). Additionally, I constructed an indicator of homelessness from WPC enrollment reports provided by program lead entities. I classified enrollees as experiencing homelessness if they were ever classified as homeless in the reports from the first two years of the program (2017 and 2018). I defined acute care utilization based on the number of outpatient emergency department (ED) visits, followed by discharge, and inpatient hospitalizations recorded in enrollee claims during the two years prior to WPC enrollment. Based on definitions commonly used in the literature,[62–64] I defined ED super-utilizers as enrollees who had an average of six or more ED outpatient visits (i.e., not leading to admission) per year during the two years prior to WPC enrollment, and inpatient super-utilizers as enrollees who had an average of four or more inpatient admissions per year during the two years prior to WPC enrollment.

Results

Overall Sample Characteristics

The study sample consisted of 73,186 adults with an initial WPC enrollment date in 2017 or 2018, who had two years of Medicaid enrollment prior to WPC initiation (Table 1.2). This included the 69% of the 106,820 total adults who enrolled in 2017 or 2018 who were also enrolled in Medi-Cal for at least two years prior to WPC (Figure 1.1). For the 19% of the sample who had more than one enrollment in WPC, this analysis used only the first enrollment date. Just over half of the sample consisted of male-identifying enrollees (51.6%) and Black and Latinx enrollees (25.9% and 23.6%, respectively). Most of the sample preferred to speak English (85.7%). A large proportion (38.9%) were classified by program staff as having experienced homelessness in 2017 or 2018.

The sample used in this study significantly differed in almost all demographic and health characteristics from the residual WPC enrollees, i.e., those who were not included in the analysis due to lacking a CIN for linkage to claims, enrolling after 2018, being under age 18, or not having two years of prior Medi-Cal enrollment. As examples, some of the most notable demographic differences were that the study sample contained fewer enrollees who were experiencing homelessness (38.9% vs. 45.9%), male (51.6% vs. 58.5%), aged 18 to 34 (26.2% vs. 34.2%), and Latinx (23.6% vs. 28.8%). The study sample also had a higher proportion of enrollees with each of the nine health condition indicators included in the LCA. Comparing the study sample to residual WPC enrollees restricted to those who enrolled in 2017 or 2018 yielded similar results (Appendix 1.1).

Table 1.2. Demographics of the study sample and residual WPC enrollees not in the sample.

Characteristic	Study Sample	Residual Enrollees	*p*-value
N	73,186	137,452	
% Homeless	38.9	45.9	<0.001
% Male	51.6	58.5	<0.001
% by Age Group			
17 and Under	0.0	2.7	<0.001
18 to 34	26.2	34.2	<0.001
35 to 49	27.0	28.3	<0.001
50 to 64	37.9	27.7	<0.001
65 and Over	9.0	7.1	<0.001
% by Race			
White	27.7	25.7	<0.001
Black	25.9	22.6	<0.001
Latinx	23.6	28.8	<0.001
API	5.6	6.6	<0.001
AIAN	0.7	0.6	0.052
Other/Unknown	16.4	15.7	<0.001
% by Language			
English	85.7	84.8	<0.001
Spanish	9.1	9.8	<0.001
Other/Unknown	5.2	5.3	0.415
% by Health Condition			
Ambulatory Care-Sensitive Conditions	51.6	34.7	<0.001
Moderate-to-Severe Cardiovascular Disease	16.8	10.4	<0.001
Kidney or Liver Disease	26.3	17.2	<0.001
Respiratory Disease	23.7	14.2	<0.001
Anxiety or Depression	46.7	33.7	<0.001
Serious Mental Illness	37.0	25.2	<0.001
Substance Use Disorder	37.4	29.7	<0.001
Other Complicating Conditions - High Acuity	11.7	7.4	<0.001
Other Complicating Conditions - Moderate-to-Low Acuity	64.3	45.4	<0.001

The study sample consisted of members of the overall WPC population who enrolled in 2017 or 2018, were age 18 and over, and were enrolled in Medi-Cal for two years prior to WPC enrollment, allowing for one month disenrolled per year (n = 73,186). The residual enrollees not included in the sample consisted of those who enrolled after 2018, or who were under age 18 or enrolled in Medi-Cal for less than two years prior to WPC enrollment, allowing for one month disenrolled per year (n = 137,452).

p-values derived from two-sample two-tailed Z-tests of proportions. Abbreviations refer to Asian or Pacific Islander (API); American Indian or Alaska Native (AIAN). Health conditions presented in this table consist of the nine model indicators used in the LCA.

Latent Class Model Selection

I selected the five-class model based on an assessment of goodness-of-fit statistics, class sizes, and clinical interpretability of the resulting groups (Table 1.3). A six-class model also provided clinically meaningful classes (Appendix 1.2), but I selected the five-class model due to superior fit statistics. AIC and BIC continually decreased from two to nine classes, indicating better fit with each additional class, but graphs indicated a point of diminishing returns after five classes (Appendix 1.3). Entropy, a measure of how well classes are differentiated,[65] peaked at five classes, though it remained below the standard threshold of >= 0.8 for all models. After five classes, average probability of being assigned to each class (class assignment certainty) reduced to low levels for some classes (Appendix 1.3). The smallest class of the five-class model contained 4.0% of the sample (2,904 individuals), which I considered close enough to the pre-selected cutoff of 5% for a class size.

Table 1.3. LCA goodness-of-fit statistics and proportion of sample in the smallest class for two to nine classes.

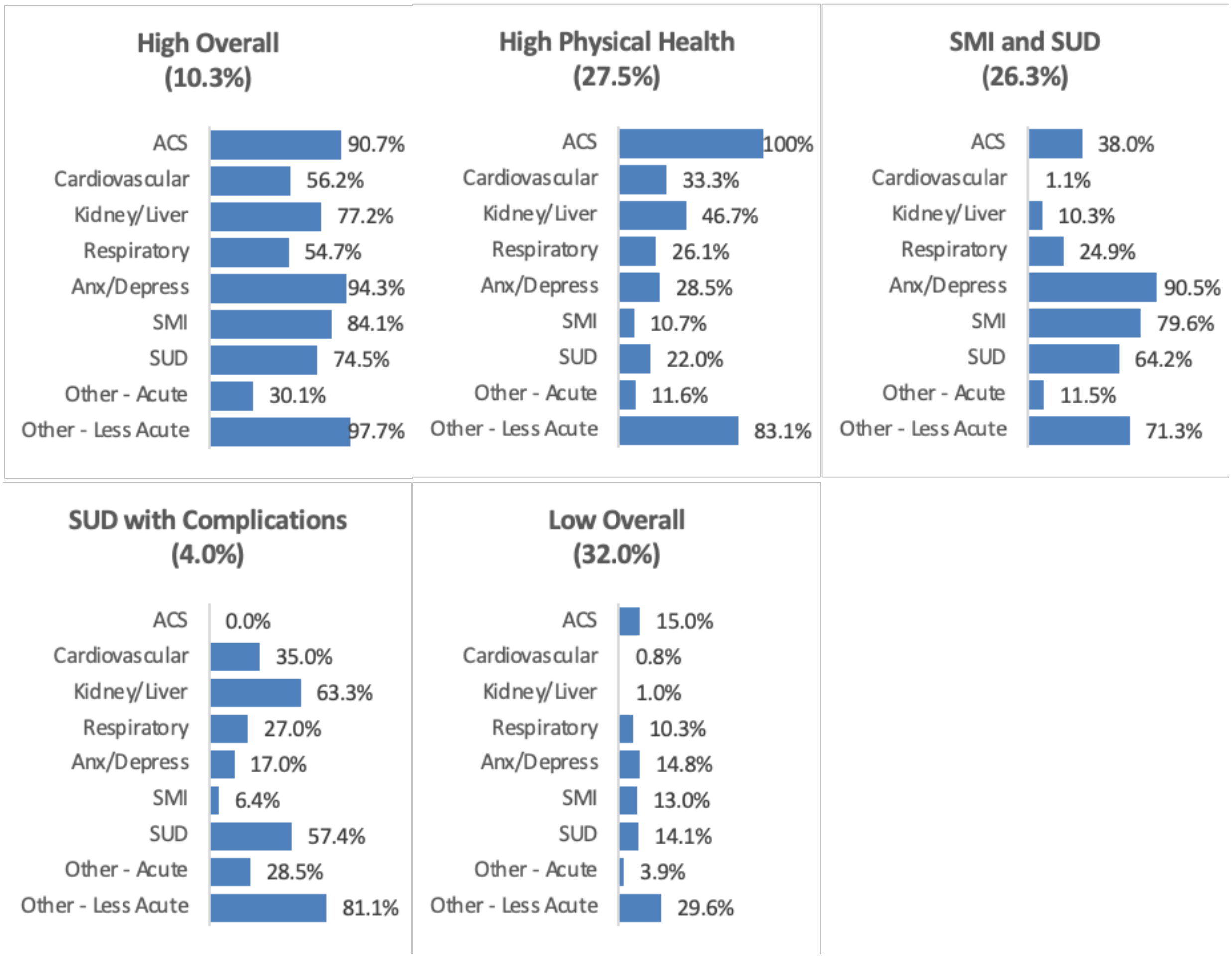
Classes	AIC	BIC	Entropy	% of Sample in Smallest Class
2	742045.1	742220.0	0.570	47.6%
3	727396.0	727662.8	0.629	26.8%
4	722269.9	722628.7	0.609	9.7%
5	721192.0	721642.8	0.656	4.0%
6	720186.6	720729.4	0.613	5.6%
7	719608.7	720243.5	0.583	6.3%
8	719164.4	719891.3	0.581	6.1%
9	718874.0	719692.8	0.608	6.2%

Latent Class Health Characteristics

The five latent classes had distinct health condition profiles (Figure 1.2). The first class, "High Overall" (10.3% of the sample), had the highest prevalence of all physical and behavioral health conditions except ambulatory care-sensitive conditions (diabetes, hyperlipidemia, hypertension, or obesity), for which it had the second highest prevalence. The second class, "High Physical Health" (27.5% of the sample), had the highest prevalence of ambulatory care-sensitive conditions, moderate prevalence of other physical health conditions, and low prevalence of behavioral health conditions. The third class, "Serious Mental Illness and Substance Use Disorder (SMI and SUD)" (26.3% of the sample), had the second highest prevalence of behavioral health conditions, and a low prevalence of physical health conditions. The fourth class, "Substance Use Disorder with Complications (SUD with Complications)" (4.0% of the sample), had a high prevalence of substance use disorder, the second highest prevalence of kidney or liver disease and moderate-to-severe cardiovascular disease, and the lowest prevalence of ambulatory care-sensitive conditions. The fifth class, "Low Overall" (32.0% of the sample), had the lowest prevalence of nearly all physical and behavioral health conditions.

The six-class model (Appendix 1.2) differed from the five-class model in its inclusion of a class for "Ambulatory Care-Sensitive (ACS) without Serious Complications." This class had a high prevalence of other complicating factors of moderate-to-low acuity, and a moderate prevalence of ambulatory care-sensitive conditions such as diabetes and hypertension. It consisted mainly of enrollees who had been assigned to the "High Physical Health" and "Low Overall" classes in the five-class model. However, this sixth class had a low certainty of class assignment (Appendix 1.3), meaning that it may not represent a meaningful group of enrollees.

Figure 1.2. Prevalence of health conditions by class in the five-class model.

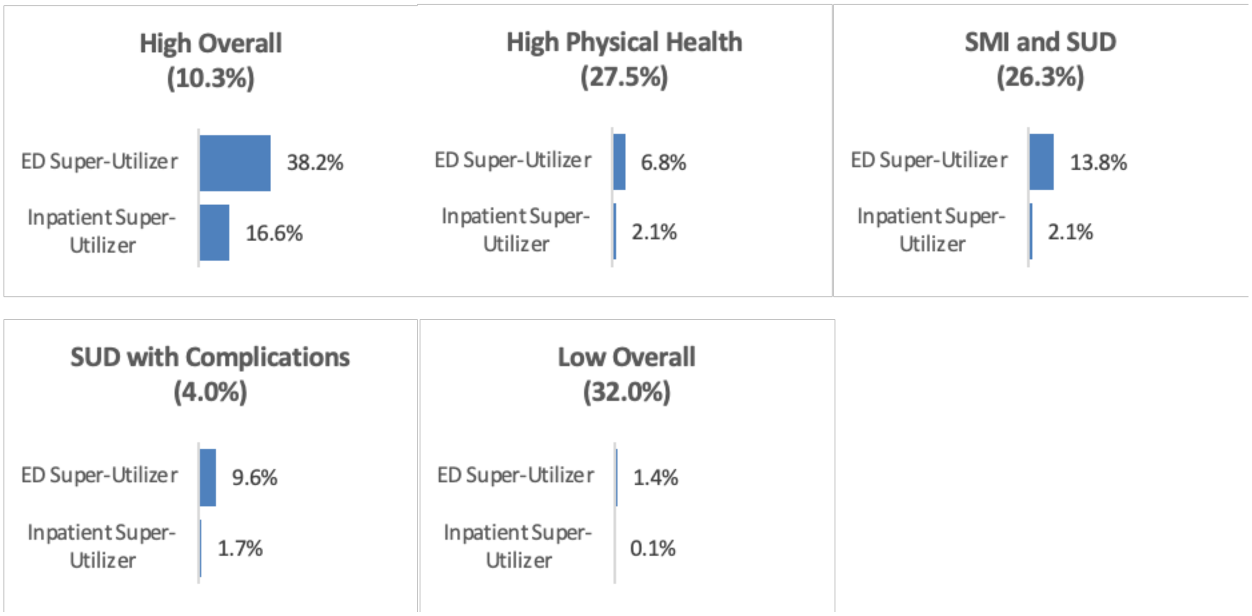


Health conditions presented in this figure consist of the nine model indicators used in the LCA: (1) Ambulatory-Care Sensitive Conditions (ACS); (2) Moderate-to-Severe Cardiovascular Disease (Cardiovascular); (3) Kidney or Liver Disease (Kidney/Liver); (4) Respiratory Disease (Respiratory); (5) Anxiety or Depression (Anx/Depress); (6) Serious Mental Illness (SMI); (7) Substance Use Disorder (SUD); (8) Other Complicating Conditions - High Acuity (Other - Acute); (9) Other Complicating Conditions - Moderate-to-Low Acuity (Other - Less Acute).

Latent Class by Enrollee Utilization

Latent classes varied in acute care utilization prior to WPC enrollment (Figure 1.3). This was expected because WPC permitted enrollment of both current high utilizers, and potential high utilizers that pilots determined, through various methods, to be at-risk of avoidable acute care use.[33] The "High Overall" class contained the highest proportion qualifying as super-utilizers of outpatient emergency department (ED) care, followed by discharge (38.2%); or super-utilizers of inpatient care, operationalized as number of hospitalizations (16.6%). Despite having high physical health needs, members of the "High Physical Health" class had the second lowest proportion of ED super-utilizers (6.8%), and a low proportion of inpatient super-utilizers (2.1%). The "SMI and SUD" class had the second highest proportion of enrollees meeting this study's definition of ED super-utilizer (13.8%), but a low proportion of inpatient super-utilizers (2.1%). Compared to the "SMI and SUD" class, the "SUD with Complications" class had slightly lower proportions of ED super-utilizers (9.6%) and inpatient super-utilizers (1.7%). The "Low Overall" class had the lowest proportions of ED super-utilizers (1.4%) and inpatient super-utilizers (0.1%).

Figure 1.3. Utilization prior to WPC enrollment by class for the five-class model.



ED Super-Utilizer: an average of 6 or more outpatient emergency department visits per year during the two years prior to WPC enrollment, significantly different proportions across classes (Pearson's $\chi 2 = 8925.1$, $df = 4$, p-value < 0.001); Inpatient Super-Utilizer: an average of 4 or more inpatient admissions per year during the two years prior to WPC enrollment, significantly different proportions across classes (Pearson's $\chi 2 = 5802.6$, $df = 4$, p-value < 0.001).

Latent Class by Demographics

There was some variation in the demographics of the latent classes (Table 1.4). Compared to the other classes, the "High Overall" class had the highest proportion of enrollees classified as homeless (51.8%) and aged 50 to 64 (56.2%), and had the lowest proportion of Latinx (18.8%) and Spanish-speaking (4.0%) enrollees. The "High Physical Health" class had the highest proportion of enrollees aged 65 and over (17.0%), and who were identified as Latinx (26.1%) or Spanish-speaking (14.7%). This class had the lowest proportion of enrollees identified as homeless (31.5%), White (23.6%), or English-speaking (77.2%). The "SMI and SUD" class had the highest proportion of English-speaking enrollees (92.7%), the second highest proportion of enrollees classified as homeless (46.6%), and the lowest proportion of patients aged 65 and over (2.6%). The "SUD with Complications" class had the highest proportion of patients identified as White (35.9%) or male (60.9%), and the lowest proportion of patients identified as Black or African American (22.0%). The “Low Overall” class had the lowest proportion of patients identified as male (50.4%), and the highest proportion of patients identified as aged 18 to 34 (40.0%), or Black or African American (27.5%).

Table 1.4. Demographics of the five classes.

Characteristic	Latent Class: High Overall	High Physical Health	SMI and SUD	SUD with Complications	Low Overall	*p*-value
N	7,536	20,104	19,251	2,904	23,391	
% of Sample	10.3	27.5	26.3	4.0	32.0	
% Homeless	51.8	31.5	46.6	44.9	34.1	<0.001
% Male	54.9	50.5	51.6	60.9	50.4	<0.001
% by Age Group						
18 to 34	10.7	8.8	34.8	18.4	40.0	<0.001
35 to 49	25.7	20.7	32.9	27.1	27.8	<0.001
50 to 64	56.2	53.5	29.7	42.9	24.8	<0.001
65 and Over	7.4	17.0	2.6	11.5	7.4	<0.001
% by Race						
White	34.6	23.6	31.9	35.9	24.5	<0.001
Black	26.7	24.9	25.5	22.0	27.5	<0.001
Latinx	18.8	26.1	21.1	20.1	25.6	<0.001
API	2.7	8.8	3.2	4.2	5.9	<0.001
AIAN	1.0	0.6	0.7	0.8	0.6	<0.001
Other/Unknown	16.2	15.9	17.6	17.1	15.9	<0.001
% by Language						
English	92.5	77.2	92.7	88.7	84.8	<0.001
Spanish	4.0	14.7	4.0	7.0	10.2	<0.001
Other	3.6	8.0	3.2	4.3	5.0	<0.001

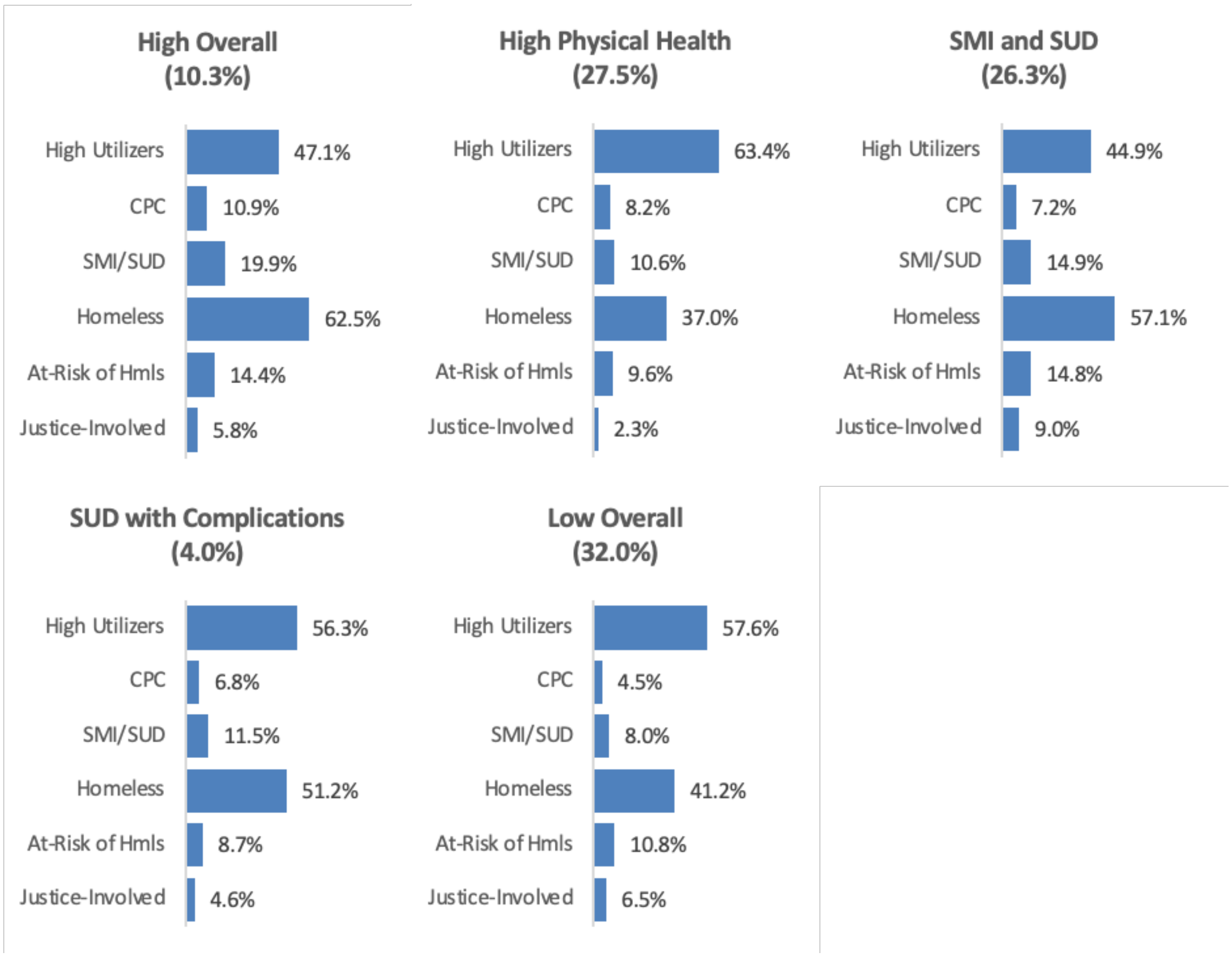
Pearson’s $\chi 2$ test indicated significantly different proportions across classes for all demographics ($p < 0.001$). Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); Asian or Pacific Islander (API); American Indian or Alaska Native (AIAN).

Latent Class by WPC Target Populations

Latent classes had similarities and differences from the six WPC target populations defined by program lead entities (Figure 1.4). For example, the chronic physical conditions target population was most prevalent in the “High Overall” and the “High Physical Health” classes (10.9% and 8.2%, respectively), which aligned with the high prevalence of physical health conditions in these classes. The SMI/SUD target population was most prevalent in the “High Overall,” “SMI and SUD,” and “SUD with Complications” classes (19.9%, 14.9% , and 11.5%, respectively), which aligned with the high prevalence of behavioral health conditions in these classes. The justice-involved target population was also most prevalent in the “SMI and SUD” class (9.0%), reflecting potential intersections between behavioral health and criminal justice system involvement.

Examples of discrepancies included that the “High Physical Health” class had the highest prevalence of the high utilizer WPC-defined target population (63.4%), even though this class had the second lowest proportion of super-utilizers based on the definitions used in this study. By contrast, the “High Overall” class had the second lowest prevalence of the high utilizer target population (47.1%), even though it had the highest proportion of super-utilizers. This likely reflects broad allowance for current and potential future high utilizers in the WPC high utilizer target population. Additionally, in all classes most enrollees were in either the high utilizer target population (44.9% to 63.4% of each class) or the homeless WPC target population (37.0% to 62.5% of each class), while few were in the WPC target populations based on health conditions (chronic physical conditions, and SMI/SUD).

Figure 1.4. WPC target population by class for the five-class model.



Target populations presented in this figure consist of the six target populations defined by the WPC program: (1) High Utilizers; (2) Chronic Physical Conditions (CPC); (3) Serious Mental Illness or Substance Use Disorder (SMI/SUD); (4) Homeless; (5) At-Risk of Homelessness (At-Risk of Hmls); (6) Justice-Involved.

Discussion

I identified five distinct classes of enrollees in a large-scale care coordination Medicaid demonstration program that aimed to reduce acute care utilization of Medicaid beneficiaries with complex needs. Classes were separated by types of health conditions and comorbidities, including the presence of ambulatory care-sensitive physical health conditions such as diabetes and hypertension, more acute physical health conditions, behavioral health conditions, and other complicating factors such as chronic pain and disabilities. Below I discuss the five classes I identified, and their similarities and differences compared to subpopulations identified in other analyses of high utilizing and medically complex populations.

First, in this analysis, I identified a small but notable class with "High Overall" health need, both physical and behavioral (10% of the sample), which also had high rates of acute care (ED and hospitalization) super-utilization. This finding was similar to other studies that classified only a small proportion of patients as having high overall acuity. For example, studies of high utilizers with complex health needs classified between 8% and 14% of patients as having the highest medical acuity and most extreme acute care utilization compared to the rest of the sample.[40,41,49] Broader analyses of general patient populations, not restricted to high utilizers or medically complex patients, have classified between 3% and 7% of patients as having high overall need and high ED utilization.[44,45,62] These patterns indicate that, even among populations selected for high utilization and medical complexity, very high health need is relatively uncommon.

Second, more unique to this study was the finding of a large "High Physical Health" needs class of predominantly older adults with high prevalence of physical health conditions, especially ambulatory care-sensitive conditions such as diabetes and hypertension (Figure 1.2);

low prevalence of behavioral health conditions; moderate-to-low acute care utilization; and a high proportion of Latinx and Spanish-speaking patients (28% of the sample). A similar class was also identified in one other study of safety net patients.[40] In other analyses, patients with high physical but low behavioral health need were split across classes defined by specific types of physical health conditions such as renal disease, cardiovascular disease, and cancer;[41,50] or across classes defined by types of utilization due to the inclusion of utilization variables as indicators in the classification models.[4,44,45] The association between low behavioral health need and a high proportion of Latinx patients in this class could arise from actual differences in health conditions, or from confounding factors such as differences in culture, language, or access to care by race and ethnicity.[66]

Third, the identification of an "SMI and SUD" class with high prevalence of mental health and substance use disorder, low prevalence of physical health conditions, and somewhat high ED and inpatient utilization (26% of the sample) was consistent with the WPC focus on targeting behavioral health needs and providing related services,[30] and was consistent with prior literature. For example, other studies of high utilizers found classes with a high prevalence of behavioral health conditions that also had high acute care utilization.[44,51,62] Fourth, and more novel, was the finding of a small "SUD with Complications" class with a high prevalence of substance use disorder, low prevalence of mental health conditions, and high physical health conditions including kidney and liver disease (4% of the sample). This class may reflect physical complications that arise from substance use disorder, and is distinct from classes identified in nearly all other studies of high utilizers. One study in a safety net health system identified a class defined by alcohol use, homelessness, and physical health conditions including high rates of liver disease (16% of the sample), which suggests that similar classes may exist in some contexts.[40]

Finally, the finding of the fifth large "Low Overall" class with low health need (32% of the sample) was especially consistent with prior studies. Analyses of high utilizing and medically complex populations have found large low-acuity classes, ranging from 28% to 33% of the study sample.[41,49,50] Broader studies of general patient populations, not restricted to high utilizers, have found low acuity classes comprising 28% to 58% of patients.[42,44,47] In this analysis, the "Low Overall" health needs class was disproportionately young, and had low acute care utilization prior to enrollment in WPC. Given the variation in enrollment strategies across WPC, members of this group were probably enrolled on the basis of social risk factors, rather than medical complexity or utilization history. For example, the Riverside Pilot targeted enrollment only on the basis of having a history of criminal justice system involvement,[33] and had the largest proportion of enrollees classified as "Low Overall" health needs in this sample (Appendix 1.4).

The discrepancies identified between the latent classes and the program-identified target populations reflect the flexible target population definitions used in the WPC program. Lead entities were required to classify enrollees into six target populations,[30] but were not required to adhere to any standardized definition of each target population. As a result, program-defined target populations only partially reflected what needs enrollees had, and what services might best address those needs. Latent class analysis based on health conditions provided useful supplemental insight. Implications of identifying patient classes based on health need will be discussed more broadly in the chapter of this dissertation that compares the program outcomes for each class.

Limitations

Though this study contributed a unique perspective on current and potential high utilizers enrolled in a large Medicaid program, it also had limitations. First, this study used a non-random sample of patients enrolled in an intervention, which contextualized findings in a real-world program but also limited generalizability to other populations such as Medicare, or Medicaid as a whole. Second, this study further restricted to adults who enrolled during the first two years of WPC, and who had a full two years of Medicaid enrollment prior to WPC initiation (allowing for one month per year unenrolled). Enrollees in the study sample had slightly different demographics and a higher prevalence of health conditions compared to residual enrollees not included in the sample. Results may thus be generalizable only to current and potential high utilizers with stable Medicaid enrollment, and who were likely to be enrolled early on in a care coordination program (e.g., those with the most acute needs). Third, the LCA relied only on indicators of health conditions, and did not include as indicators other patient attributes such as utilization or demographics. This decision ensured that classes were defined based on health status rather than potential confounding factors such as age, but limited comparisons to other studies that incorporated additional indicators when identifying latent classes. Finally, the LCA used indicators constructed from claims data, representing diagnoses reported at encounters that were billed to Medicaid. The indicators may under-represent some health conditions, and do not fully capture differences in severity of disease.

Implications

My analyses indicated that interventions focused on reducing high utilization should consider patients with different types of health needs, including those with high physical health needs, high behavioral health needs, or a combination of high physical and behavioral health needs. However, those without complex conditions could also be enrolled to prevent future high utilization. Evaluators and practitioners should leverage empirical classification methods such as LCA to classify patients into meaningful and distinct clinical categories to design better interventions and improve patient outcomes. Classification analyses can provide important insights into how program impacts vary across subpopulations,[38] as long as meaningful classes are identified. When enrollment criteria are flexible, as in complex large-scale interventions such as WPC, classification can clarify to what extent program-defined target populations are suitable for use in analysis, and can allocate heterogeneous populations into groups based on acuity to assist with targeting of resources.

Appendices

Appendix 1.1. Comparison to residual sample limited to those who enrolled in 2017 or 2018.

Appendix 1.1. Table 1. Demographics of the study sample and residual WPC enrollees from 2017 and 2018.

Characteristic	Study Sample	Residual Enrollees	*p*-value
N	73,186	34,540	
% Homeless	38.9	53.1	<0.001
% Male	51.6	65.8	<0.001
% by Age Group			
17 and Under	0.0	2.6	<0.001
18 to 34	26.2	35.8	<0.001
35 to 49	27.0	30.7	<0.001
50 to 64	37.9	26.5	<0.001
65 and Over	9.0	4.3	<0.001
% by Race			
White	27.7	28.7	0.002
Black	25.9	24.3	<0.001
Latinx	23.6	25.6	<0.001
API	5.6	4.3	<0.001
AIAN	0.7	0.7	0.944
Other/Unknown	16.4	16.4	0.688
% by Language			
English	85.7	90.8	<0.001
Spanish	9.1	7.2	<0.001
Other/Unknown	5.2	2.0	<0.001
% by Health Condition			
Ambulatory Care-Sensitive Conditions	51.6	26.7	<0.001
Moderate-to-Severe Cardiovascular Disease	16.8	7.9	<0.001
Kidney or Liver Disease	26.3	13.5	<0.001
Respiratory Disease	23.7	11.9	<0.001
Anxiety or Depression	46.7	30.6	<0.001
Serious Mental Illness	37.0	26.8	<0.001
Substance Use Disorder	37.4	30.1	<0.001
Other Complicating Conditions - High Acuity	11.7	6.4	<0.001
Other Complicating Conditions - Moderate-to-Low Acuity	64.3	38.4	<0.001

The study sample consisted of members of the overall WPC population who enrolled in 2017 or 2018, were age 18 and over, and were enrolled in Medi-Cal for two years prior to WPC enrollment, allowing for one month disenrolled per year (n = 73,186). The residual enrollees not included in the sample consisted of those who enrolled in 2017 or 2018, and who were under age 18 or enrolled in Medi-Cal for less than two years prior to WPC enrollment, allowing for one month disenrolled per year (n = 34,540).

p-values derived from two-sample two-tailed Z-tests of proportions. Abbreviations refer to Asian or Pacific Islander (API); American Indian or Alaska Native (AIAN). Health conditions presented in this table consist of the nine model indicators used in the LCA.

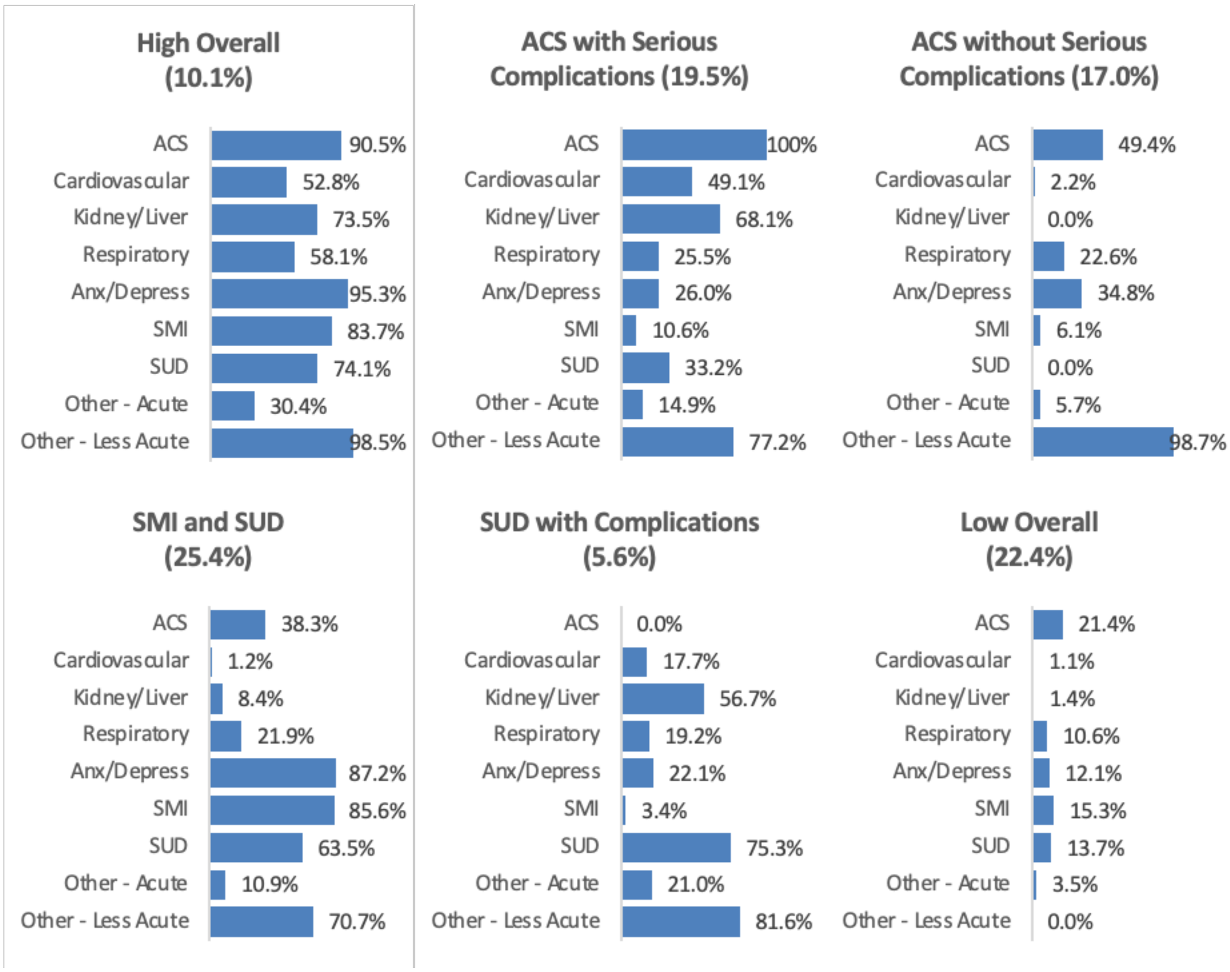
Appendix 1.2. Results of six-class model.

Appendix 1.2. Table 1. Demographics of the six classes

	Latent Class						
Characteristic	**High Overall**	**ACS with Serious Complications**	**ACS without Serious Complications**	**SMI and SUD**	**SUD with Complications**	**Low Overall**	***p*-value**
N	7,405	14,273	12,461	18,605	4,072	16,370	
% of Sample	10.1	19.5	17.0	25.4	5.6	22.4	
% Homeless	51.9	34.9	25.9	46.5	48.1	35.7	<0.001
% Male	53.7	56.9	37.5	52.6	62.4	52.9	<0.001
% by Age Group							
18 to 34	11.1	6.8	26.4	35.1	24.3	40.0	<0.001
35 to 49	25.9	19.6	26.2	33.1	29.9	26.8	<0.001
50 to 64	55.6	55.8	36.5	29.2	38.5	25.1	<0.001
65 and Over	7.3	17.9	10.9	2.6	7.2	8.0	<0.001
% by Race							
White	35.1	24.5	24.2	31.4	37.3	23.2	<0.001
Black	26.9	24.6	25.1	26.0	22.5	28.1	<0.001
Latinx	18.4	25.9	26.2	20.8	20.4	26.2	<0.001
API	2.6	8.7	7.5	3.3	3.2	6.0	<0.001
AIAN	1.0	0.7	0.6	0.7	0.9	0.5	<0.001
Other/Unknown	16.0	15.7	16.3	17.8	15.8	15.9	<0.001
% by Language							
English	92.8	78.4	78.7	92.7	91.3	85.1	<0.001
Spanish	3.7	14.1	14.1	3.9	5.7	10.0	<0.001
Other	4.9	6.7	3.5	7.6	3.0	3.7	<0.001

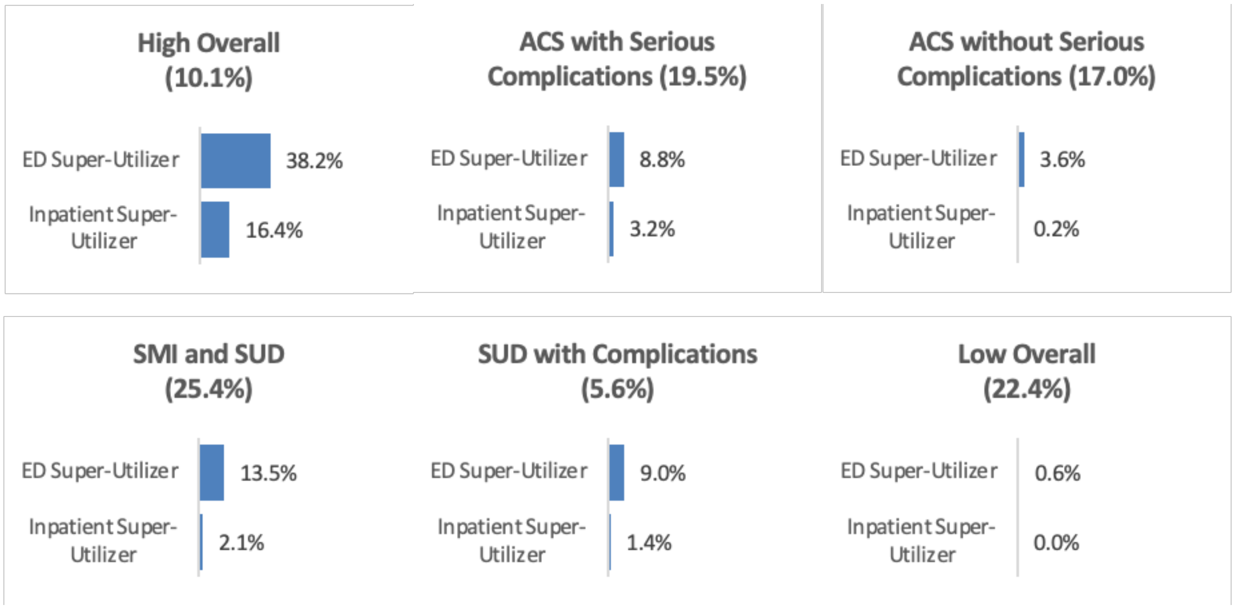
Pearson's $\chi 2$ test indicated significantly different proportions across classes for all demographics ($p < 0.001$). Abbreviations refer to ambulatory care-sensitive conditions (ACS); serious mental illness (SMI); substance use disorder (SUD); Asian or Pacific Islander (API); American Indian or Alaska Native (AIAN).

Appendix 1.2. Figure 1. Prevalence of health conditions by class for the six-class model.



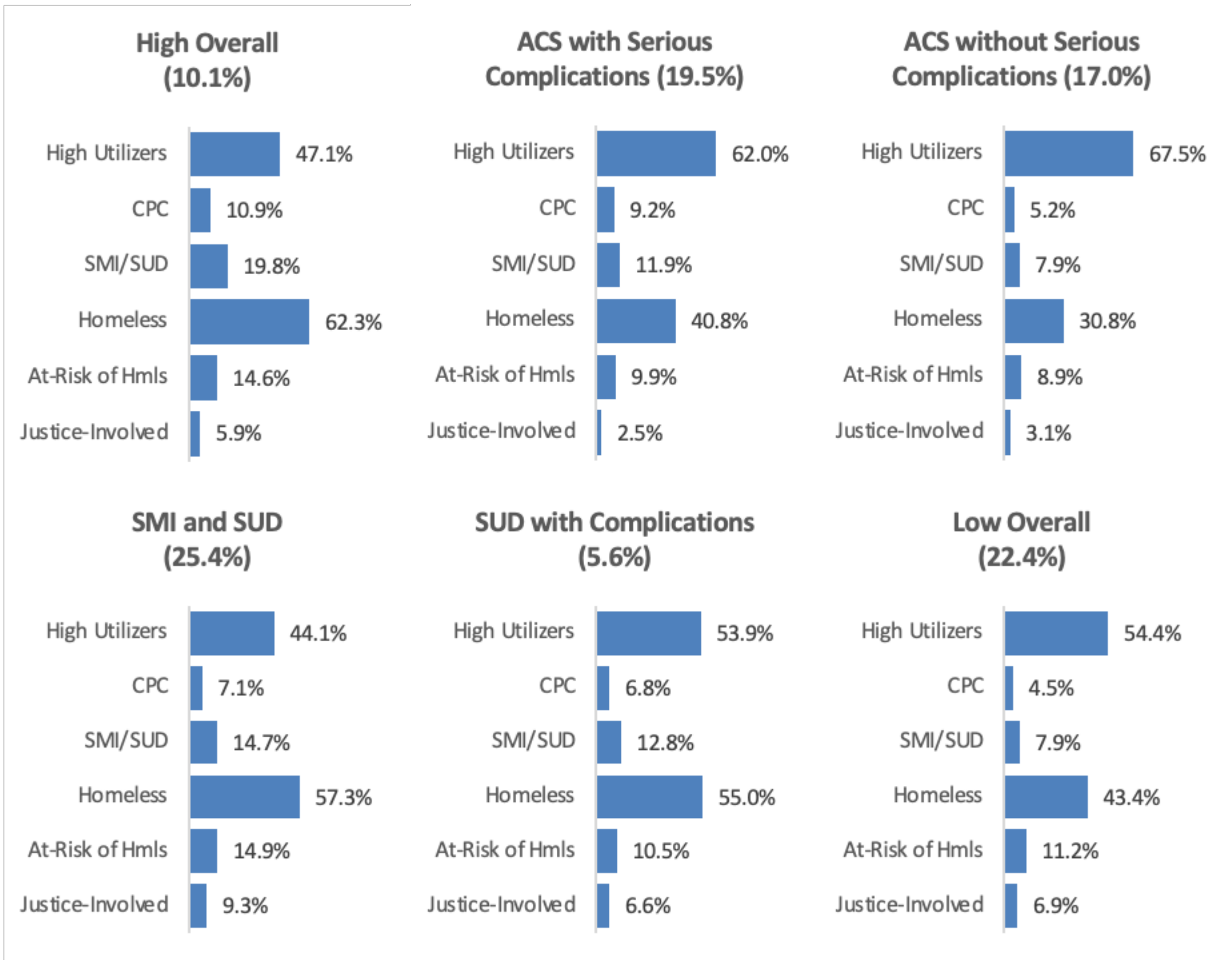
Health conditions presented in this figure consist of the nine model indicators used in the LCA: (1) Ambulatory-Care Sensitive Conditions (ACS); (2) Moderate-to-Severe Cardiovascular Disease (Cardiovascular); (3) Kidney or Liver Disease (Kidney/Liver); (4) Respiratory Disease (Respiratory); (5) Anxiety or Depression (Anx/Depress); (6) Serious Mental Illness (SMI); (7) Substance Use Disorder (SUD); (8) Other Complicating Conditions - High Acuity (Other - Acute); (9) Other Complicating Conditions - Moderate-to-Low Acuity (Other - Less Acute).

Appendix 1.2 Figure 2. Utilization by class for the six-class model.



ED Super-Utilizer: an average of 6 or more outpatient emergency department visits per year during the two years prior to WPC enrollment, significantly different proportions across classes (Pearson's $\chi 2$ = 8809.8, *df* = 4, *p*-value < 0.001); Inpatient Super-Utilizer: an average of 4 or more inpatient admissions per year during the two years prior to WPC enrollment, significantly different proportions across classes (Pearson's $\chi 2$ = 5626.6, *df* = 4, *p*-value < 0.001).

Appendix 1.2. Figure 3. WPC target population by class for the six-class model.



Target populations presented in this figure consist of the six target populations defined by the WPC program: (1) High Utilizers; (2) Chronic Physical Conditions (CPC); (3) Serious Mental Illness or Substance Use Disorder (SMI/SUD); (4) Homeless; (5) At-Risk of Homelessness (At-Risk of Hmls); (6) Justice-Involved.

Appendix 1.3. Comparison of five-class and six-class model results.

Appendix 1.3. Table 1. Average probability of assignment to each class, among those who were assigned to it.

	Average Probability of Class Members Being Assigned to This Class	
Class Label	**5-Class Model**	**6-Class Model**
High Overall	0.76	0.77
High Physical Health	0.79	-
ACS without Serious Complications	-	0.52
ACS with Serious Complications	-	0.84
SMI and SUD	0.75	0.73
SUD with Complications	0.74	0.66
Low Overall	0.80	0.80

This table indicates that the new class that emerged in the six-class model ("ACS without Serious Complications") had a low certainty of class assignment (0.52).

Average probability of assignment to each class was taken from the diagonal elements of the posterior probability matrix. Values closer to 1 indicate that people assigned to Class *k* had a high probability of being in Class *k* relative to their probabilities of being in other classes (i.e., high certainty of class assignment). Values of 0.8 and above are considered indicators of good class assignment.[67]

Appendix 1.3. Table 2. Percent of each class in the five-class model that was assigned to each class in the six-class model.

Class in Five-Class Model	Percent Assigned to Each Class in Six-Class Model						Row Total
	High Overall	ACS with Serious Complications	ACS without Serious Complications	SMI and SUD	SUD with Complications	Low Overall	
High Overall	94.9	4.5	0.0	0.6	0.0	0.0	100.0
High Physical Health	0.0	69.6	30.4	0.0	0.0	0.0	100.0
SMI and SUD	1.2	0.0	2.7	93.5	2.5	0.0	100.0
SUD with Complications	0.2	0.0	10.8	0.4	88.6	0.1	100.0
Low Overall	0.0	0.0	23.5	2.1	4.5	70.0	100.0

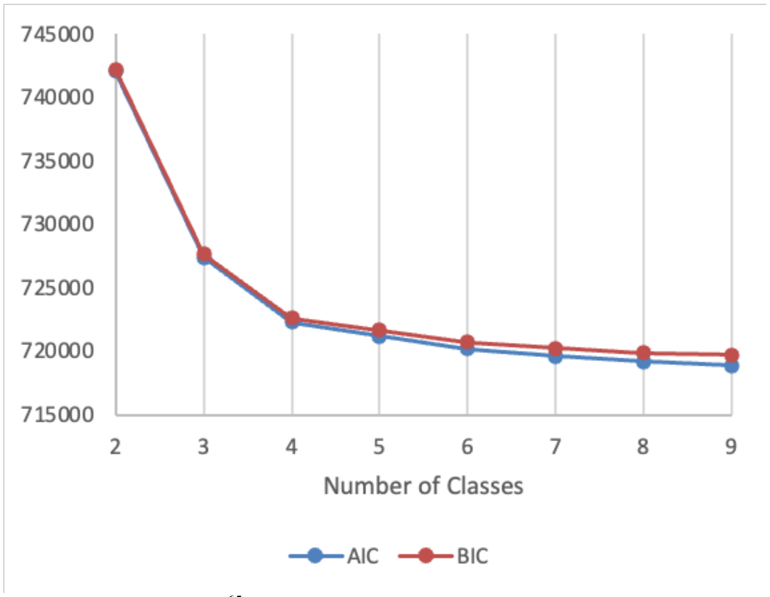
The new class that emerged in the six-class model ("ACS without Serious Complications") mostly included enrollees from two classes from the five-class model: 'High Physical Health', and 'Low Overall'. Abbreviations refer to ambulatory care-sensitive conditions (ACS); serious mental illness (SMI); substance use disorder (SUD).

Appendix 1.3. Table 3. Percent of each class in the six-class model that was assigned to each class in the five-class model.

Class in Six-Class Model	Percent Assigned to Each Class in Five-Class Model					Row Total
	High Overall	High Physical Health	SMI and SUD	SUD with Complications	Low Overall	
High Overall	96.7	0.0	3.2	0.1	0.0	100.0
ACS with Serious Complications	2.3	97.7	0.0	0.0	0.0	100.0
ACS without Serious Complications	0.0	48.8	4.2	2.5	44.5	100.0
SMI and SUD	0.2	0.0	97.0	0.1	2.7	100.0
SUD with Complications	0.0	0.0	11.7	62.6	25.8	100.0
Low Overall	0.0	0.0	0.0	0.0	100.0	100.0

The new class that emerged in the six-class model ("ACS without Serious Complications") mostly included enrollees from two classes from the five-class model: 'High Physical Health', and 'Low Overall'. Abbreviations refer to ambulatory care-sensitive conditions (ACS); serious mental illness (SMI); substance use disorder (SUD).

Appendix 1.3. Figure 1. Visualization of AIC and BIC for two to nine classes.



As is common in LCA,[65] AIC and BIC continued to decrease as number of classes increased, so there was no global minimum to use as an indicator of model fit. In this situation, a plot of AIC or BIC can be inspected to identify an "elbow" that indicates diminishing returns in model fit as the number of classes increases.[65] The plot for this analysis had an "elbow" around four to five classes, indicating that more than five classes resulted in diminishing returns in improving fit.

Appendix 1.4. Enrollee health needs classes by WPC Pilot county for study sample.

Appendix 1.4. Table 1. Percent of WPC Pilot county enrollees by health needs classes for study sample.

		Percent of Enrollees in Sample by Health Needs Classes					
WPC Pilot County	**Number of Enrollees in Sample**	**High Overall**	**High Physical Health**	**SMI and SUD**	**SUD with Complications**	**Low Overall**	**Total**
Alameda	7,101	12.9	25.1	33.8	4.6	23.7	100.0
Contra Costa	23,805	3.8	34.7	15.0	3.8	42.8	100.0
Kern	410	*	*	*	*	38.3	100.0
Kings	165	*	*	*	*	27.9	100.0
Los Angeles	19,820	14.3	22.7	33.6	2.7	26.7	100.0
Marin	470	*	*	*	*	24.9	100.0
Mendocino	224	*	*	*	*	10.7	100.0
Monterey	92	*	*	*	*	*	100.0
Napa	206	*	*	*	*	22.8	100.0
Orange	4,238	12.1	23.6	28.5	3.6	32.3	100.0
Placer	188	*	*	*	*	22.3	100.0
Riverside	1,139	4.0	9.9	26.4	3.9	55.8	100.0
Sacramento	611	18.7	26.7	21.6	7.4	25.7	100.0
San Bernardino	573	*	*	*	*	12.2	100.0
San Diego	188	*	*	*	*	*	100.0
San Francisco	6,677	9.4	16.8	31.7	7.4	34.8	100.0
San Joaquin	667	22.5	26.2	32.1	4.8	14.4	100.0
San Mateo	2,325	12.5	39.1	23.9	3.9	20.7	100.0
Santa Clara	2,444	12.5	41.2	24.0	4.8	17.6	100.0
Santa Cruz	342	*	*	*	*	8.5	100.0
Shasta	179	*	*	*	*	*	100.0
Small Counties	55	*	*	*	*	*	100.0
Solano	127	*	*	*	*	*	100.0
Sonoma	344	*	*	*	*	16.6	100.0
Ventura	796	18.2	32.7	29.9	4.4	14.8	100.0

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD).

* indicates suppressed due to small sample size to protect confidentiality.

Appendix 1.5. Prevalence of specific health conditions in the study sample.

Appendix 1.5. Table 1. Prevalence of specific health conditions in the study sample, by LCA indicator.

Indicator		Condition	% with Condition
1.	Ambulatory Care-Sensitive Conditions	Diabetes	20.0
		Hyperlipidemia	15.3
		Hypertension	37.2
		Obesity	13.8
2.	Moderate-to-Severe Cardiovascular Disease	Acute myocardial infarction	2.1
		Atrial fibrillation	2.8
		Heart failure	6.6
		Ischemic heart disease	7.6
		Stroke	4.6
		Peripheral vascular disease	3.6
3.	Kidney or Liver Disease	Chronic kidney disease	16.5
		Liver disease	8.4
		Viral hepatitis (A through E)	7.6
4.	Respiratory Disease	Asthma	14.1
		Chronic Obstructive Pulmonary Disease (COPD)	14.3
5.	Anxiety or Depression	Anxiety	29.6
		Depression	35.4
6.	Serious Mental Illness	Bipolar disorder	21.2
		Personality disorders	4.5
		Schizophrenia and psychotic disorders	27.8
7.	Substance Use Disorder	Alcohol use disorder	18.8
		Drug use disorder	28.0
8.	Other Complicating Conditions - High Acuity	Alzheimer's disease and dementia	2.6
		Cancer, breast	0.8
		Cancer, colorectal	0.5
		Cancer, endometrial	0.2
		Cancer, lung	0.3
		Cancer, prostate	0.4
		Hip/pelvic fracture	0.9
		Cerebral palsy	0.2
		Cystic fibrosis	0.5
		HIV/AIDS	3.4
		Leukemia and lymphoma	0.5
		Multiple sclerosis	0.4
		Muscular dystrophy	0.1
		Spina bifida	0.2
		Spinal cord injury	1.1
		Traumatic brain injury	0.9

Indicator	Condition	% with Condition
9. Other Complicating Conditions - Moderate-to-Low Acuity	Acquired hypothyroidism	5.1
	Anemia	15.1
	Benign prostatic hyperplasia	2.5
	Cataract	6.2
	Glaucoma	3.9
	Osteoporosis	1.1
	Arthritis	16.9
	ADHD	3.9
	Autism spectrum disorders	0.3
	Epilepsy	5.2
	Fibromyalgia, chronic pain, and fatigue	24.0
	Intellectual disabilities	1.4
	Learning disabilities	0.3
	Migraine and chronic headache	7.4
	Mobility impairment	2.3
	Other developmental delays	0.4
	Pressure and chronic ulcers	4.5
	PTSD	7.5
	Blindness and visual impairment	0.3
	Deafness and hearing impairment	2.3
	Tobacco use	18.6

III. LATENT TRAJECTORIES OF ACUTE CARE UTILIZATION AND INTERSECTIONS WITH HEALTH NEEDS IN A MEDICAID POPULATION

Abstract

Background: Interest has grown in reducing the acute care utilization of high utilizers who frequent the emergency department (ED) and have high rates of hospitalizations. Interventions that target high utilizers are effective when they impact patterns and drivers of high utilization. **Objective:** To understand the acute care utilization patterns of adults prior to enrollment in a large Medicaid care coordination demonstration program, and to describe associations between patient health needs and utilization patterns. **Methods:** Group-based trajectory modeling (GBTM) was used to classify 73,186 enrollees based on trajectory of outpatient ED visits and hospitalizations during the eight quarters prior to enrollment in the program. Classes were characterized by demographics, persistence of high utilization over consecutive quarters, and health needs (defined in a prior cross-sectional latent class analysis). **Results:** GBTM indicated a two-class model: "Moderate-to-High" utilization (18.6%, mean of 2.2 ED and 0.5 hospitalizations per quarter) and "Low" utilization" (81.4%, mean of 0.3 ED and < 0.1 hospitalizations per quarter). Both classes had an increasing trend in ED and hospitalizations, though they differed in amount of growth, persistence of high utilization, and health conditions representing physical and behavioral health needs. In the "Moderate-to-High" class, 94% of enrollees had high physical health needs, behavioral health needs, or both, and in the "Low" class, 62% of enrollees had high physical or behavioral health needs. **Implications:** Depending on enrollment criteria, interventions that target high utilizers may enroll people with a documented history of high utilization, as well as people with a high predicted risk of future high

utilization, leading to heterogeneity in enrollee utilization history prior to enrollment. Understanding patterns and drivers of high utilization, such as the association between health needs and high utilization observed in this study, is important in implementation and evaluation of interventions that target high utilizers of care.

Background

Patients who use large amounts of acute care have become the target of many interventions to improve health outcomes and reduce avoidable expenditure.[12] To inform tailoring of interventions, studies have identified heterogeneous classes of high utilizers based on demographics, diagnoses, and utilization patterns.[51,50,62,41,40,4] Longitudinal variation in utilization has emerged as a particularly important consideration, with evidence indicating that only small proportions of patients have persistent high use over time.[2,4,68–71] However, prior analyses that classified high utilizers either treated utilization as cross-sectional,[41,51,62] or used utilization in post hoc longitudinal analyses of classes that were identified through a cross-sectional approach.[4] To better understand high utilizers and inform interventions, there is a need to identify classes of patients based on their longitudinal utilization patterns.

Longitudinal classification approaches have been widely used in the health and behavioral sciences to identify distinct clinical and developmental trajectories in heterogeneous populations.[72–77] Studies have classified patients based on longitudinal trajectories of health status and symptoms,[78–84] medication adherence,[85–87] and cost of care.[88–93] Almost absent from this literature, however, is classification of patients based on utilization trajectories over time. One analysis classified high-risk patients based on longitudinal risk scores that reflected their probability of hospitalization, but did not model actual acute care utilization.[94] Two additional studies classified patients based on trajectories of acute care utilization, but relied on relatively small samples in specific contexts (geriatric care and chronic kidney disease).[95,96] Similar analyses in broader populations are lacking. Furthermore, though cost of care and utilization can be correlated, studies that classified patients based on longitudinal cost trajectories resulted in classes that were highly influenced by the high cost of end-of-life care.[89,90,92,93] There remains a need for analyses of utilization trajectories that are not confounded by cost.

Additionally, it is unclear whether certain health conditions are associated with different trajectories of acute care use. Compared to the general population, high utilizers often have high physical health needs, such as chronic medical conditions,[1,6,7] and high behavioral health needs, such as serious mental illness and substance use disorder.[1,7] One study of a nationally representative sample found that patients with persistent high utilization had more physical comorbidities and greater mental stress compared to patients with low or one-time high utilization.[6] In another study, patients experiencing homelessness with behavioral health conditions had persistent high use of acute care over time.[4] Further research is needed to confirm if associations between comorbidities and longitudinal trajectories of acute care use exist in additional populations, and to understand if there are unexpected populations that may have implications for program planning and evaluation, such as those with low comorbidity and high utilization, or high comorbidity and low utilization.

The study that I present in this chapter addressed two gaps in the literature related to high utilizers. First, I contributed new understanding of longitudinal trajectories of acute care utilization in a large sample of Medicaid patients. Second, I compared the results of this longitudinal classification with the results of a latent class analysis (described in Chapter 2) to understand intersections of acute care utilization and health needs. I conducted this analysis using data from Whole Person Care (WPC), a large Medicaid demonstration program in California. The WPC program is described in the Introduction and in Chapter 2.

Methods

Study Sample

The study sample consisted of 73,186 adults who enrolled in WPC in 2017 or 2018. I described details of the sample in Chapter 2. I included only those who had a full two years of Medicaid enrollment prior to WPC, allowing for one month of disenrollment per year, which happens frequently during the renewal period.

Latent Trajectory Analysis

In this analysis, I modeled acute care utilization using two longitudinal observed variables: number of outpatient emergency department (ED) visits, that did not lead to admission, per quarter; and number of hospitalizations per quarter. I generated these variables by setting the date eight quarters before each enrollee's first WPC enrollment date as their time zero, and counting the number of ED and hospitalizations in each quarter starting from that date. To avoid capturing the effect of the intervention, I limited the analysis to the eight quarters prior to each enrollee's first date of WPC enrollment.

I used group-based trajectory modeling (GBTM), also known as latent class growth analysis,[97] to identify heterogeneous latent classes of WPC enrollees based on trajectories of acute care utilization. GBTM is a subtype of growth mixture modeling (GMM)[98–101] that assumes no within-class variance of intercepts or slopes. I selected GBTM over GMM for several reasons. First, GBTM has been frequently used in studies that classified patients based on longitudinal trajectories of health care utilization[95,96] and health care cost.[88–92] Second, GBTM is consistent with the theoretical assumption that there is, in reality, a continuous distribution of various trajectories throughout the study sample, rather than literal distinct groups of patients with completely separate trajectories.[73,77] Third, GBTM is a simplified version of GMM, and therefore is often preferred in practice over GMM because it is less susceptible to errors and convergence issues.[97,99] Important considerations when developing any GMM analysis, including GBTM, include whether and how to allow for nonlinear growth,[102,103] whether the distribution of the longitudinal observed variable violates assumptions of normality,[104] and whether multiple variables should be modeled jointly as "parallel processes."[105] I conducted analysis in three steps to address these considerations.

In the first step, as recommended in the literature,[99,106] I implemented ordinary single-class growth models, i.e., random effects regression models, separately for ED and hospitalizations. Based on the results of the growth models, I assessed the potential fit of non-normal distributions for these skewed count data. Based on model dispersion parameters and exploratory analysis that showed that observed variances exceeded the means (Appendix 2.1), I proceeded with a negative binomial distribution to allow for flexibility from the equidispersion assumptions of the Poisson distribution.[107] I decided to use a flexible "latent basis" approach to address nonlinearity, which allowed the slope to vary between each time point, thus freeing the class trajectories from assumptions of a specific functional form such as quadratic or cubic growth.[103] In the second step, I implemented GBTMs with two to four classes separately for ED and hospitalizations, using latent basis models with a negative binomial distribution. I fixed slope and intercept variances at zero to define the models as GBTMs.[73,97] In the third step, I implemented parallel process GBTMs with two to four classes that defined classes based on a combination of ED and hospitalizations together. These models each generated one latent class variable that accounted for trends in both ED and hospitalizations, rather than separate latent class variables for ED and hospitalizations. I assigned patients to classes based on their highest posterior probability of class membership and described class characteristics. Additionally, as a sensitivity analysis I reran the LCA from Chapter 2 using probability of utilization trajectory class membership as a distal outcome, to estimate the statistical significance of the associations between health and utilization classes while retaining the original results of the LCA. I implemented all models in Mplus Version 7.[57]

Characterization of Latent Trajectory Classes

I assessed utilization trajectory latent class demographics and health conditions, described in detail in Chapter 2. Additionally, I analyzed associations between the resulting latent trajectory classes and persistent high utilization. I examined persistence as a characteristic of the trajectory classes, not as a label for the classes themselves, because the trajectories that defined the classes consisted of the average levels and slopes for each class and did not specifically reflect the average persistence or quarters in a row that enrollees had high utilization. I defined persistent high utilization based on a similar latent class analysis of high-utilizing patients experiencing homelessness.[4] That study defined super-utilizers as those with at least one hospitalization or at least two ED visits per quarter, and found significant differences between transitory and persistent super-utilizers when using a threshold of three or more quarters to classify patients as persistently high. Based on that analysis, I defined persistent high utilization as having at least one hospitalization or at least two outpatient ED visits for three or more consecutive quarters.

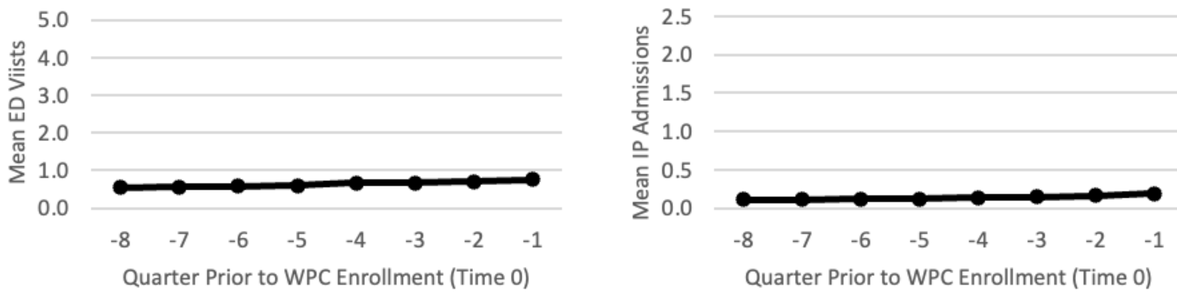
Results

Ordinary Growth Models

Ordinary growth models that fit one trajectory for the overall sample, without identifying subpopulations, indicated low but increasing ED and hospitalizations on average during the eight quarters prior to WPC enrollment. Enrollees had zero events in a large proportion of quarters (Appendix 2.1). However, I still proceeded with an ordinary negative binomial distribution instead of a zero-inflated distribution because the unadjusted GBTM did not contain meaningful predictors to include in the inflate equation to predict a value of zero; and because challenges arose related to achieving model convergence when an inflate equation was added. Though trends appeared linear (Figure 2.1), I proceeded with the latent basis approach allowing flexibility in slope between each quarter, rather than imposing a functional form such as linear or quadratic growth, to capture idiosyncrasies and variation in longitudinal patterns between classes.

Enrollees had overall mean ED over the eight quarters of 0.64 visits per enrollee per quarter, and ED rose from 0.55 visits to 0.76 visits per quarter during the study period, a 39.2% increase. Enrollees had overall mean hospitalizations of 0.13 per quarter, and hospitalizations rose from 0.11 to 0.19 hospitalizations per quarter during the study period, a 68.6% increase. These averages were less than commonly used thresholds for high utilization, such as six or more ED visits per year, or four or more hospitalizations per year.[62–64] Approximately 12% of the overall sample had persistent high utilization (Appendix 2.1).

Figure 2.1. Mean ED (left) and hospitalizations (right) per quarter in the overall study sample.



Parallel Process GBTM

Table 2.1 shows AIC, BIC and entropy, which are commonly used fit statistics that I evaluated to decide between two-, three-, or four-class parallel process models. Lower AIC and BIC values are favorable and indicate better model fit when comparing two models, and higher entropy values closer to one are favorable and indicate clearer delineation of the latent classes. Table 2.1 results indicated that a two-class or three-class model was preferred. I selected the two-class model because it resulted in higher entropy and certainty of class assignment. The two-class model also provided a large enough sample size in the smallest class to permit meaningful comparisons when comparing health characteristics between classes. Though the three-class model had lower entropy, it also had lower AIC and BIC indicating better model fit based on those statistics, and I included it in Appendix 2.3 for comparison. The three-class model identified a notable class of "High" utilizers with the most extreme utilization (5.5% of the sample), but the small size of this class posed challenges to meaningful comparisons with health characteristics classes.

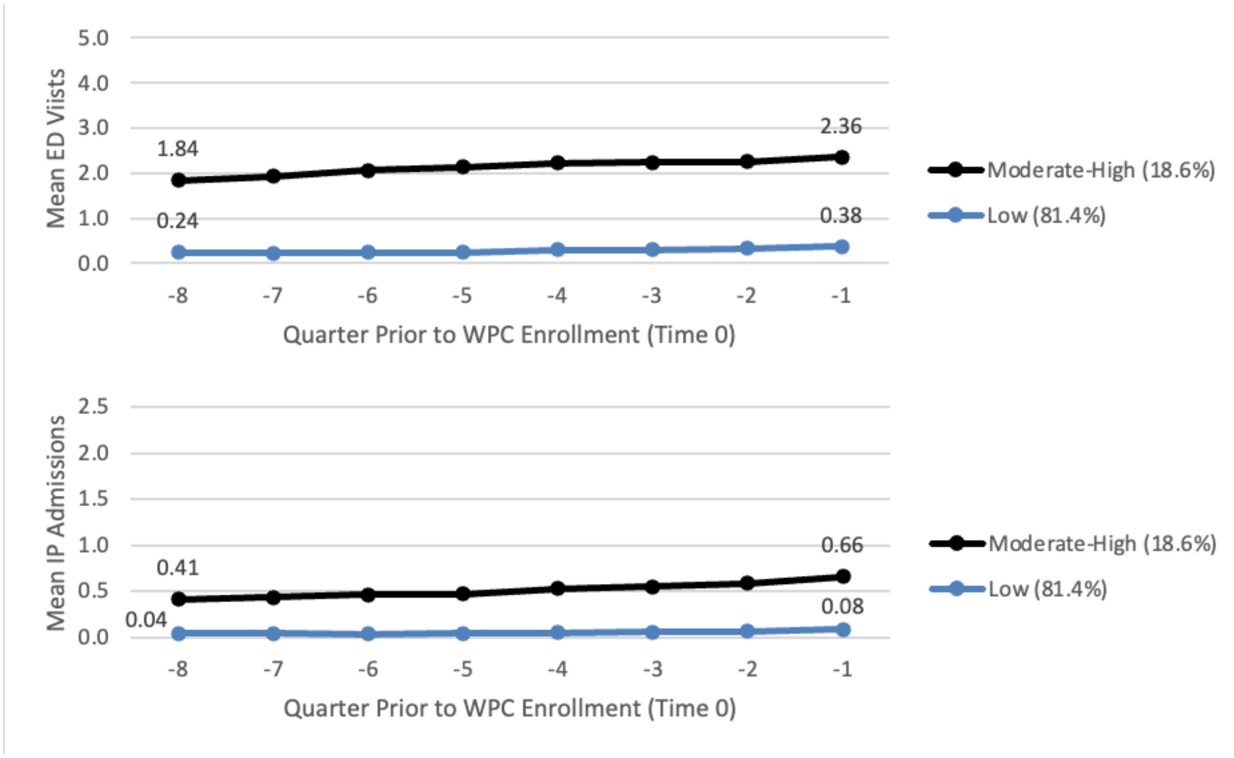
Table 2.1. Goodness-of-fit statistics for parallel process GBTMs of ED with hospitalization (IP) with two to four classes.

Outcome	Classes	AIC	BIC	Entropy	% of Sample in Smallest Class
ED and IP	2	1529595.1	1530045.9	0.880	18.6%
	3	1497357.1	1497964.4	0.805	5.5%
	4	1489998.0	1490761.7	0.777	5.0%

Models estimated using a negative binomial distribution, and a latent basis approach allowing for different slopes between each time point.

The two-class model identified enrollees with “Moderate-to-High” utilization (18.6% of the sample), and “Low” utilization (81.4% of the sample). Mean estimated ED and hospitalization utilization increased over time for both classes (Figure 2.2). The “Moderate-to-High” class had overall mean ED over the eight quarters of 2.20 visits per quarter, and ED increased by 28.2% during the study period. The “Low” utilization trajectory class had overall mean ED of 0.28 visits per quarter, and ED increased by 59.1%. The “Moderate-to-High” utilization trajectory class had an overall mean of 0.53 hospitalizations per quarter, and hospitalizations increased by 60.6%. The “Low” utilization trajectory class had an overall mean of 0.05 hospitalizations per quarter, and hospitalizations increased by 86.9%. Sensitivity analysis consisting of single process GBTMs for ED and hospitalizations produced similar results to the parallel process models. The single process models are summarized in Appendix 2.2.

Figure 2.2. Model estimated mean ED (top) and hospitalizations (bottom) per quarter for the two-class parallel process model.



Trajectory Class by Demographics

Demographics varied across the utilization trajectory classes (Table 2.2). The "Moderate-to-High" utilization class had higher proportions of enrollees identified as experiencing homelessness (52.7%), ages 35 to 49 or 50 to 64 (30.3% and 40.1%, respectively), White or Black (31.6% and 27.0%, respectively), and English-speaking (92.6%). The "Low" utilization class had higher proportions of enrollees identified as age 18 to 34 (26.5%), age 65 and over (9.9%), Latinx (24.2%), and speaking a language other than English (15.8%).

Table 2.2. Demographics of the two utilization trajectory classes.

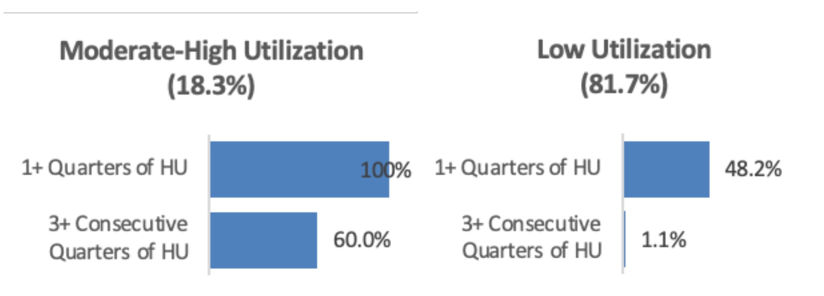
Characteristic	Latent Class: Moderate-to-High Utilization	Latent Class: Low Utilization	*p*-value
N	13,622	59,564	
% of Sample	18.6	81.4	
% Experiencing Homeless	52.7	35.8	<0.001
% Male	54.4	50.9	<0.001
% by Age Group			
18 to 34	24.8	26.5	<0.001
35 to 49	30.3	26.2	<0.001
50 to 64	40.1	37.4	<0.001
65 and Over	4.8	9.9	<0.001
% by Race			
White	31.6	26.8	<0.001
Black	27.0	25.7	0.001
Latinx	21.3	24.2	<0.001
API	2.5	6.3	<0.001
AIAN	0.9	0.6	<0.001
Other/Unknown	16.6	16.4	0.510
% by Language			
English	92.6	84.2	<0.001
Spanish	4.9	10.0	<0.001
Other	2.5	5.8	<0.001

Pearson's $\chi 2$ test indicated significantly different proportions across classes for almost all demographics ($p < 0.001$). Abbreviations refer to Asian or Pacific Islander (API); American Indian or Alaska Native (AIAN).

Trajectory Class by Persistent High Utilization

Utilization trajectory classes varied by persistence of high utilization (Figure 2.3). All enrollees in the "Moderate-to-High" utilization class had at least one quarter where they met the criteria for high utilization, and 60.0% were persistent high utilizers, defined based on prior literature[4] as having at least one hospitalization or at least two outpatient ED visits for three or more consecutive quarters. Approximately half of enrollees in the "Low" utilization class (48.2%) had at least one quarter where they met the criteria for high utilization, and only 1.1% were persistent high utilizers. Appendix 2.1 contains additional details on patterns of persistent utilization by quarter.

Figure 2.3. High utilization (HU) and persistence by utilization trajectory class for the two-class parallel process model.

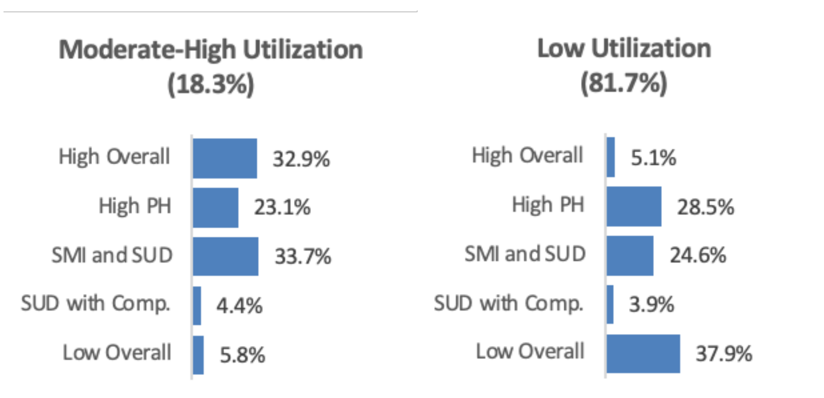


Trajectory Class by Health Needs

Descriptive analysis showed associations between health needs class, determined in the prior LCA, and utilization trajectory class from the parallel process GBTM (Figure 2.4). The "Moderate-to-High" trajectory had the largest proportions of enrollees with "High Overall" health needs including both physical and behavioral comorbidities; "Serious Mental Illness

(SMI) and Substance Use Disorder (SUD)" behavioral health needs with few physical comorbidities; and "SUD with Complications" health needs including both SUD and physical comorbidities. The "Low" utilization trajectory had the largest proportions of enrollees with "High Physical Health" needs with few behavioral comorbidities; and "Low Overall" health needs with few comorbidities of any type. A model regressing probability of utilization trajectory class membership as a distal outcome on health needs class confirmed a statistically significant association between utilization and health needs, with the "High Overall" health needs class having the highest probability of being in the "Moderate-to-High" utilization trajectory class (Appendix 2.5).

Figure 2.4. Health needs latent class by utilization trajectory class for the two-class parallel process model.



Health needs latent classes presented in this figure were defined in Chapter 2, and consist of: (1) High Overall; (2) High Physical Health (PH); (3) Serious Mental Illness (SMI) and Substance Use Disorder (SUD); (4) SUD with Complications; (5) Low Overall.

Discussion

Based on trajectories of acute care utilization prior to enrollment, I identified two distinct classes of enrollees of a large-scale Medicaid care coordination program that targeted patients with high utilization and complex social and health needs. Though both classes had increasing utilization prior to enrollment, they varied in the level and rate of growth, persistence of utilization, and demographic and health characteristics. Further dividing the sample into three classes identified a small class of enrollees with very high utilization that persisted over consecutive quarters (Appendix 2.3). The three-class approach could be useful for identifying the most extreme high utilizers to focus on in research or interventions, though the two-class approach was more appropriate for this study to ensure adequate subpopulation sizes for joint analysis of utilization and health needs.

The first class, 18% of the sample, had moderate-to-high rates of outpatient ED visits and hospitalizations. Most of this class had persistent high utilization. This class had the largest proportions of enrollees classified as experiencing homeless, with high overall health needs, and with high behavioral health needs. Prior studies noted similar intersections between high utilization of acute care services, homelessness status,[1,7,8] and behavioral health comorbidity.[1,7,44,51,62] Interestingly, this class also had the lowest proportion of enrollees aged 65 and over, indicating that the high medical complexity experienced by many older adults was not a key driver of high utilization in the study sample. The association between behavioral health and high acute care utilization suggests that care coordination or other interventions targeting enrollees with serious mental illness or substance use disorder could be an important component of reducing avoidable service use.

The second class, 82% of the sample, had low rates of outpatient ED visits and hospitalizations. Almost no enrollees in this class had persistent high utilization, and this class had a moderate percent increase in ED and a large percent increase in hospitalizations over time. One prior study of latent utilization trajectories in a narrow sample of patients with renal disease classified 35% of patients into a similar low utilizer class.[96] However, the authors used a three-class model that included an additional 58% in an intermediate utilizer class; it is possible that with a two-class model they may have generated a similarly large low utilizer trajectory group. This class contained the largest proportion of patients with high physical health needs, further highlighting the role of behavioral health in driving acute care utilization for this population.

An additional notable difference between the classes was a higher prevalence in the "Low" utilization class of enrollees who preferred to speak Spanish and who were identified as Latinx (Table 2.2). This finding also arose in the three-class model (Appendix 2.3). There are several possible explanations for why Latinx enrollees had lower average acute care utilization. As shown in Chapter 2, the "High Physical Health" needs class included a high proportion of Latinx enrollees. It is possible that utilization rates were lower for this demographic group because behavioral health needs were more associated with high utilization than physical health needs. Additionally, it is possible that limitations on access to care or cultural differences led to a larger proportion of Latinx patients in the "Low" utilization class.[66] WPC enrollment strategies (discussed in the Introduction chapter) relied mainly on referrals and review of administrative data, and it is possible that some aspect of these strategies led to differential enrollment by race and ethnicity. Further analysis would be needed to explore potential reasons for racial differences in utilization in low-income and Medicaid-enrolled populations.

Compared to the large percent increases in hospitalizations, the percent increases in ED were small-to-moderate for both classes over the study period. The greater growth in hospitalizations could be a result of two factors. First, because ED rates were already high it would require a larger absolute change to generate a large percent increase in ED during the study period. Second, most of the entities engaged in the WPC program leveraged referrals to identify prospective enrollees.[108] It is possible that people who were hospitalized during the WPC enrollment period were more likely to be flagged for referral, meaning that people with a sharp uptick in hospitalizations may have been more likely to be enrolled.

Limitations

This study offered novel insights into the longitudinal utilization trajectories of a large population of patients in a care coordination program that aimed to reduce avoidable acute care utilization, but results should be interpreted in light of limitations. The population was, by definition, heterogeneous and may have contained additional utilization trajectories beyond those identified. Analysis of more targeted samples, such as patients seeking care for selected medical or behavioral health diagnoses, or patients in selected demographic groups, could provide more resolution on unique longitudinal patterns. For example, one study of a small population of adults with functional disabilities identified nonlinear trajectories with notable drops and peaks.[95] I discussed additional limitations related to sample selection and generalizability in Chapter 2.

Implications

Health services researchers and analysts should consider longitudinal methods when classifying patients based on utilization. Compared to cross-sectional summaries of visits in a given quarter or year, longitudinal analysis allows for quantification of trends, both linear and nonlinear, and a deeper understanding of the persistence of high utilization over time. These details can inform targeted outreach to engage patients with different utilization patterns in tailored interventions, and can inform evaluations by indicating what utilization targets might be realistic for enrollee subpopulations. Latent class approaches such as GMM and GBTM offer the special advantage of revealing patterns and thresholds for high utilization that analysts might not recognize a priori. Though studies have used these methods to understand other health care outcomes such as health status and cost over time, there is a need for research that uses GMM and GBTM to characterize utilization. Additionally, because behavioral health is often associated with high acute care utilization, government agencies and health care organizations seeking to curb avoidable service use should consider the behavioral health needs of the target population. Interventions that support enrollees in addressing challenges associated with serious mental illness and substance use disorder have the potential to reduce emergency visits and hospitalizations.

Appendices

Appendix 2.1. Descriptive analysis of utilization over time.

Appendix 2.1. Table 1. Descriptive analysis of outpatient emergency department (ED) and inpatient hospitalization (IP) count variables.

Outcome	Quarter	Mean	Variance	SD	Min	50th %ile	75th %ile	99th %ile	Max	% 0's
ED	-8	0.55	2.58	1.61	0	0	1	7	>50	73.7
	-7	0.56	2.62	1.62	0	0	1	7	>50	73.6
	-6	0.59	2.79	1.67	0	0	1	7	>50	72.5
	-5	0.61	2.90	1.70	0	0	1	7	>50	72.0
	-4	0.67	3.10	1.76	0	0	1	7	>50	69.0
	-3	0.68	3.19	1.79	0	0	1	8	>50	69.0
	-2	0.70	3.28	1.81	0	0	1	8	>50	67.9
	-1	0.76	3.63	1.91	0	0	1	8	>50	66.0
IP	-8	0.11	0.29	0.53	0	0	0	2	>13	92.7
	-7	0.11	0.27	0.52	0	0	0	2	>13	92.7
	-6	0.12	0.29	0.54	0	0	0	2	>13	92.5
	-5	0.12	0.29	0.54	0	0	0	2	>13	92.3
	-4	0.14	0.36	0.60	0	0	0	3	>13	91.2
	-3	0.15	0.36	0.60	0	0	0	3	>13	90.6
	-2	0.16	0.41	0.64	0	0	0	3	>13	90.0
	-1	0.19	0.51	0.71	0	0	0	3	>13	88.7

Quarters refer to the quarter prior to WPC enrollment, with Quarter -8 referring to the 8th quarter prior to WPC enrollment, and Quarter -1 referring to the quarter prior to WPC enrollment.

Abbreviations refer to the standard deviation (SD); percentile (%ile); minimum (Min), maximum (Max), and the percent of the values that were equal to zero (% 0's).

I omitted exact values for the maximum for confidentiality.

Appendix 2.1. Table 2. Descriptive analysis of high utilization and persistence by quarter.

Item	Percent
% With 1+ Quarters of High Utilization	57.9
% With 3+ Consecutive Quarters of High Utilization Starting from First Occurrence of High Utilization	10.0
% With 3+ Consecutive Quarters of High Utilization Starting from Any Quarter	12.1
% With 3 + Consecutive or Non-Consecutive Quarters of High Utilization	21.3
% With High Utilization by Quarter of First Occurrence of High Utilization	
Quarter -8	15.7
Quarter -7	8.9
Quarter -6	6.8
Quarter -5	5.6
Quarter -4	5.9
Quarter -3	5.2
Quarter -2	4.9
Quarter -1	4.9
No High Utilization	42.1

High utilization defined based on a similar latent class analysis of high-utilizing patients experiencing homelessness,[4] as having at least one hospitalization or at least two outpatient ED visits in the quarter.

Quarters refer to the quarter prior to WPC enrollment, with Quarter -8 referring to the 8th quarter prior to WPC enrollment, and Quarter -1 referring to the quarter prior to WPC enrollment.

Appendix 2.1. Table 3. Persistence of high utilization during consecutive quarters after first occurrence of high utilization.

Quarter of First Occurrence of High Utilization	N	Number of Consecutive Quarters with High Utilization After Quarter of First Occurrence of High Utilization (% of Row)								Total
		0	1	2	3	4	5	6	7	
-8	11,482	55.0	16.4	8.1	4.4	2.7	2.0	1.5	9.9	100.0
-7	6,506	67.4	16.0	6.3	3.2	1.8	1.3	4.0	-	100.0
-6	4,945	70.3	15.4	6.3	2.8	1.2	4.1	-	-	100.0
-5	4,118	70.6	16.7	5.2	2.8	4.6	-	-	-	100.0
-4	4,293	74.9	14.0	5.1	6.0	-	-	-	-	100.0
-3	3,799	77.3	13.4	9.3	-	-	-	-	-	100.0
-2	3,621	74.3	25.7	-	-	-	-	-	-	100.0
-1	3,586	100.0	-	-	-	-	-	-	-	100.0
No High Utilization	30,836									
Total	73,186									

High utilization defined based on a similar latent class analysis of high-utilizing patients experiencing homelessness,[4] as having at least one hospitalization or at least two outpatient ED visits in the quarter.

Quarters refer to the quarter prior to WPC enrollment, with Quarter -8 referring to the 8th quarter prior to WPC enrollment, and Quarter -1 referring to the quarter prior to WPC enrollment.

Appendix 2.1. Table 4. Persistence of high utilization during any consecutive or non-consecutive quarters after first occurrence of high utilization.

Quarter of First Occurrence of High Utilization	**N**	**Number of Quarters (Consecutive or Non-Consecutive) with High Utilization After Quarter of First Occurrence of High Utilization (% of Row)**								**Total**
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	
-8	11,482	16.0	16.7	15.3	12.6	11.3	9.6	8.6	9.9	100.0
-7	6,506	24.5	23.9	18.7	12.9	9.7	6.2	4.0	-	100.0
-6	4,945	30.9	27.7	19.3	11.3	6.7	4.1	-	-	100.0
-5	4,118	37.5	30.9	17.4	9.6	4.6	-	-	-	100.0
-4	4,293	52.5	28.0	13.5	6.0	-	-	-	-	100.0
-3	3,799	63.6	27.1	9.3	-	-	-	-	-	100.0
-2	3,621	74.3	25.7	-	-	-	-	-	-	100.0
-1	3,586	100.0	-	-	-	-	-	-	-	100.0
No High Utilization	30,836									
Total	73,186									

High utilization defined based on a similar latent class analysis of high-utilizing patients experiencing homelessness,[4] as having at least one hospitalization or at least two outpatient ED visits in the quarter.

Quarters refer to the quarter prior to WPC enrollment, with Quarter -8 referring to the 8th quarter prior to WPC enrollment, and Quarter -1 referring to the quarter prior to WPC enrollment.

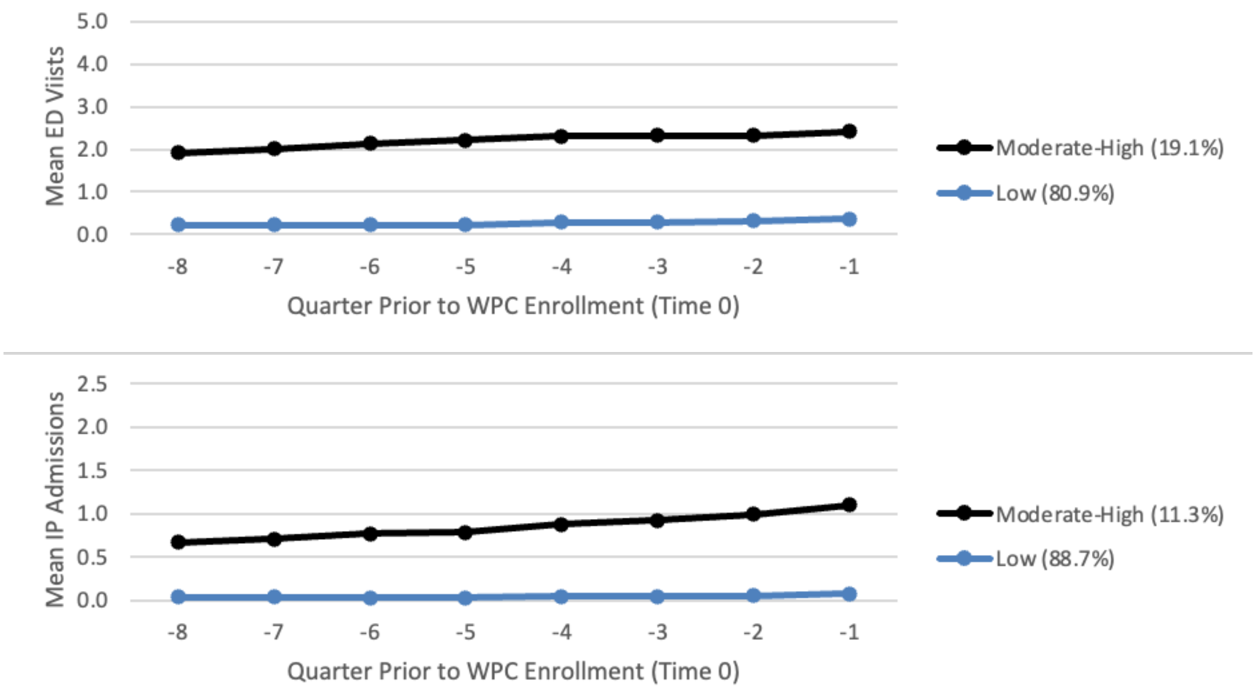
Appendix 2.2. Results of two-class and three-class single process models.

Appendix 2.2. Table 1. Goodness-of-fit statistics for single process GBTMs of ED and hospitalizations with two to four classes.

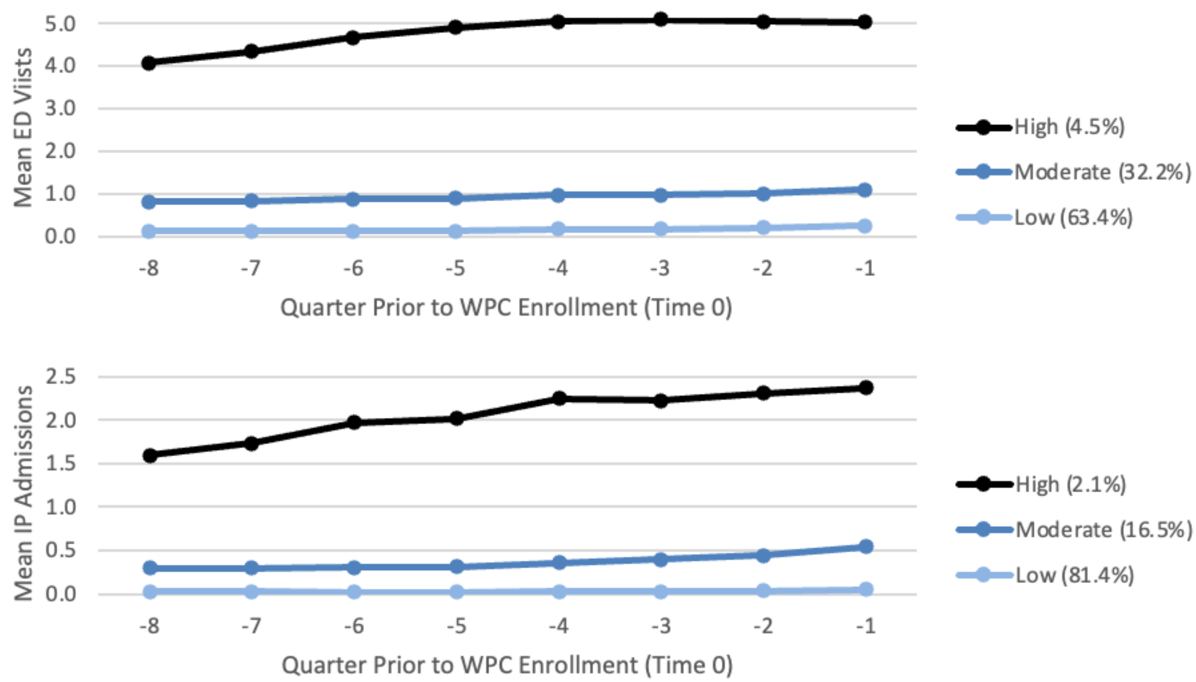
Outcome	Classes	AIC	BIC	Entropy	% of Sample in Smallest Class
ED	2	1116577.4	1116807.4	0.855	19.1%
	3	1091005.6	1091318.4	0.791	4.7%
	4	1084465.4	1084861.1	0.735	1.9%
IP	2	406629.7	406859.8	0.875	10.6%
	3	399440.0	399752.8	0.801	2.3%
	4	398240.5	398636.2	0.741	0.6%

Models estimated using a negative binomial distribution, and a latent basis approach allowing for different slopes between each time point.

Appendix 2.2. Figure 1. Model estimated mean ED (top) and hospitalizations (bottom) per quarter for the two-class single process models.

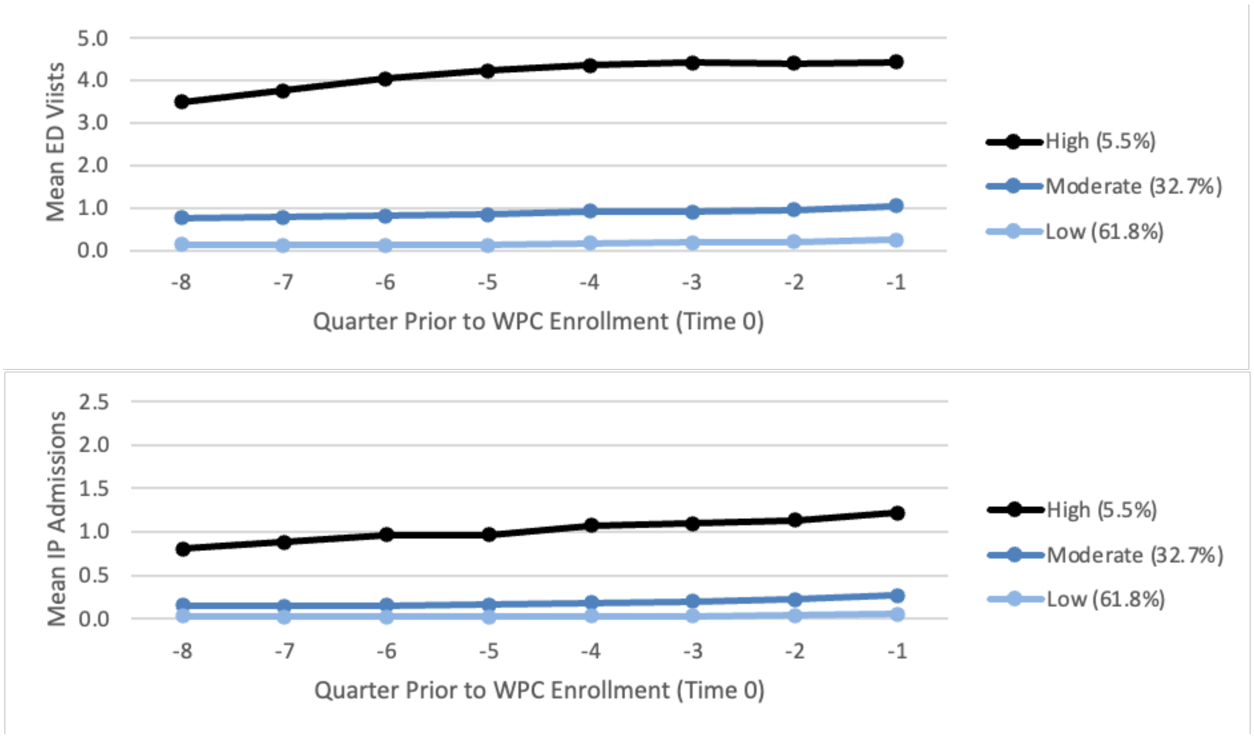


Appendix 2.2. Figure 2. Model estimated mean ED (top) and hospitalizations (bottom) per quarter for the three-class single process models.



Appendix 2.3. Results of three-class parallel process model.

Appendix 2.3. Figure 1. Model estimated mean ED (top) and hospitalizations (bottom) per quarter for the three-class parallel process model.

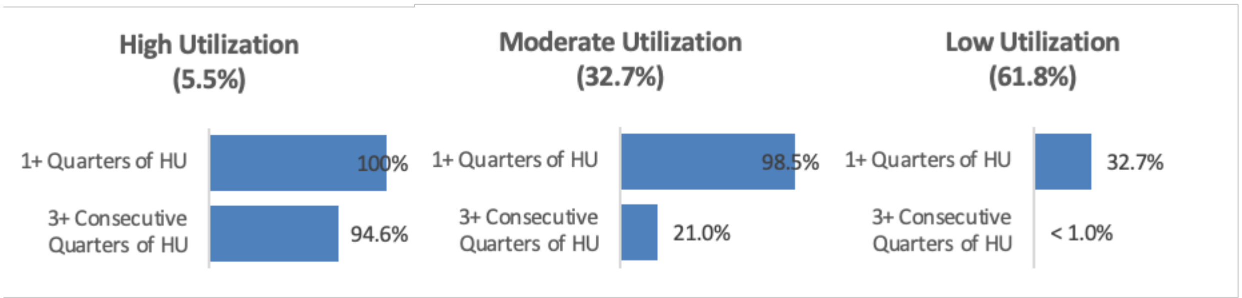


Appendix 2.3. Table 1. Demographics of the three utilization trajectory classes.

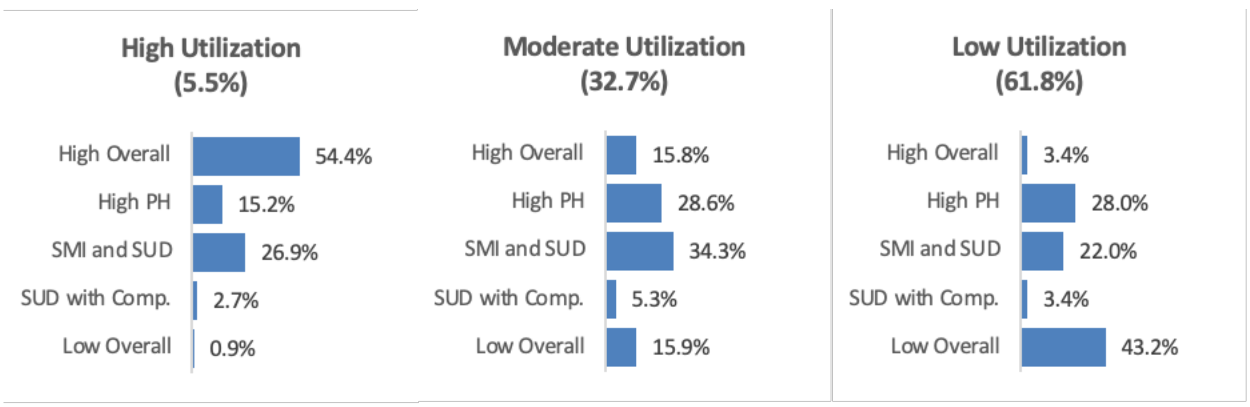
Characteristic	Latent Class High	Latent Class Moderate	Latent Class Low	*p*-value
N	4,037	23,906	45,243	
% of Sample	5.5	32.7	61.8	
% Experiencing Homeless	60.9	43.4	34.6	<0.001
% Male	60.2	50.0	51.7	<0.001
% by Age Group				
18 to 34	20.5	28.4	25.5	<0.001
35 to 49	31.8	28.8	25.6	<0.001
50 to 64	43.4	37.2	37.8	<0.001
65 and Over	4.3	5.6	11.2	<0.001
% by Race				
White	32.4	29.7	26.2	<0.001
Black	28.3	26.2	25.6	0.001
Latinx	18.8	23.7	24.0	<0.001
API	1.7	3.6	7.0	<0.001
AIAN	0.9	0.8	0.6	<0.001
Other/Unknown	18.0	16.0	16.5	0.004
% by Language				
English	94.0	82.9	89.7	<0.001
Spanish	3.1	10.5	7.4	<0.001
Other	2.8	6.6	2.9	<0.001

Pearson's $\chi 2$ test indicated significantly different proportions across classes for all demographics ($p < 0.001$). Abbreviations refer to Asian or Pacific Islander (API); American Indian or Alaska Native (AIAN).

Appendix 2.3. Figure 2. High utilization (HU) and persistence by utilization trajectory class for the three-class parallel process model.



Appendix 2.3. Figure 3. Health needs latent class by utilization trajectory class for the three-class parallel process model.



Health needs latent classes presented in this figure were defined in Chapter 2, and consist of: (1) High Overall; (2) High Physical Health; (3) Serious Mental Illness (SMI) and Substance Use Disorder (SUD); (4) SUD with Complications; (5) Low Overall.

Appendix 2.4. Comparison of two-class and three-class parallel process model results.

Appendix 2.4. Table 1. Average probability of assignment to each class, among those who were assigned to it.

	Average Probability of Class Members Being Assigned to This Class	
Class Label	**2-Class Model**	**3-Class Model**
High	-	0.93
Moderate-to-High	0.93	-
Moderate	-	0.89
Low	0.98	0.92

This table indicates that though probabilities dropped slightly for the three-class model, all classes had a high certainty of class assignment (>0.8).

Average probability of assignment to each class was taken from the diagonal elements of the posterior probability matrix. Values closer to 1 indicate that people assigned to Class *k* had a high probability of being in Class *k* relative to their probabilities of being in other classes (i.e., high certainty of class assignment). Values of 0.8 and above are considered indicators of good class assignment.[67]

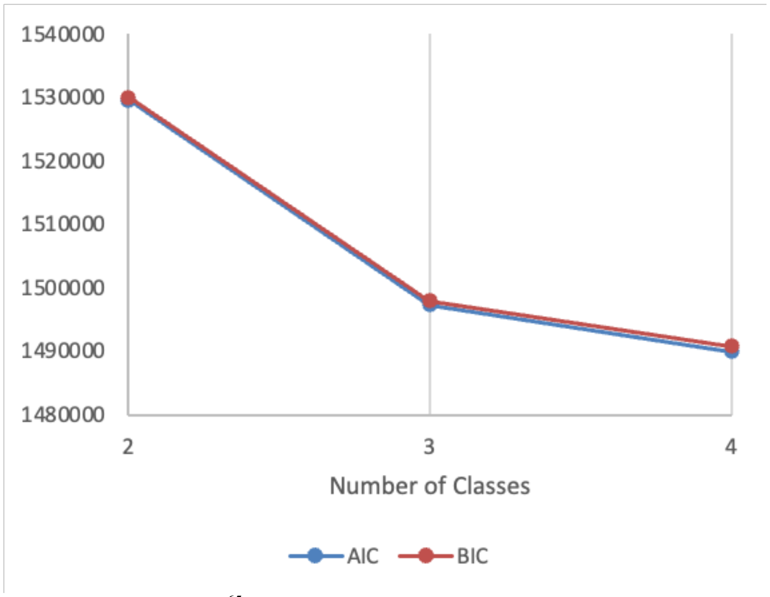
Appendix 2.4. Table 2. Percent of each class in the two-class model that was assigned to each class in the three-class model.

	Percent Assigned to Each Class in Three-Class Model		
Class in Two-Class Model	**High**	**Moderate**	**Low**
Moderate-to-High	29.1	70.9	0.0
Low	0.0	24.0	76.1

Appendix 2.4. Table 3. Percent of each class in the three-class model that was assigned to each class in the two-class model.

	Percent Assigned to Each Class in Three-Class Model	
Class in Three-Class Model	**Moderate-to-High**	**Low**
High	100.0	0.0
Moderate	39.8	60.2
Low	0.0	100.0

Appendix 2.4. Figure 1. Visualization of AIC and BIC for two to four classes.



As is common in LCA,[65] AIC and BIC continued to decrease as number of classes increased, so there was no global minimum to use as an indicator of model fit. In this situation, a plot of AIC or BIC can be inspected to identify an "elbow" that indicates diminishing returns in model fit as the number of classes increases.[65] The plot for this analysis had an "elbow" at three classes, indicating that more than three classes resulted in diminishing returns in improving fit.

Appendix 2.5. Regression of utilization trajectory class on health needs class.

Appendix 2.5. Table 1. Results of regression of probability of being in “Moderate-to-High” utilization trajectory class on health needs class.

Health Needs Class	Coefficient	Confidence Interval	p-value
High Overall (Reference)	0.00	-	-
High Physical Health	-4.47	-4.73 to -4.21	<0.001
SMI and SUD	-3.47	-3.73 to -3.21	<0.001
SUD with Complications	-2.45	-2.81 to -2.08	<0.001
Low Overall	-45.19	-57.87 to -32.52	<0.001

Coefficients reflect the effect on probability of being in the “Moderate-to-High” utilization trajectory class (rather than the “Low” utilization trajectory class), comparing each health needs class to the “High Overall” health needs class as a reference. Compared to the “High Overall” health needs class, all other classes had a significantly lower probability of being in the “Moderate-to-High” utilization class, with the “Low Overall” health needs group having the lowest probability.

Model estimated using the posterior probability of being in the “Moderate-to-High” utilization trajectory class as the outcome (rather than binary assignment to the highest probability class) to reflect the probabilistic nature of class assignment and capture assignment error.

Model estimated using the Mplus (R3STEP) approach to ensure the health needs classes did not change with the addition of the utilization trajectory classes as a distal outcome.

Appendix 2.6. Enrollee utilization trajectory classes by WPC Pilot county for study sample.

Appendix 2.6. Table 1. Percent of WPC Pilot county enrollees by utilization trajectory classes for study sample.

WPC Pilot County	Number of Enrollees in Sample	Percent of Enrollees in Sample by Utilization Trajectory Classes		
		Moderate-High Utilization	**Low Utilization**	**Total**
Alameda	7,101	22.7	77.3	100.0
Contra Costa	23,805	8.3	91.7	100.0
Kern	410	14.2	85.9	100.0
Kings	165	18.2	81.8	100.0
Los Angeles	19,820	22.0	78.0	100.0
Marin	470	25.7	74.3	100.0
Mendocino	224	43.8	56.3	100.0
Monterey	92	47.8	52.2	100.0
Napa	206	27.7	72.3	100.0
Orange	4,238	20.8	79.2	100.0
Placer	188	29.3	70.7	100.0
Riverside	1,139	7.6	92.5	100.0
Sacramento	611	32.1	67.9	100.0
San Bernardino	573	31.2	68.8	100.0
San Diego	188	50.5	49.5	100.0
San Francisco	6,677	23.4	76.6	100.0
San Joaquin	667	52.2	47.8	100.0
San Mateo	2,325	25.2	74.8	100.0
Santa Clara	2,444	24.4	75.6	100.0
Santa Cruz	342	26.3	73.7	100.0
Shasta	179	56.4	43.6	100.0
Small Counties	55	*	*	100.0
Solano	127	63.0	37.0	100.0
Sonoma	344	37.2	62.8	100.0
Ventura	796	33.5	66.5	100.0

Utilization trajectory classes were defined in Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD).

* indicates suppressed due to small sample size to protect confidentiality.

IV. DIFFERENTIAL EFFECTS OF CROSS-SECTOR CARE COORDINATION FOR SUBPOPULATIONS OF MEDICAID PATIENTS

Abstract

Background: Coordination of health care and social services can improve health and reduce avoidable acute care utilization for patients with complex needs. Little is understood about the effect of cross-sector care coordination for enrollees with different health needs and utilization histories prior to receipt of services. **Objective:** To understand how an intervention that coordinated health care and social services impacted different enrollee classes, defined based on health needs and pre-enrollment utilization trajectories documented in claims data. **Methods:** I conducted a pre-post interrupted time series analysis using segmented multilevel models to evaluate change in number of enrollee outpatient emergency department (ED) visits and hospitalizations over eight quarters following enrollment in a cross-sector care coordination program. I incorporated an interaction with enrollee classes identified through prior latent class analyses as moderators to understand differential patterns across groups. **Results:** Nearly every class had decreased rates of ED visits and hospitalizations after enrollment. The one exception was the class with low overall health needs and moderate-to-high pre-enrollment utilization, which had a non-significant decrease in hospitalization rates. This class also had significantly smaller reductions in ED visit rates compared to all other classes. Enrollees with substance use disorder (SUD) with complications and moderate-to-high utilization also had significantly smaller reductions in ED visit and hospitalization rates compared to several classes. Enrollees with serious mental illness (SMI) and SUD, with low or moderate-to-high utilization, had significantly larger reductions in hospitalizations compared to several classes. **Implications:**

Organizations implementing cross-sector care coordination interventions should anticipate that program effects will vary depending on enrollee health and pre-enrollment utilization trajectories. Analyses of enrollee subpopulations can help target and tailor interventions, and can provide insight into opportunities for high beneficial impact on utilization and health outcomes. Programs should consider potential trade-offs between focusing on small subpopulations that may experience a larger impact, and large subpopulations that may experience a smaller impact from the intervention.

Background

Over the past decade, health care leaders have increasingly recognized social and economic factors as key drivers of patient health outcomes and utilization.[109,110] Both theoretical frameworks[111] and empirical research[1,6–8] underscore associations between social disadvantage and high use of acute care. As a result, health care systems, payors, and their community-based partners have developed interventions to address non-medical needs of at-risk patients, with some success in reducing avoidable utilization and increasing use of preventive and other outpatient services.[112,113] These interventions include care coordination for patients with complex health and social needs, who may also have high use of acute health care services such as emergency department (ED) and inpatient care.[114] Though definitions vary, core components of care coordination include linking care to multiple providers and members of the enrollee's support network, with supports for information sharing and decision-making.[13,15] This approach has been broadly used within the medical sector to refer between primary care and different types of specialty care to improve care and outcomes.[17,16,18–20,23,26,27]

A growing number of interventions have coordinated care across health and social services, referred to in this chapter as cross-sector care coordination.[114] Due to differences in organization and financing between health and social services,[115,116] this type of care coordination requires more complex processes and infrastructure, such as more diverse teams and creative mechanisms to share information and accountability, to link across sectors that are historically siloed and have separate systems of care delivery. One systematic review identified enrollee needs assessment, in-person contact with enrollees, and standardized protocols for coordinating care as common in cross-sector care coordination programs.[114] Some cross-sector care coordination interventions have been large-scale and multi-faceted, enrolling thousands of patients with a range of needs, and engaging many clinical and community partners.[30,117–119]

One aspect of cross-sector care coordination that remains underexplored is whether the intervention leads to the desired outcomes for enrollees with different health needs and utilization history. To gain such insight, identification of enrollees into meaningful subgroups is needed.[38] Prior research examined the impact of cross-sector care coordination on outcomes including health care utilization, with mixed findings including significant reductions in ED visits and hospitalizations for some programs,[25,28] non-significant but notable reductions in ED visits and hospitalizations for other programs,[22,24] and no change for one program that relied solely on telephone-based care coordination.[21] These studies typically reported effects for all enrollees together, rather than disaggregating based on enrollee attributes. Estimated effects of care coordination on utilization might be more consistent across studies if similar subpopulations were compared.

Ignoring enrollee heterogeneity is especially problematic when evaluating impact of the intervention on utilization because fluctuations in utilization and regression to the mean can threaten validity when interventions target outlier high utilizers.[120,121] For example, one study of enrollees in an intensive care management program found that cost peaked and started dropping prior to enrollment, and concluded that evaluations may overstate program impact if they fail to consider temporal trends in cost in cost and utilization for medically complex enrollees.[122] Research is needed to understand how the impacts of cross-sector care coordination programs vary for enrollees with different pre-enrollment experiences.

I addressed this gap in knowledge through a pre-post analysis of data from the Whole Person Care (WPC) program that provided cross-sector care coordination, described in the Introduction and in Chapter 2. I examined impact on enrollee classes, defined in prior analyses based on health conditions and utilization trajectories. This analysis examined whether enrollees with different acute care trajectories and clinical profiles had similar experiences following receipt of care coordination.

Methods

Study Sample

The study sample consisted of 73,186 adults who enrolled in WPC in 2017 or 2018 and who had two full years of Medi-Cal enrollment prior to WPC enrollment. The sample was described in further detail in Chapters 2 and 3. All of the sample received care coordination through WPC, regardless of if they were classified as high or low health need or utilization in this analysis. WPC enrollment criteria allowed for enrollment based on factors such as social need and predicted risk of high utilization,[33] leading to the inclusion of some enrollees with low health need and low utilization who still received support from the program.

Study Period

I centered the study period to each enrollee's first date of enrollment in WPC, meaning calendar months varied depending on enrollment date. The study period consisted of a pre-period, defined as eight quarters prior to enrollment in WPC, and a post-period, defined as eight quarters after enrollment in WPC starting from the first enrollment date. In the pre-period, due to inclusion criteria all members of the sample were enrolled in Medi-Cal for a full eight quarters, allowing for one month of disenrollment per year which is common during transitional periods. In the post-period, length of enrollment varied (Appendix 3.4).

Variables

I created two outcome variables to evaluate change in acute care utilization associated with enrollment in WPC for each enrollee class. These consisted of number of enrollee outpatient emergency department visits that were followed by discharge, per quarter (ED); and number of enrollee inpatient hospitalizations per quarter (IP). My independent variable of interest was a 10-level categorical variable that classified enrollees using a cross-tabulation of 5 health needs classes and 2 utilization trajectory classes, based on the results of the latent class analysis (LCA) and group-based trajectory modeling (GBTM) in previous chapters.

I described covariates in further detail in Chapter 2. These consisted of enrollee demographics (gender, age, race, and language); whether the enrollee was experiencing homelessness; whether the enrollee was in the justice-involved WPC target population; the enrollee's annual Chronic Illness and Disability Payment System (CDPS) score; the year first enrolled in WPC (2017 or 2018); county of first enrollment in WPC; and number of months from first enrollment in WPC to last enrollment in WPC during the eight quarter post-period.

Pre-Post Analysis

I used segmented regression to compare acute care utilization during eight quarters prior to and eight quarters after enrollment in WPC, with the post-period starting at the first WPC enrollment date. Segmented regression is widely used to evaluate health-related outcomes in non-randomized observational studies with an interrupted time series design.[123,124] Typical segmented regression includes an interaction between a time variable and an intervention variable to allow different regression lines to be estimated prior to and after the intervention. Estimated model parameters can be compared to assess change in slope and intercept between the pre-period and the post-period.

To implement segmented models, I constructed an intervention dummy variable set to 0 prior to WPC enrollment (Quarter 1 through Quarter 8) and set to 1 after WPC enrollment (Quarter 9 through Quarter 16). I constructed a time variable consisting of an incremental count of quarters, with the first quarter set to zero for ease of model interpretation (0 through 15). To allow estimates to vary by enrollee subgroup, I constructed a three-way interaction of the intervention dummy variable, time, and an enrollee class variable. Using an interaction term in one integrated model, rather than stratifying and running one model per enrollee class, facilitated inter-class comparisons. The class variable was constructed as a cross-tabulation of enrollee health needs classes and enrollee utilization trajectory classes, defined in Chapter 3. On average, enrollees had moderate certainty of assignment to their joint health needs and utilization trajectory class (Appendix 3.1).

I used multilevel models with enrollee as a random effect to address the correlated nature of the longitudinal data, and adjusted the standard errors to account for clustering by county. To account for overdispersion I used a negative binomial distribution that relaxed the assumption of the Poisson distribution that the mean is equal to the variance.[107] I addressed varying length of Medi-Cal enrollment by including Medi-Cal enrollment as an "exposure" variable in the count models. I treated Medi-Cal enrollment as an exposure rather than a covariate because Medi-Cal enrollment defined the period when ED and hospitalizations could be documented in claims data, and was thus important for standardizing the number of visits to be able to compare across groups. To check robustness of results to changes in model specifications, I ran variations of the main models without selected covariates, and without clustered standard errors (Appendix 3.2). I implemented all models in Stata 16.1 using the *menbreg* command.

To understand change in utilization trajectory associated with WPC enrollment, I used linear combinations of estimated model coefficients to calculate the difference in pre-period and post-period slope for each class. To understand how pre-post differences varied across classes, I used linear combinations of estimated model coefficients to compare the pre-post differences of each class to each other class. I presented unexponentiated values, representing additive change in *ln*(Number of Events), in all tables to allow for analysis of difference on the linear scale. Where relevant, I also included exponentiated values, representing multiplicative or percent change in number of events, in the text to improve interpretability. Appendix 3.3 contains additional detail on calculations, which were implemented with the Stata *lincom* command.

Results

Overview of Sample by Class

Table 3.1 shows the distribution of the sample by joint health need and utilization trajectory classes. Three of the classes comprised 74.1% of the sample: "Low Overall" health needs with "Low Utilization" trajectory (30.9%), "High Physical Health" health needs with

"Low Utilization" trajectory (23.2%), and "SMI and SUD" health needs with "Low Utilization" trajectory (20.0%). The remaining classes ranged from 0.8% to 6.3% of the sample.

Table 3.1. Sample distribution by joint health needs and utilization trajectory classes.

Health Needs Classes	**Utilization Trajectory Classes**	**N**	**%**
High Overall	Moderate-High Utilization	4,482	6.1
High Physical Health	Moderate-High Utilization	3,153	4.3
SMI and SUD	Moderate-High Utilization	4,595	6.3
SUD with Complications	Moderate-High Utilization	596	0.8
Low Overall	Moderate-High Utilization	796	1.1
High Overall	Low Utilization	3,054	4.2
High Physical Health	Low Utilization	16,951	23.2
SMI and SUD	Low Utilization	14,656	20.0
SUD with Complications	Low Utilization	2,308	3.2
Low Overall	Low Utilization	22,595	30.9
	Total	73,186	100.0

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3. Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD).

Medi-Cal and WPC Enrollment

In the post-period, Medi-Cal enrollment varied for each enrollee, though 81.6% of the sample was enrolled for at least 22 of the 24 months (Appendix 3.4). Also, in the post-period, WPC enrollment varied for each enrollee, and only 35.8% of the sample was enrolled for at least 22 of the 24 months (Appendix 3.4). Variation in WPC enrollment length was expected due to different approaches to program graduation used in each WPC Pilot.[33]

Descriptive Analysis of Outcomes by Class

For nearly all classes, actual mean number of ED visits consistently increased during the pre-period, indicating a positive rate of change prior to WPC enrollment, and consistently decreased during the post-period, indicating a negative rate of change after WPC enrollment (Appendix 3.5) Several classes, such as those with "High Overall" and "SMI and SUD" health needs with "Moderate-to-High Utilization" trajectories during the pre-period, had a plateau in ED visits during the quarter prior to enrollment in WPC, indicating that some of the effect identified through modeling could be due to factors other than the program for these classes. This pattern was most pronounced for the small class of enrollees with "Low Overall" health needs and "Moderate-to-High Utilization" trajectory, which had a clear decline in rate of change of ED visits starting four quarters prior to WPC enrollment.

As with ED visits, for nearly all classes, actual mean number of hospitalizations consistently increased during the pre-period, and consistently decreased during the post-period (Appendix 3.5). Several classes, such as those with "High Overall" and "High Physical Health" needs with "Moderate-to-High Utilization" trajectories during the pre-period had a small decline in hospitalizations during the quarter prior to enrollment in WPC, indicating that some of the modeled effect could be due to factors other than the program.

Unadjusted Analysis of Outcomes by Class

Appendix 3.6 presents unadjusted pre-post analysis of ED visits by joint health needs and utilization trajectory class.

Adjusted Analysis of Outcomes by Class

For all classes, adjusted rates of change in ED visits decreased significantly from the pre-period to the post-period (Table 3.2).

Table 3.2. Adjusted difference from pre-period to post-period in rate of change of mean outpatient ED visits per quarter, by health needs and utilization trajectory classes.

Health Needs Classes	**Utilization Trajectory Classes**	**Rate of Change During 2 Years Prior to Enrollment**	**Rate of Change During 2 Years Post Enrollment**	**Difference in Rate of Change Before and Rate of Change After (Post - Pre)**	***p*-value**
High Overall	Moderate-High Utilization	0.01	-0.05	-0.06	<0.001*
High Physical Health	Moderate-High Utilization	0.00	-0.05	-0.05	<0.001*
SMI and SUD	Moderate-High Utilization	0.01	-0.05	-0.06	<0.001*
SUD with Complications	Moderate-High Utilization	0.00	-0.05	-0.05	<0.001*
Low Overall	Moderate-High Utilization	-0.01	-0.03	-0.03	0.001*
High Overall	Low Utilization	0.04	-0.03	-0.06	<0.001*
High Physical Health	Low Utilization	0.05	-0.03	-0.08	<0.001*
SMI and SUD	Low Utilization	0.04	-0.03	-0.07	<0.001*
SUD with Complications	Low Utilization	0.04	-0.04	-0.08	<0.001*
Low Overall	Low Utilization	0.06	-0.03	-0.09	<0.001*

"Rate of Change" refers to the unexponentiated slope, which is the change in *ln*(Number of Events) associated with an increase of 1 quarter. For example, a rate of 0.01 indicates a multiplicative increase of $exp(0.01) = 1.01$, or a 1% increase estimated number of visits from quarter x to quarter $x + 1$. Appendix 3.5 presents predicted number of ED visits and hospitalizations at the start and end of each period, by class.

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale, and have a null value of 0.0.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); pre-period (Pre); post-period (Post).

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; *p*-values calculated using Stata *lincom* command.

I found multiple cross-class differences in rates of change for ED visit rates. Table 3.3 shows the comparison of the rates of decline in ED visits by health and utilization trajectory classes. A positive value indicates greater decrease in rate of change, or a potentially greater program effect, for the reference class listed in the left-hand column, compared to the comparison class listed on the top.

ED rates of the enrollee class with “Low Overall” health needs with “Moderate-to-High Utilization” pre-enrollment trajectory declined significantly less than all other classes, possibly due to the early decline in mean ED rates prior to WPC enrollment for this class (Appendix 3.5). For example, the decline for this class was 7% (Absolute Value of Cross-Class Difference = 0.07; 1.07 exponentiated or a 7% difference in difference) lower than the class with “Low Overall” health needs with “Low Utilization,” and was 2% to 5% less of a decline compared to all other classes. For this class of “Low Overall” health needs with “Moderate-to-High Utilization” trajectory, the adjusted model predicted a 4% decrease in ED visits per quarter during the pre-period, from 2.51 to 2.42, and a 20% decrease in ED visits per quarter during the post-period, from 1.84 to 1.47. By comparison, for the class of “High Overall” health needs with “Moderate-to-High Utilization” trajectory, the adjusted model predicted a 6% increase in ED visits per quarter during the pre-period, from 2.35 to 2.49, and a 29% decrease in ED visits per quarter during the post-period, from 2.10 to 1.48.

ED rates of the enrollee class with “SUD with Complications” health needs and “Moderate-to-High Utilization” trajectory also declined significantly less than several other classes. For example, the decline for this class was 3% less than “High Physical Health” and “SUD with Complications” health needs with “Low Utilization,” and 2% less than “SMI and SUD” health needs with “Low Utilization.” For this class of “SUD with Complications” health needs with “Moderate-to-High Utilization” trajectory, the adjusted model predicted a 3% decrease in ED visits per quarter during the pre-period, from 2.09 to 2.03, and a 31% decrease in ED visits per quarter during the post-period, from 1.75 to 1.21.

ED rates of the enrollee class with “High Physical Health” needs with “Low Utilization” declined significant more than the class of “High Overall” health needs with “Moderate-to-High Utilization.” For the “High Physical Health” needs with “Low Utilization” class, the adjusted model predicted a 39% increase in ED visits per quarter during the pre-period, from 0.37 to 0.51, and an 18% decrease in ED visits per quarter during the post-period, from 0.48 to 0.39. Additionally, ED rates of the enrollee class with “High Physical Health Needs” with “Moderate-to-High Utilization” declined significantly less than the class of “SUD with Complications” health needs and “Low Utilization.” For the “High Physical Health” needs with “Moderate-to-High Utilization” class, the adjusted model predicted a 1% increase in ED visits per quarter during the pre-period, from 1.86 to 1.89, and a 29% decrease in ED visits per quarter during the post-period, from 1.57 to 1.11.

Table 3.3. The relative decline in ED visits across health needs and utilization trajectory classes.

Reference		Differences in Rates of Change Cross Class ($\text{Difference}_{\text{Comparison}}$ - $\text{Difference}_{\text{Reference}}$)									
		Moderate-High Utilization					**Low Utilization**				
Health Needs Classes	**Utilization Trajectory Classes**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**
High Overall	Moderate-High	-									
High Physical Health	Moderate-High	-0.01	-								
SMI and SUD	Moderate-High	0.01	0.01	-							
SUD with Complications	Moderate-High	-0.01	0.00	-0.02	-						
Low Overall	Moderate-High	**-0.03***	**-0.02***	**-0.04***	**-0.02***	-					
High Overall	Low	0.01	0.01	0.00	0.02	**0.04***	-				
High Physical Health	Low	**0.02***	0.02	0.01	**0.03***	**0.05***	0.01	-			
SMI and SUD	Low	0.01	0.01	0.00	**0.02***	**0.04***	0.00	-0.01	-		
SUD with Complications	Low	0.02	**0.03***	0.01	**0.03***	**0.05***	0.01	0.00	0.01	-	
Low Overall	Low	0.04	0.04	0.03	0.05	**0.07***	0.03	0.02	0.03	0.02	-

A positive value indicates greater decrease in rate of change, or a potentially greater program effect, for the reference class listed in the left-hand column, compared to the comparison class listed on the top.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to High Overall health needs (HO); High Physical Health needs (HPH); Serious Mental Illness or Substance Use Disorder health needs (SMI-SUD); SUD with Complications health needs (SUD-C); and Low Overall health needs (LO); pre-period (Pre); post-period (Post).

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale. Unexponentiated estimated coefficients represent the change in *ln*(Number of Events) associated with each additional quarter, and have a null value of 0.0.

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; p-values calculated using Stata *lincom* command.

Adjusted rates of change in hospitalizations decreased significantly from the pre-period to the post-period for all classes except for the "Low Overall" health needs "Moderate-to-High Utilization" trajectory class (Table 3.4).

Table 3.4. Adjusted difference from pre-period to post-period in rate of change of mean hospitalizations per quarter, by health needs and utilization trajectory classes.

Health Needs Classes	**Utilization Trajectory Classes**	**Rate of Change During 2 Years Prior to Enrollment**	**Rate of Change During 2 Years Post Enrollment**	**Difference in Rate of Change Before and Rate of Change After (Post - Pre)**	***p*-value**
High Overall	Moderate-High Utilization	0.02	-0.05	-0.07	<0.001*
High Physical Health	Moderate-High Utilization	0.00	-0.04	-0.05	<0.001*
SMI and SUD	Moderate-High Utilization	0.03	-0.07	-0.10	<0.001*
SUD with Complications	Moderate-High Utilization	-0.02	-0.05	-0.03	0.008*
Low Overall	Moderate-High Utilization	0.00	-0.05	-0.05	0.231
High Overall	Low Utilization	0.06	-0.03	-0.09	<0.001*
High Physical Health	Low Utilization	0.06	-0.03	-0.09	<0.001*
SMI and SUD	Low Utilization	0.08	-0.04	-0.11	<0.001*
SUD with Complications	Low Utilization	0.07	-0.04	-0.10	<0.001*
Low Overall	Low Utilization	0.07	-0.05	-0.11	<0.001*

"Rate of Change" refers to the unexponentiated slope, which is the change in *ln*(Number of Events) associated with an increase of 1 quarter. For example, a rate of 0.01 indicates a multiplicative increase of *exp*(0.01) = 1.01, or a 1% increase estimated number of visits from quarter x to quarter $x + 1$. Appendix 3.5 presents predicted number of ED visits and hospitalizations at the start and end of each period, by class.

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale, and have a null value of 0.0.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); pre-period (Pre); post-period (Post).

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; p-values calculated using Stata *lincom* command.

I found multiple cross-class differences in rates of change for hospitalizations. Table 3.5 shows the comparison of the rates of decline in hospitalizations by health and utilization trajectory classes, in the same format as Table 3.3 (described above). Hospitalization rates of the enrollee class with "SUD with Complications" health needs and "Moderate-to-High Utilization" declined significantly less than seven other classes. For example, the decline for this class was 9% less than "Low Overall" health needs with "Low Utilization," 8% less than "SMI and SUD" with "Low Utilization," 7% less than "SUD with Complications" health needs with "Low Utilization" and "SMI and SUD" with "Moderate-to-High Utilization," 6% less than "High Overall" and "High Physical Health" with "Low Utilization," and 4% less than "High Overall" health needs with "Moderate-to-High Utilization." For this class of "SUD with Complications" health needs with "Moderate-to-High Utilization" trajectory, the adjusted model predicted a 12% decrease in hospitalizations per quarter during the pre-period, from 1.08 to 0.95, and a 28% decrease in hospitalizations per quarter during the post-period, from 0.85 to 0.61. By comparison, for the class of "High Overall" health needs with "Moderate-to-High Utilization" trajectory, the adjusted model predicted a 16% increase in hospitalizations per quarter during the pre-period, from 0.91 to 1.05, and a 28% decrease in hospitalizations per quarter during the post-period, from 0.89 to 0.64.

Hospitalization rates for the "Low Overall" health needs and "Low Utilization" trajectory class declined 9% more than the class with "SUD with Complications" health needs with "Moderate-to-High Utilization," 7% more than "High Physical Health" needs with "Moderate-to-High Utilization," 5% more than "High Overall" health needs with "Moderate-to-High Utilization," and 2% more than "High Physical Health" needs with "Low Utilization." For this class of "Low Overall" health needs with "Low Utilization," the adjusted model predicted a 58%

increase in hospitalizations during the pre-period, from 0.14 to 0.22, and a 29% decrease in hospitalizations during the post-period, from 0.30 to 0.21.

Additionally, hospitalization rates of the enrollee class with “SMI and SUD” health needs with “Low Utilization” trajectory declined significantly more than several other classes. For example, the decline for this class was 8% more than “SUD with Complications” health needs with “Moderate-to-High Utilization,” 7% more than “High Physical Health” needs with “Moderate-to-High Utilization,” 6% more than “Low Overall” health needs with “Moderate-to-High Utilization,” and 4% more than “High Overall” health needs with “Moderate-to-High Utilization.” For this class of “SMI and SUD” health needs with “Low Utilization,” the adjusted model predicted a 70% increase in hospitalizations per quarter during the pre-period, from 0.14 to 0.24, and a 23% decrease in hospitalizations per quarter during the post-period, from 0.26 to 0.20. Hospitalization rates of the enrollee class with “SMI and SUD” health needs with “Moderate to High Utilization” trajectory also declined significantly more than all other classes with “Moderate to High Utilization.” For this class of “SMI and SUD” health needs with “Moderate-to-High Utilization, the adjusted model predicted a 27% increase in hospitalizations per quarter during the pre-period, from 0.66 to 0.83, and a 37% decrease in hospitalizations per quarter during the post-period, from 0.71 to 0.45.

Table 3.5. The relative decline in hospitalizations across health needs and utilization trajectory classes.

		Differences in Rates of Change Cross Class ($\mathbf{Difference_{Comparison} - Difference_{Reference}}$)									
Reference		**Moderate-High Utilization**					**Low Utilization**				
Health Needs Classes	**Utilization Trajectory Classes**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**
High Overall	Moderate-High	-									
High Physical Health	Moderate-High	**-0.02***	-								
SMI and SUD	Moderate-High	**0.03***	**0.05***	-							
SUD with Complications	Moderate-High	**-0.04***	-0.02	**-0.07***	-						
Low Overall	Moderate-High	-0.02	0.00	**-0.05***	0.02	-					
High Overall	Low	0.02	**0.04***	-0.02	**0.06***	0.03	-				
High Physical Health	Low	0.02	**0.04***	-0.01	**0.06***	0.04	0.00	-			
SMI and SUD	Low	**0.04***	**0.07***	0.01	**0.08***	**0.06***	0.03	0.02	-		
SUD with Complications	Low	0.04	**0.06***	0.00	**0.07***	0.05	0.02	0.01	-0.01	-	
Low Overall	Low	**0.05***	**0.07***	0.01	**0.09***	0.06	0.03	**0.02***	0.00	0.01	0.05

A positive value indicates greater decrease in rate of change, or a potentially greater program effect, for the reference class listed in the left-hand column, compared to the comparison class listed on the top.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to High Overall health needs (HO); High Physical Health needs (HPH); Serious Mental Illness or Substance Use Disorder health needs (SMI-SUD); SUD with Complications health needs (SUD-C); and Low Overall health needs (LO); pre-period (Pre); post-period (Post).

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale. Unexponentiated estimated coefficients represent the change in *ln*(Number of Events) associated with each additional quarter, and have a null value of 0.0.

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; *p*-values calculated using Stata *lincom* command.

Discussion

This analysis identified reductions in ED visits and hospitalizations associated with enrollment in WPC, a program that coordinated medical care, behavioral health care, and social services for Medicaid enrollees with complex needs. In adjusted models, all enrollee classes, defined based on health needs and pre-enrollment utilization, had significantly decreased rates of ED visits and hospitalizations after enrolling in WPC, except for the class of "Low Overall" health needs with "Moderate-to-High Utilization" which had a non-significant decrease in hospitalizations. These consistent findings indicated that services provided under WPC likely reduced acute care service use for enrollees. Similarly, the interim evaluation of WPC included a comparison of adjusted trends in rates of ED visits and hospitalizations for WPC enrollees, not classified into subpopulations, with a control group of Medicaid beneficiaries. Those findings showed a decrease in both types of acute care utilization compared to controls during the second year of the program.[33]

The finding that a small class of enrollees with "Low Overall" health needs and "Moderate-to-High Utilization" trajectories (1.1% of the sample) did not experience as much reduction in ED visits and hospitalizations than almost all other classes requires further research. This class had high proportions of female enrollees (62.1%), young enrollees aged 18 to 34 (53.6%), and enrollees identified as Black or African American (30.9%) and Latinx (25.8%), but a low proportion of enrollees experiencing homelessness (35.3%). This class also had a decrease in average ED visits per quarter starting several quarters before WPC enrollment, and had the lowest levels of hospitalization of all the classes that had "Moderate-to-High Utilization" (Appendix 3.5). There are multiple potential explanations for the seemingly paradoxical finding of this class with low health needs but high utilization. It is possible that these enrollees may have frequented the ED due to social, economic, or behavioral factors, not measured by the variables included in this study. Additionally, it is possible that enrollees in this class had undiagnosed conditions or higher severity that were not reflected in claims data, but still resulted in high utilization. Disparities in diagnoses for women and people of color have been documented for conditions including mental illness, cancer, heart disease, and lung disease.[125,126]

Another notable small class of enrollees consisted of those with “SUD with Complications” health needs and “Moderate-to-High Utilization” trajectory prior to enrollment (0.8% of the sample), which had smaller decreases in ED visits and hospitalizations compared to some classes. The most noteworthy characteristics of this class were a high proportion of male enrollees (61.6%) and enrollees experiencing homelessness (52.4%). It is possible that WPC services did not adequately coordinate the care of these enrollees, or did not provide other types of assistance that were needed.

Additionally, enrollees with “SMI and SUD” health needs, with both “Low Utilization” (20.0% of the sample) and “Moderate to High Utilization” (6.3% of the sample) prior to WPC enrollment, had large decreases in hospitalization rates from the pre-period to the post-period. This pattern may indicate that cross-sector care coordination was especially effective at reducing rates of admissions for enrollees experiencing serious mental illness or substance use disorder. This finding is consistent with aspects of WPC implementation that supported behavioral health referrals and services. For example, approximately half of WPC Pilots selected enrollees with behavioral health conditions as a target population.[30] Program regulations also required WPC Pilots to partner with at least one specialty mental health agency, and in a survey of early implementation pilot representatives ranked mental health providers as having high buy-in for data sharing and care coordination relative to other social services and health care providers.[33]

Beyond WPC, patients with behavioral health conditions have been the target of other cross-sector care coordination interventions that provided linkages to medical, social, and behavioral health services.[24,127–129] There is potential for holistic care including health and social support to have greater beneficial impact for this population compared to health support alone.

Several other classes had significantly different decreases in ED visits and hospitalizations. For example, enrollees with “High Physical Health” needs and “Low Utilization” trajectory had a significantly greater decrease in ED visits than the “High Overall,” “SUD with Complications,” and “Low Overall” health needs classes with “Moderate-to-High” utilization. This class also had a significantly greater decrease in hospitalizations than the “High Physical Health” and “SUD with Complications” health needs classes that had “Moderate-to-High” utilization. Furthermore, enrollees with “High Physical Health” needs and “Moderate-to-High” utilization had significantly smaller decreases in ED visits and hospitalizations compared to several other classes. The finding of opposite results for enrollees with similar physical health needs but different pre-period utilization indicates that prior utilization may have had a stronger influence on post-enrollment acute care utilization than physical health status.

Finally, for ED visits, enrollees with “Low Overall” health needs and “Low Utilization” trajectory prior to WPC enrollment had a significantly larger decrease in rates than the class with “Low Overall” health need and “Moderate-to-High Utilization,” For hospitalizations, the “Low Overall” health needs and “Low Utilization” class had multiple significantly larger decreases compared to four classes, three of which also had “Moderate-to-High Utilization” during the pre-period. Though these findings may seem counter-intuitive because enrollees in this class by definition had low pre-enrollment utilization, they are a result of large decreases in rates, particularly hospitalization, after WPC enrollment; and not large changes in mean level of utilization (Appendix 3.5). The finding of a larger decrease in rate among historically low utilizers compared to some classes of high utilizers was consistent with other studies of cross-sector care coordination, such as one analysis that found no significant effect on utilization for a "high-needs" subgroup of enrollees.[21] Similarly, another evaluation of care coordination for frequent ED users found that high acute care utilization at baseline predicted slower rates of decrease after enrollment.[24] Smaller decreases in rates among high utilizers may reflect the difficulty of changing entrenched behaviors and addressing complex health conditions that lead to acute care utilization.

Limitations

Results should be interpreted in light of two key limitations. First, because the focus of this study was to understand differences in the impact of cross-sector care coordination between subgroups of enrollees, and because appropriate matching to controls would likely require identification of control group latent classes beyond the scope of this dissertation, this analysis relied only on data from the treatment group and did not include a control group of Medi-Cal enrollees not enrolled in WPC. Therefore, the within-class differences presented could be a result of regression to the mean. Several classes had plateaus and even declines prior to WPC enrollment in actual mean numbers of ED visits and hospitalizations (Appendix 3.5), indicating that some of the observed decrease in rate of change from the pre-period to the post-period may be explained by factors other than enrollment in WPC. However, an interim evaluation of the overall enrolled population, not classified into subpopulations, found declines in ED visits and hospitalizations relative to controls, indicating that care coordination had an impact.[33] Second, this study relied on assignment of enrollees to latent classes based on their greatest posterior probability of class membership. Enrollees in the smaller classes in particular had only moderate certainty of class assignment (Appendix 3.1), and so results may be more reliable for the larger classes with higher certainty of class assignment. I described additional limitations related to sample selection, generalizability, and enrollee classification in Chapters 2 and 3.

Implications

Cross-sector care coordination programs that include both health and social services, and offer interventions to reduce acute care utilization for current and potential high utilizers, may have different effects on enrollees with different health needs and utilization trajectories prior to enrollment. To maximize resource efficiency and program effectiveness, government agencies and health care organizations developing these programs should consider the clinical histories of the target population, and should tailor service type and intensity accordingly. In programs that aim to reduce acute care utilization, trade-offs may arise when deciding whether to focus on small subpopulations with high pre-enrollment utilization, or large subpopulations with low pre-enrollment utilization. For example, this study provided evidence that cross-sector care coordination had a significantly limited impact on a small but potentially important class of enrollees with low overall health needs (as documented in claims) but high utilization prior to enrollment. Similarly, this study found limited reductions in acute care utilization for another small but potentially impactful class of enrollees who had SUD with physical health complications and high utilization prior to enrollment. Government agencies and health care organizations should evaluate whether it is an efficient use of resources to focus on small but high utilizing groups that may require intensive services.

Additionally, this study found that cross-sector care coordination resulted in a significantly greater reduction in hospitalizations for the large population of enrollees with SMI and SUD, compared to patients with physical health conditions alone, regardless of whether prior utilization was low or high. Cross-sector care coordination may be an effective strategy for reducing inpatient stays for people with mental illness and substance use disorder. Future research should evaluate the effect of cross-sector care coordination for enrollee subpopulations based on health needs, utilization history, and other factors such as demographics and social risk in order to understand high impact opportunities to improve patient care and health outcomes. Research on the differential effects of cross-sector care coordination for enrollees with varying health needs and utilization histories can provide novel insights into who may benefit most from holistic supports, and can contribute to tailored intervention development and evaluation.

Appendices

Appendix 3.1. Class assignment certainty for joint health needs and enrollee utilization trajectory classes.

Appendix 3.1. Table 1. Average probability of assignment to each class, among those who were assigned to it.

			Average Probability of Class Members Being Assigned to This Class		
Health Needs Classes	**Utilization Trajectory Classes**	**% of Sample**	**P(Health Needs Class)**	**P(Utilization Trajectory Class)**	**P(Joint Class)**
High Overall	Moderate-High Utilization	6.1	0.81	0.96	0.78
High Physical Health	Moderate-High Utilization	4.3	0.82	0.91	0.75
SMI and SUD	Moderate-High Utilization	6.3	0.75	0.93	0.69
SUD with Complications	Moderate-High Utilization	0.8	0.74	0.91	0.68
Low Overall	Moderate-High Utilization	1.1	0.69	0.86	0.59
High Overall	Low Utilization	4.2	0.69	0.93	0.64
High Physical Health	Low Utilization	23.2	0.79	0.97	0.77
SMI and SUD	Low Utilization	20.0	0.75	0.97	0.73
SUD with Complications	Low Utilization	3.2	0.74	0.96	0.71
Low Overall	Low Utilization	30.9	0.81	0.99	0.80

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD).

This table indicates that the members of the Low Overall - Moderate-High Utilization, and the High Overall - Low Utilization classes had the lowest average certainties of joint class assignment.

Average probability of assignment to each class was taken from the diagonal elements of the posterior probability matrix. For each enrollee, health needs class assignment probability was multiplied by utilization trajectory class probability to calculate joint class probability. Values closer to 1 indicate that people assigned to Class *k* had a high probability of being in Class *k* relative to their probabilities of being in other classes (i.e., high certainty of class assignment). Values of 0.8 and above are considered indicators of good class assignment.[67]

Appendix 3.2. Robustness check of models with varying specifications.

Appendix 3.2. Table 1. Significant difference in difference in slope of mean outpatient ED visits per quarter, for varying model specifications, comparing all health needs and utilization classes.

Reference		Models with Significant Difference in Difference Compared to Reference (Difference$_{Comparison}$ - Difference$_{Reference}$)									
		Moderate-High Utilization					**Low Utilization**				
Health Needs Classes	**Utilization Trajectory Classes**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**
High Overall	Moderate-High	-									
High Physical Health	Moderate-High		-								
SMI and SUD	Moderate-High		2	-							
SUD with Complications	Moderate-High	5			-						
Low Overall	Moderate-High	1,2,3, 4,5,6	1,2,3, 4,5,6	1,2,3, 4,5	1,3, 4,5	-					
High Overall	Low					1,2,3, 4,5	-				
High Physical Health	Low	1,2,3, 4	2	2	1,2,3, 4,5	1,2,3, 4,5,6		-			
SMI and SUD	Low		2		1, 4	1,2,3, 4,5,6		6	-		
SUD with Complications	Low		1,2, 4	6	1,2, 4	1,2,3, 4,5,6	6		6	-	
Low Overall	Low	2	2	2	2	1,2,3, 4,5,6	2	2	2		-

Numbers 1 through 6 indicate that the difference in difference, for the reference versus the comparison, was significant in the model ($p < 0.05$). Numbers refer to models with the following specifications:

1. Main model (described in text).
2. Main model, with no clustered standard errors.
3. Main model, with Medi-Cal Enrollment replacing WPC enrollment as covariate.
4. Main model, with no covariate for months enrolled in Medi-Cal or WPC.
5. Main model, with no covariate for CDPS score.
6. Unadjusted model, including random effects and clustered standard errors.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to High Overall health needs (HO); High Physical Health needs (HPH); Serious Mental Illness or Substance Use Disorder health needs (SMI-SUD); SUD with Complications health needs (SUD-C); and Low Overall health needs (LO); pre-period (Pre); post-period (Post).

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale. Unexponentiated estimated coefficients represent the change in *ln*(Number of Events) associated with each additional quarter, and have a null value of 0.0.

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

Appendix 3.2. Table 2. Significant difference in difference in slope of mean hospitalizations per quarter, for varying model specifications, comparing all health needs and utilization classes.

		Models with Significant Difference in Difference Compared to Reference (Difference$_{Comparison}$ - Difference$_{Reference}$)									
Reference		**Moderate-High Utilization**					**Low Utilization**				
Health Needs Classes	**Utilization Trajectory Classes**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**
High Overall	Moderate-High	-									
High Physical Health	Moderate-High	1,2,3,4	-								
SMI and SUD	Moderate-High	1,2,3,4	1,2,3,4	-							
SUD with Complications	Moderate-High	1,3,4,5		1,2,3,4,5	-						
Low Overall	Moderate-High			1,3,4,5,6		-					
High Overall	Low		1,2,3,4		1,2,3,4,5		-				
High Physical Health	Low	2	1,2,3,4		1,2,3,4,5			-			
SMI and SUD	Low	1,2,3,4	1,2,3,4		1,2,3,4	1,2,3,4,5,6	2	2	-		
SUD with Complications	Low	2	1,2,3,4		1,2,3,4,5,6	5,6	6	6		-	
Low Overall	Low	1,2,3,4	1,2,3,4		1,2,3,4,5	2		1,2,4			-

Numbers 1 through 6 indicate that the difference in difference, for the reference versus the comparison, was significant in the model ($p < 0.05$). Numbers refer to models with the following specifications:

1. Main model (described in text).
2. Main model, with no clustered standard errors.
3. Main model, with Medi-Cal Enrollment replacing WPC enrollment as covariate.
4. Main model, with no covariate for months enrolled in Medi-Cal or WPC.
5. Main model, with no covariate for CDPS score.
6. Unadjusted model, including random effects and clustered standard errors.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to High Overall health needs (HO); High Physical Health needs (HPH); Serious Mental Illness or Substance Use Disorder health needs (SMI-SUD); SUD with Complications health needs (SUD-C); and Low Overall health needs (LO); pre-period (Pre); post-period (Post).

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale. Unexponentiated estimated coefficients represent the change in *ln*(Number of Events) associated with each additional quarter, and have a null value of 0.0.

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

Appendix 3.3. Estimated regression coefficients and formulas used to calculate selected parameters.

Appendix 3.3. Table 1. Estimated regression coefficients and formulas.

Coefficient or Formula	Component in Regression Equation	Shorthand in Results Section	Interpretation
$\widehat{\beta_0}$	$\widehat{\beta_0}$	-	Reference group intercept in the pre-period.
$\widehat{\beta_1}$	$\widehat{\beta_1} \times Quarter$	Pre Slope (Reference)	Reference class slope in the pre-period.
$\widehat{\beta_2}$	$\widehat{\beta_2} \times Intervention$	-	Reference group level change at the start of the intervention.
$\widehat{\beta_3}$	$\widehat{\beta_3} \times Quarter \times Intervention$	Difference (Post - Pre) (Reference)	Reference class difference in slopes between the pre-period and the post-period.
$\widehat{\beta_4}$	$\widehat{\beta_4} \times Class$	-	Difference between the comparison group and the reference group in intercept in the pre-period.
$\widehat{\beta_5}$	$\widehat{\beta_5} \times Class \times Quarter$	-	Difference between the comparison group and the reference group in slope in the pre-period.
$\widehat{\beta_6}$	$\widehat{\beta_6} \times Class \times Intervention$	-	Difference between the comparison group and the reference group in level at the start of the intervention.
$\widehat{\beta_7}$	$\widehat{\beta_7} \times Class \times Quarter \times Intervention$	-	Difference between the comparison group and the reference group in slope in the post-period compared with the pre-period.
$\widehat{\beta_1} + \widehat{\beta_5}$	See above.	Pre Slope (Comparison)	Comparison class slope in the pre-period
$\widehat{\beta_1} + \widehat{\beta_3}$	See above.	Post Slope (Reference)	Reference class slope in the post-period.
$\widehat{\beta_1} + \widehat{\beta_3} + \widehat{\beta_5} + \widehat{\beta_7}$	See above.	Post Slope (Comparison)	Comparison class slope in the post-period.
$\widehat{\beta_3} + \widehat{\beta_7}$	See above.	Difference (Post - Pre) (Comparison)	Comparison class difference in slopes between the pre-period and the post-period.
$\widehat{\beta_7}$	See above.	Difference from Reference ($\text{Difference}_{\text{Class}}$ - $\text{Difference}_{\text{Reference}}$)	Comparison class difference in slopes between the pre-period and the post-period.

Interpretations based in part on Linden 2015.[130] Unexponentiated estimated coefficients represent the change in *ln*(Number of Events), and have a null value of 0.0. Exponentiated coefficients (e.g., $e^{\widehat{\beta_3}+\widehat{\beta_7}}$). refer to incidence rate ratios (IRRs), which represent the multiplicative or percentage change in number of events, and have a null value of 1.0.

Appendix 3.4. Descriptive analysis of post-period Medi-Cal enrollment and WPC enrollment.

Appendix 3.4. Table 1. Post-period Medi-Cal and WPC enrollment.

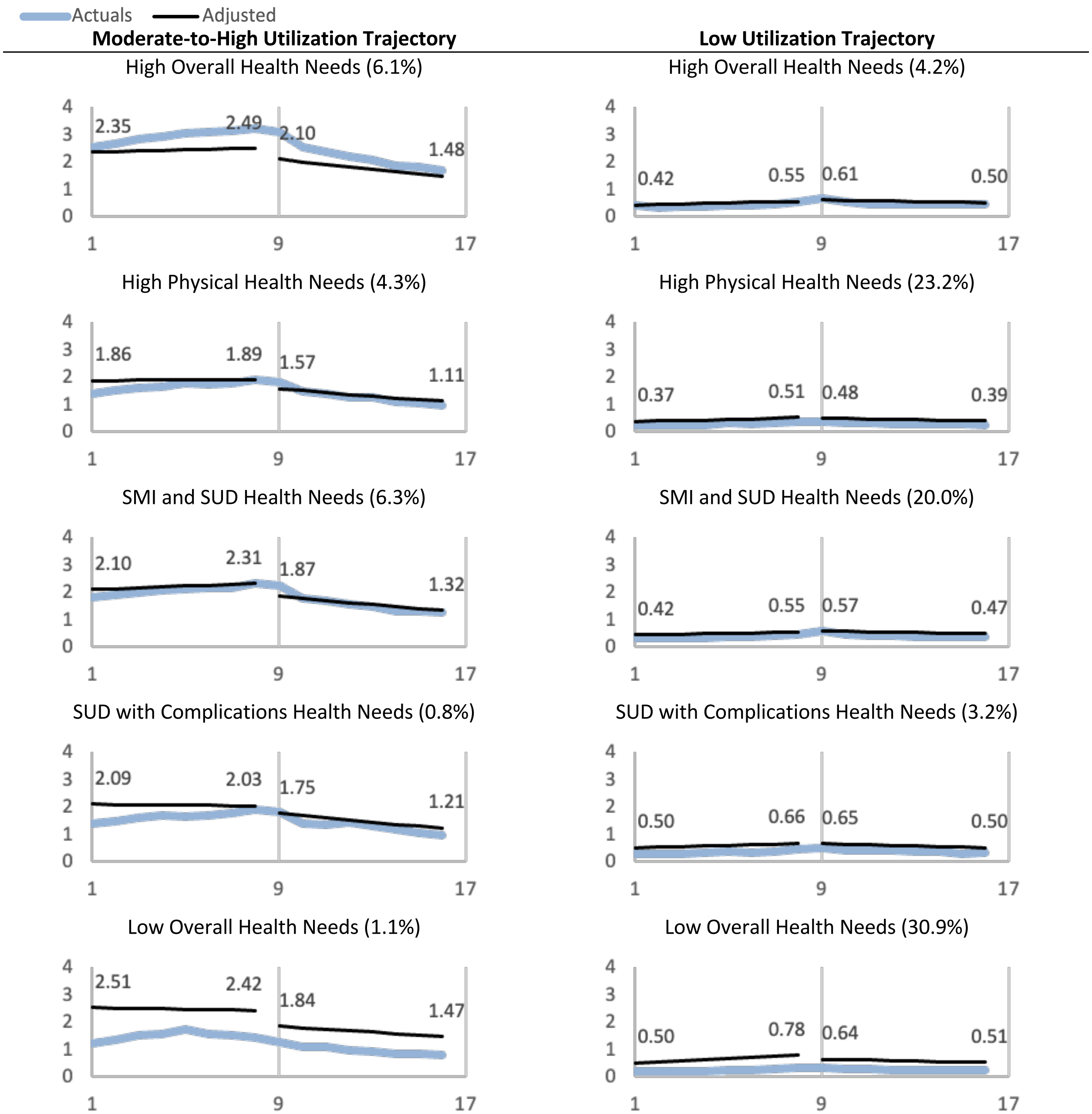
	Post-Period Medi-Cal Enrollment	**Post-Period WPC Enrollment**
Mean Months (SD)	21.9 (5.0)	14.1 (8.6)
% Enrolled by Duration		
1 to 3 months	1.4	14.5
4 to 6 months	1.9	12.1
7 to 9 months	2.1	11.3
10 to 12 months	2.4	7.6
13 to 15 months	2.9	10.2
16 to 18 months	3.2	4.5
19 to 21 months	4.4	4.1
22 to 24 months	81.6	35.8

Post-period Medi-Cal enrollment calculated as the total number of months each enrollee was enrolled in Medi-Cal during the eight quarters starting from first enrollment in WPC.

Post-period WPC enrollment calculated as the total number of months between each enrollee's first and last enrollment date during the eight quarter post-period, including start and end months.

Appendix 3.5. Graphs of predicted and actual means.

Appendix 3.5. Figure 1. Adjusted predictions of number of ED visits, and actual values.

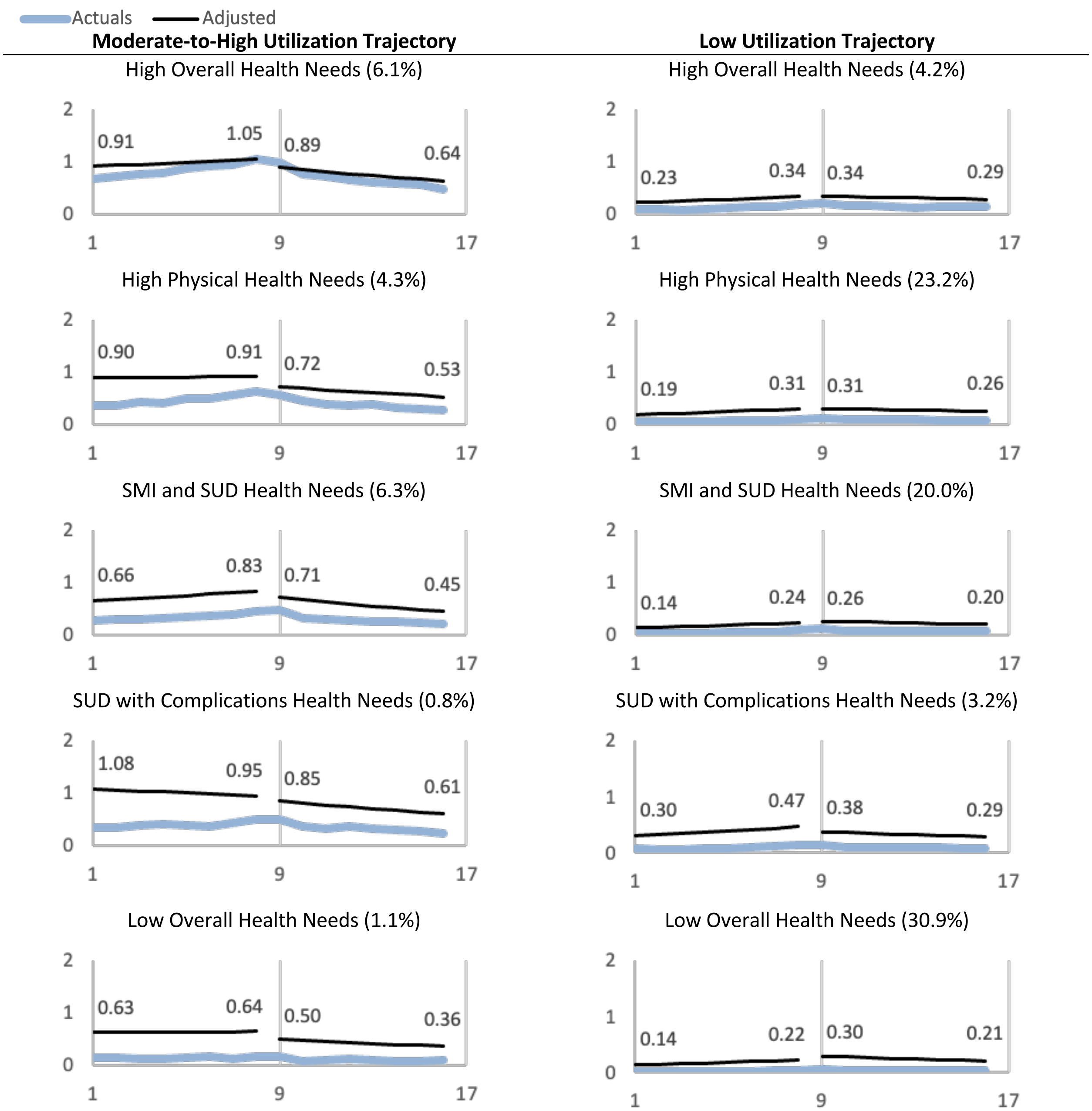


Labeled with predicted means at Quarters 1, 8, 9, and 16. Line at $x = 9$ indicates start of post-period.

x-axis = Quarters of the Study Period. *y*-axis = Number of Events.

Unadjusted predictions closely followed actual values, and are omitted here to simplify the graphs.

Appendix 3.5. Figure 2. Adjusted predictions of number of hospitalizations, and actual values.



Labeled with predicted means at Quarters 1, 8, 9, and 16. Line at $x = 9$ indicates start of post-period.

x-axis = Quarters of the Study Period. y-axis = Number of Events

Unadjusted predictions closely followed actual values, and are omitted here to simplify the graphs.

Appendix 3.6. Unadjusted analysis of outcomes by class.

Appendix 3.6. Table 1. Unadjusted difference from pre-period to post-period in rate of change of mean outpatient ED visits per quarter, by health needs and utilization trajectory classes.

Health Needs Classes	**Utilization Trajectory Classes**	**Rate of Change During 2 Years Prior to Enrollment**	**Rate of Change During 2 Years Post Enrollment**	**Difference in Rate of Change Before and Rate of Change After (Post - Pre)**	***p*-value**
High Overall	Moderate-High Utilization	0.03	-0.09	-0.12	<0.001*
High Physical Health	Moderate-High Utilization	0.03	-0.09	-0.12	<0.001*
SMI and SUD	Moderate-High Utilization	0.03	-0.09	-0.11	<0.001*
SUD with Complications	Moderate-High Utilization	0.03	-0.09	-0.12	<0.001*
Low Overall	Moderate-High Utilization	0.01	-0.07	-0.08	<0.001*
High Overall	Low Utilization	0.06	-0.06	-0.11	<0.001*
High Physical Health	Low Utilization	0.07	-0.05	-0.13	<0.001*
SMI and SUD	Low Utilization	0.05	-0.06	-0.12	<0.001*
SUD with Complications	Low Utilization	0.07	-0.07	-0.15	<0.001*
Low Overall	Low Utilization	0.09	-0.06	-0.16	<0.001*

"Rate of Change" refers to the unexponentiated slope, which is the change in *ln*(Number of Events) associated with an increase of 1 quarter. For example, a rate of 0.01 indicates a multiplicative increase of *exp*(0.01) = 1.01, or a 1% increase estimated number of visits from quarter x to quarter $x + 1$. Appendix 5 presents predicted number of ED visits and hospitalizations at the start and end of each period, by class.

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale, and have a null value of 0.0.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); pre-period (Pre); post-period (Post).

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; p-values calculated using Stata *lincom* command.

Appendix 3.6. Table 2. The relative decline in ED visits across health needs and utilization trajectory classes.

Reference		Differences in Rates of Change Cross Class ($\text{Difference}_{\text{Comparison}}$ - $\text{Difference}_{\text{Reference}}$)									
		Moderate-High Utilization					Low Utilization				
Health Needs Classes	**Utilization Trajectory Classes**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**
High Overall	Moderate-High	-									
High Physical Health	Moderate-High	0.00	-								
SMI and SUD	Moderate-High	-0.01	-0.01	-							
SUD with Complications	Moderate-High	0.00	0.00	0.01	-						
Low Overall	Moderate-High	**-0.04***	**-0.04***	-0.03	-0.04	-					
High Overall	Low	-0.01	-0.01	0.00	-0.01	0.03	-				
High Physical Health	Low	0.01	0.00	0.02	0.01	**0.04***	0.01	-			
SMI and SUD	Low	0.00	-0.01	0.01	0.00	**0.03***	0.00	**-0.01***	-		
SUD with Complications	Low	0.03	0.02	**0.03***	0.03	**0.06***	**0.03***	0.02	**0.03***	-	
Low Overall	Low	0.03	0.03	0.04	0.03	**0.07***	0.04	0.03	0.04	0.01	-

A positive value indicates greater decrease in rate of change, or a potentially greater program effect, for the reference class listed in the left-hand column, compared to the comparison class listed on the top.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); pre-period (Pre); post-period (Post).

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale. Unexponentiated estimated coefficients represent the change in *ln*(Number of Events) associated with each additional quarter, and have a null value of 0.0.

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; p-values calculated using Stata *lincom* command.

Appendix 3.6. Table 3. Unadjusted difference from pre-period to post-period in rate of change of mean hospitalizations per quarter, by health needs and utilization trajectory classes.

Health Needs Classes	**Utilization Trajectory Classes**	**Rate of Change During 2 Years Prior to Enrollment**	**Rate of Change During 2 Years Post Enrollment**	**Difference in Rate of Change Before and Rate of Change After (Post - Pre)**	***p*-value**
High Overall	Moderate-High Utilization	0.07	-0.10	-0.16	<0.001*
High Physical Health	Moderate-High Utilization	0.07	-0.09	-0.17	<0.001*
SMI and SUD	Moderate-High Utilization	0.06	-0.10	-0.16	<0.001*
SUD with Complications	Moderate-High Utilization	0.04	-0.09	-0.13	<0.001*
Low Overall	Moderate-High Utilization	0.03	-0.08	-0.10	0.016*
High Overall	Low Utilization	0.10	-0.06	-0.15	<0.001*
High Physical Health	Low Utilization	0.11	-0.05	-0.16	<0.001*
SMI and SUD	Low Utilization	0.10	-0.06	-0.16	<0.001*
SUD with Complications	Low Utilization	0.12	-0.08	-0.20	<0.001*
Low Overall	Low Utilization	0.10	-0.07	-0.16	<0.001*

"Rate of Change" refers to the unexponentiated slope, which is the change in *ln*(Number of Events) associated with an increase of 1 quarter. For example, a rate of 0.01 indicates a multiplicative increase of *exp*(0.01) = 1.01, or a 1% increase estimated number of visits from quarter x to quarter $x + 1$. Appendix 5 presents predicted number of ED visits and hospitalizations at the start and end of each period, by class.

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale, and have a null value of 0.0.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); pre-period (Pre); post-period (Post).

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; *p*-values calculated using Stata *lincom* command.

Appendix 3.6. Table 4. The relative decline in hospitalizations across health needs and utilization trajectory classes.

		Differences in Rates of Change Cross Class ($\text{Difference}_{\text{Comparison}}$ - $\text{Difference}_{\text{Reference}}$)									
Reference		**Moderate-High Utilization**					**Low Utilization**				
Health Needs Classes	**Utilization Trajectory Classes**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**	**HO**	**HPH**	**SMI-SUD**	**SUD-C**	**LO**
High Overall	Moderate-High	-									
High Physical Health	Moderate-High	0.00	-								
SMI and SUD	Moderate-High	0.00	-0.01	-							
SUD with Complications	Moderate-High	-0.03	-0.03	-0.03	-						
Low Overall	Moderate-High	-0.06	-0.06	**-0.06***	-0.03	-					
High Overall	Low	-0.01	-0.01	-0.01	0.02	0.05	-				
High Physical Health	Low	0.00	-0.01	0.00	0.03	0.06	0.01	-			
SMI and SUD	Low	-0.01	-0.01	0.00	0.03	**0.05***	0.00	0.00	-		
SUD with Complications	Low	0.04	0.04	0.04	**0.07***	**0.10***	**0.05***	**0.04***	0.04	-	
Low Overall	Low	0.00	0.00	0.00	0.03	0.06	0.01	0.01	0.01	-0.04	-

A positive value indicates greater decrease in rate of change, or a potentially greater program effect, for the reference class listed in the left-hand column, compared to the comparison class listed on the top.

Health needs and utilization trajectory classes were defined in Chapter 2 and Chapter 3.

Abbreviations refer to serious mental illness (SMI); substance use disorder (SUD); pre-period (Pre); post-period (Post).

Values are unexponentiated estimated coefficients from multilevel negative binomial regression using enrollee as a random effect, and adjusting standard errors for clustering by county. Unexponentiated values are presented to allow analysis of difference on the linear scale. Unexponentiated estimated coefficients represent the change in *ln*(Number of Events) associated with each additional quarter, and have a null value of 0.0.

Appendix 3.3 contains the interpretation of regression coefficients and formulas used to calculate selected parameters.

* $p < 0.05$; p-values calculated using Stata *lincom* command.

V. SUMMARY AND IMPLICATIONS

Summary

These analyses indicated that in Whole Person Care (WPC), a large-scale cross-sector care coordination program that linked health and social services for Medicaid enrollees in California, significant heterogeneity arose in enrollee health needs and pre-enrollment utilization history. Furthermore, change in rate of acute care utilization after receipt of services varied by health needs and prior utilization. Latent class analysis categorized enrollees into five classes based on health needs, measured using medical and behavioral health diagnoses in Medicaid claims during the two years prior to WPC enrollment. The classes consisted of enrollees with "High Overall" health needs (10.3%), "High Physical Health" needs (27.5%), "Serious Mental Illness (SMI) and Substance Use Disorder (SUD)" health needs (26.3%), "SUD with Complications" health needs (4.0%), and "Low Overall" health needs (32.0%). These populations aligned with WPC program-defined target populations to some extent, though there were discrepancies. For example, though LCA categorized over a quarter of enrollees into the "High Physical Health" needs class, less than 10% of the sample was in the "Chronic Physical Conditions" WPC target population. Similarly, though LCA categorized over a quarter of enrollees into the "SMI and SUD" needs class, only 12% of the sample was in the "SMI/SUD" WPC target population. It is possible that program-defined target populations were used internally to improve program implementation. However, my analyses showed that for evaluation, relying on programmatic designations such as WPC target populations would risk underrepresenting the health needs of enrollees with notable comorbidities.

Analysis of prior utilization trajectories using group-based trajectory modeling (GBTM) further highlighted the value of data-driven classification of enrollees in large and complex interventions, especially those that target current and potential high utilizers. GBTM analysis supplemented the LCA, and identified two classes of enrollees with “Moderate-to-High” utilization trajectory (18.3%), and “Low” utilization trajectory (81.7%). Like the LCA, GBTM revealed discrepancies between patterns in the data and a WPC program-defined target population. Though over half of enrollees were in the WPC “High Utilizers” target population, a much smaller proportion were categorized into the “Moderate-to-High” utilization trajectory class based on number of acute care encounters documented in Medicaid claims data during the two years prior to WPC enrollment. This was expected because some WPC Pilots classified enrollees into the WPC “High Utilizers” target population based risk of future high utilization, rather than prior utilization alone. For example, Contra Costa’s primary target population was “High Utilizers,” and they based enrollment on an innovative predictive risk model that identified adults expected to have future avoidable acute care use.[33] Compared to the variety and uncertainty in target population definitions, GBTM analysis provided a standardized approach to systematically assess enrollees.

The final analysis assessed the acute care utilization of WPC enrollees in the above classes before and after enrollment in WPC, and showed that rates of outpatient ED visits followed by discharge and hospitalizations decreased for all classes during the two-year post period relative to the two-year pre-period, except for a small but notable class with “Low Overall” health needs and “Moderate-to-High” pre-enrollment utilization (1.1%) which had a non-significant decrease in hospitalization rates. In cross-class comparisons, decreases in rates were typically smaller for enrollees with “Moderate-to-High” utilization trajectories prior to enrollment, especially those with “Low Overall” and “SUD with Complications” health needs. This finding supported my a priori hypothesis that care coordination would have a smaller effect on enrollees with high utilization prior to enrollment compared to enrollees with low utilization, because high utilizers may have had more entrenched needs or behaviors. Additionally, enrollees with “SMI and SUD” health needs, with both “Moderate-to-High” and “Low” prior utilization trajectories, had a large decrease in rates of hospitalizations compared to the other classes. This could be due to aspects of WPC that focused on behavioral health, such as the requirement that pilots partner with at least one specialty mental health agency, and implementation of sobering centers in some pilots.[30] These results provide evidence that care coordination may have had a marginally greater impact on acute care utilization of some classes of enrollees, but additional evidence is needed to confirm this trend.

Overall Limitations

There were limitations to these analyses. First, reliance on claims data led to potential under-representation of diagnoses and utilization, limited understanding of disease severity, and limited details on enrollee social and economic experiences. Though analysis identified a large subpopulation of patients with “Low Overall” health needs, it is possible that some conditions were not documented in claims for members of this group. Second, selection of a non-random sample of intervention enrollees increased relevance in a real-world context, but limited generalizability to other populations and settings. For example, the identified classes might not generalize to states other than California with a different demographic composition or landscape of services and policies, or to patients enrolled in other insurance such as Medicare in which the population could be older and have greater or different medical complexity. Third, assignment of enrollees to classes based on their highest probability of class assignment introduced potential misclassification error. Fourth, lack of a control group limited causal interpretation of the within-class changes in rates of acute care utilization from the pre-period to the post-period. These limitations could be addressed in future research.

Implications for Research and Practice

Cross-sector care coordination is a valuable approach to addressing social determinants of health, improving health outcomes, and reducing avoidable utilization. Prior research found mixed results regarding reductions in acute care utilization after cross-sector care coordination, but used small samples of intervention enrollees and did not disaggregate by enrollee subpopulation.[21,22,24,25,28] In light of this gap in research, the findings of this study have implications for researchers and evaluators, as well as government agencies and health care organizations implementing care coordination or other interventions that target heterogeneous groups of current and potential high utilizers. Examples of programs for which this study's implications could be relevant include WPC itself,[30] the State of California CalAIM Enhanced Care Management (ECM) program scheduled for full implementation in 2023,[131] the Hennepin Health initiative in Minnesota,[29,132–134] and the Johns Hopkins Community Health Partnership in Maryland.[117]

There were two key implications of this research, described in additional detail below. First, there are several dimensions that can be used to characterize subpopulations of heterogeneous enrollees in cross-sector care coordination and other programs that target high utilizers. These include prior and anticipated future utilization, health and social complexity, subpopulation size, and expected impact of the intervention for each subpopulation. Data-driven classification approaches such as LCA and GBTM can surface meaningful information about enrollee heterogeneity, but even without in-depth quantitative analysis program managers and analysts can still conceptualize target populations in terms of these dimensions to inform implementation and evaluation. Second, cross-sector care coordination and other interventions that aim to reduce acute care utilization may have a greater impact on some enrollees than others. Program managers can increase return on investment by implementing tailored strategies that focus care based on identified and prioritized subpopulations.

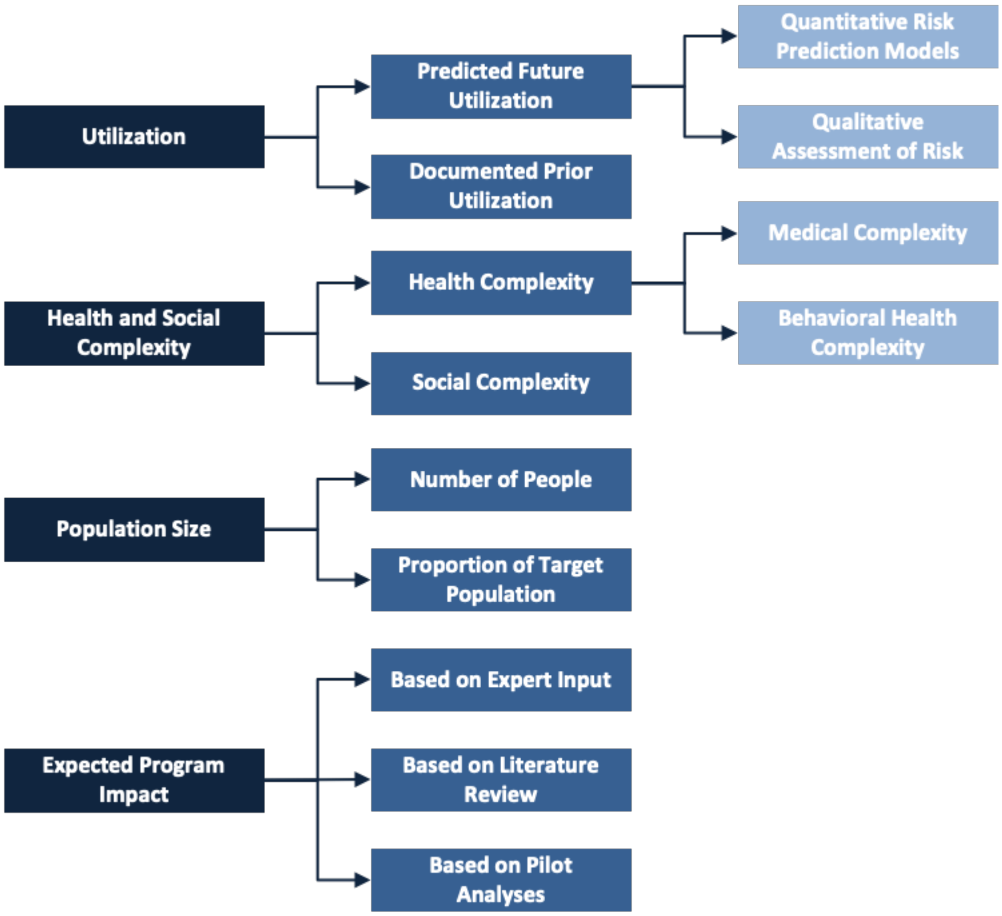
Framework for Characterizing Heterogeneous Enrollee Populations

This dissertation demonstrated that identifying enrollee heterogeneity was useful in systematically characterizing subpopulations in a California Medicaid demonstration program that focused on a large population of current and potential future high utilizers. It is important to use data-driven methods to classify heterogeneity in other real-world programs that target patients with complex health needs and utilization histories, or in which enrollment criteria can be implemented differently and include criteria chosen by implementing entities. For example, in California, in a new Enhanced Care Management (ECM) Medicaid benefit under the CalAIM program, the eligibility criteria for each of the six "Populations of Focus,"[135] allow flexibility (e.g., enroll people who "*meet one or more of the following criteria*"); allow subjectivity (e.g., enroll people "*for whom coordination of services would likely result in improved health outcomes and/or decreased utilization*"); and use intersectional definitions including social needs, health needs, and utilization histories (e.g., enroll people who are "*transitioning from incarceration...[and have]...Chronic mental illness [or] Substance Use Disorder*"). Successful outcomes of this program could depend on use of LCA, or less technical approaches, to understand subpopulations of enrollees and gain insight into what intervention strategies could be most effective given enrollee characteristics.

This dissertation highlighted four key dimensions that care coordination programs and other interventions that target high utilizers can use to meaningfully characterize heterogeneous subpopulations of enrollees (Summary and Implications Figure 1). Subpopulations can be characterized in terms of: (1) utilization, including documented prior utilization and anticipated risk of future utilization based on predictive risk models or qualitative assessment of risk; (2) health and social complexity, including the extent to which basic needs are met as well as medical and behavioral health needs; (3) subpopulation size, including absolute number of people and the relative proportion of the overall population that is in each subpopulation; and (4) expected impact of the program for each subpopulation, assessed prior to the program or during early implementation through expert input, literature review, or pilot analyses.

Classifying heterogeneous enrollees into subpopulations based on these dimensions can help government agencies, program managers, and other stakeholders clarify who is enrolled and why. This in turn can inform program conceptualization and development. For example, in WPC, clearer distinction between current high utilizers and potential future high utilizers might have changed who was assigned to the "High Utilizers" program-defined target population, leading to a different understanding of the program during implementation and evaluation. Similarly, quantifying the high prevalence of mental health conditions and substance use disorder among enrollees, and identifying the significant associations between behavioral health needs and high pre-enrollment acute care utilization, could have influenced program decisions to strengthen behavioral health staffing, partnerships, and intervention strategies in WPC.

Summary and Implications Figure 1. Framework for characterizing heterogeneous populations enrolled in care coordination or other programs that target high utilizers.



Strategies for Increasing Program Impact Based on Classification

After identifying subpopulations, program managers can develop strategies tailored to different subpopulations to achieve a greater return on investment from the program. Specific strategies depend on the context, but could include: more intensive supports for large populations with high needs and histories of high utilization; varied and specialized supports for populations with mixed sizes, needs, and utilization histories; and lighter support and monitoring for small populations with low needs and histories of low utilization (Summary and Implications Table 1).

This dissertation found that in WPC, enrollees with "SMI and SUD" health needs, with both low and high prior utilization, had especially large decreases in hospitalizations. This may be due to WPC targeting people with behavioral health conditions and providing tailored behavioral health supports.[30,33] Other cross-sector care coordination interventions have also focused improving health and reducing avoidable utilization for people with SMI or SUD, indicating the widespread importance of this population.[24,127–129] Additionally, prior research on cross-sector care coordination found smaller reductions in acute care utilization for enrollees with high utilization prior to enrollment.[21,24] This trend was reflected to some extent in this dissertation, though WPC impact also varied by health need in addition to utilization history. It may be necessary to provide more specialized or intensive care coordination services to reduce acute care utilization for enrollees with a history of persistent high service use.

Summary and Implications Table 1. Example strategies for increasing program impact, by four dimensions for characterizing heterogeneous populations enrolled in care coordination or other programs that target high utilizers.

	Dimensions for Characterizing Enrollees					
Priority	**Util-ization**	**Health and Social Complexity**	**Population Size**	**Expected Program Impact**	**Example WPC Classes**	**Example Strategies**
High	High	High	High	High		• Intensive care coordination including frequent in-person contact may be required to have an impact. • Strong behavioral health supports for enrollees with mental illness or substance use disorder.
	High	Low	High	High		
	High	High	High	Low		
	High	High	Low	High	SMI-SUD – High Util.	
	Low	High	High	High	SMI-SUD – Low Util.	
Moderate	High	Low	High	Low		• Tailor care coordination to the diverse utilization patterns and health needs of these subpopulations. • Consider trade-offs between population size and expected program impact, e.g., it may be worthwhile to target lower utilizers if there are many of them and utilization trends are expected to notably decline.
	High	Low	Low	High		
	High	High	Low	Low	HPH – High Util.	
	Low	Low	High	High	LO – Low Util.	
	Low	High	High	Low	HPH – Low Util.	
	Low	High	Low	High		
Low	High	Low	Low	Low	LO – High Util.	• Low-touch care coordination such as phone-based or infrequent contact may be adequate. • Monitor for shifts into higher priority subpopulations.
	Low	Low	High	Low		
	Low	Low	Low	High		
	Low	High	Low	Low	HO – Low Util.	
	Low	Low	Low	Low		

Abbreviations refer to Serious Mental Illness and Substance Use Disorder health needs (SMI-SUD); High Physical Health needs (HPH); Low Overall health needs (LO), High Overall health needs (HO), and Utilization (Util.).

Opportunities for Future Research

More research is needed to validate whether the subpopulations identified in this research exist in other programs that target high utilizers; whether similar reductions in ED visits and hospitalizations would be observed after program enrollment; and to what extent differences in rates of acute care utilization can be causally attributed to participation in care coordination. There is ample opportunity to deepen evaluation insights and tailor interventions by using subpopulation analysis to better understand patient health needs and utilization histories.

BIBLIOGRAPHY

1. Bell J, Turbow S, George M, Ali MK. Factors associated with high-utilization in a safety net setting. *BMC Health Serv Res*. 2017;17(1):273. doi:10.1186/s12913-017-2209-0
2. Johnson TL, Rinehart DJ, Durfee J, et al. For Many Patients Who Use Large Amounts Of Health Care Services, The Need Is Intense Yet Temporary. *Health Affairs*. 2015;34(8):1312-1319. doi:10.1377/hlthaff.2014.1186
3. Harris LJ, Graetz I, Podila PSB, Wan J, Waters TM, Bailey JE. Characteristics of Hospital and Emergency Care Super-utilizers with Multiple Chronic Conditions. *The Journal of Emergency Medicine*. 2016;50(4):e203-e214. doi:10.1016/j.jemermed.2015.09.002
4. Szymkowiak D, Montgomery AE, Johnson EE, Manning T, O'Toole TP. Persistent Super-Utilization of Acute Care Services Among Subgroups of Veterans Experiencing Homelessness. *Medical Care*. 2017;55(10):893-900. doi:10.1097/MLR.0000000000000796
5. Chambers C, Chiu S, Katic M, et al. High Utilizers of Emergency Health Services in a Population-Based Cohort of Homeless Adults. *Am J Public Health*. 2013;103(S2):S302-S310. doi:10.2105/AJPH.2013.301397
6. Kim K, Rosenberg MA. Determinants of Persistent High Utilizers in U.S. Adults Using Nationally Representative Data. *North American Actuarial Journal*. 2020;24(1):1-21. doi:10.1080/10920277.2019.1585880
7. Labby D, Wright B, Broffman L, Holtorf M. Drivers of High-cost Medical Complexity in a Medicaid Population. *Med Care*. 2020;58(3):208-215. doi:10.1097/MLR.0000000000001261

8. Rogers A, Hu YR, Schickedanz A, Gottlieb L, Sharp A. Understanding High-Utilizing Patients Based on Social Risk Profiles: a Latent Class Analysis Within an Integrated Health System. *J Gen Intern Med*. 2020;35(7):2214-2216. doi:10.1007/s11606-019-05510-9
9. Mautner DB, Pang H, Brenner JC, et al. Generating Hypotheses About Care Needs of High Utilizers: Lessons from Patient Interviews. *Population Health Management*. 2013;16(S1):S-26. doi:10.1089/pop.2013.0033
10. Blumenthal D, Chernof B, Fulmer T, Lumpkin J, Selberg J. Caring for High-Need, High-Cost Patients — An Urgent Priority. *New England Journal of Medicine*. 2016;375(10):909-911. doi:10.1056/NEJMp1608511
11. Emeche U. Is a Strategy Focused on Super-Utilizers Equal to the Task of Health Care System Transformation? Yes. *The Annals of Family Medicine*. 2015;13(1):6-7. doi:10.1370/afm.1746
12. Iovan S, Lantz PM, Allan K, Abir M. Interventions to Decrease Use in Prehospital and Emergency Care Settings Among Super-Utilizers in the United States: A Systematic Review. *Med Care Res Rev*. 2020;77(2):99-111. doi:10.1177/1077558719845722
13. Agency for Healthcare Research and Quality. Care Coordination. Published 2018. https://www.ahrq.gov/ncepcr/care/coordination.html
14. Schor EL. Ten Essential Characteristics of Care Coordination. *JAMA Pediatr*. 2019;173(1):5-5. doi:10.1001/jamapediatrics.2018.3107
15. Schultz EM, McDonald KM. What is care coordination?: *International Journal of Care Coordination*. 2014;17(1-2):5-24. doi:10.1177/2053435414540615

16. Gorin SS, Haggstrom D, Han PKJ, Fairfield KM, Krebs P, Clauser SB. Cancer Care Coordination: a Systematic Review and Meta-Analysis of Over 30 Years of Empirical Studies. *Ann Behav Med*. 2017;51(4):532-546. doi:10.1007/s12160-017-9876-2
17. De Regge M, De Pourcq K, Meijboom B, Trybou J, Mortier E, Eeckloo K. The role of hospitals in bridging the care continuum: a systematic review of coordination of care and follow-up for adults with chronic conditions. *BMC Health Serv Res*. 2017;17(1):550. doi:10.1186/s12913-017-2500-0
18. Horvitz-Lennon M, Kilbourne AM, Pincus HA. From Silos To Bridges: Meeting The General Health Care Needs Of Adults With Severe Mental Illnesses. *Health Affairs*. 2006;25(3):659-669. doi:10.1377/hlthaff.25.3.659
19. Ingersoll S, Valente SM, Roper J. Nurse Care Coordination for Diabetes: A Literature Review and Synthesis. *Journal of Nursing Care Quality*. 2005;20(3):208-214.
20. Katz EB, Carrier ER, Umscheid CA, Pines JM. Comparative Effectiveness of Care Coordination Interventions in the Emergency Department: A Systematic Review. *Annals of Emergency Medicine*. 2012;60(1):12-23.e1. doi:10.1016/j.annemergmed.2012.02.025
21. Kim SE, Michalopoulos C, Kwong RM, Warren A, Manno MS. Telephone Care Management's Effectiveness in Coordinating Care for Medicaid Beneficiaries in Managed Care: A Randomized Controlled Study. *Health Services Research*. 2013;48(5):1730-1749. doi:10.1111/1475-6773.12060
22. Lin MP, Blanchfield BB, Kakoza RM, et al. ED-based care coordination reduces costs for frequent ED users. *The American journal of managed care*. 2017;23(12):762-766.

23. Overholser L, Callaway C. Improving Care Coordination to Optimize Health Outcomes in Cancer Survivors. *Journal of the National Comprehensive Cancer Network*. 2019;17(5.5):607-610. doi:10.6004/jnccn.2019.5009
24. Nossel IR, Lee RJ, Isaacs A, Herman DB, Marcus SM, Essock SM. Use of Peer Staff in a Critical Time Intervention for Frequent Users of a Psychiatric Emergency Room. *PS*. 2016;67(5):479-481. doi:10.1176/appi.ps.201500503
25. O'Toole TP, Buckel L, Bourgault C, et al. Applying the Chronic Care Model to Homeless Veterans: Effect of a Population Approach to Primary Care on Utilization and Clinical Outcomes. *Am J Public Health*. 2010;100(12):2493-2499. doi:10.2105/AJPH.2009.179416
26. Tomasone JR, Brouwers MC, Vukmirovic M, et al. Interventions to improve care coordination between primary healthcare and oncology care providers: a systematic review. *ESMO Open*. 2016;1(5):e000077. doi:10.1136/esmoopen-2016-000077
27. Tricco AC, Antony J, Ivers NM, et al. Effectiveness of quality improvement strategies for coordination of care to reduce use of health care services: a systematic review and meta-analysis. *CMAJ*. 2014;186(15):E568-E578. doi:10.1503/cmaj.140289
28. Roberts SR, Crigler J, Ramirez C, Sisco D, Early GL. Working With Socially and Medically Complex Patients: When Care Transitions Are Circular, Overlapping, and Continual Rather Than Linear and Finite. *The Journal for Healthcare Quality (JHQ)*. 2015;37(4):245-265. doi:10.1097/JHQ.0000000000000006
29. Vickery KD, Shippee ND, Menk J, et al. Integrated, Accountable Care For Medicaid Expansion Enrollees: A Comparative Evaluation of Hennepin Health. *Med Care Res Rev*. 2018;77(1):46-59. doi:10.1177/1077558718769481

30. Chuang E, Pourat N, Haley LA, O'Masta B, Albertson E, Lu C. Integrating Health And Human Services In California's Whole Person Care Medicaid 1115 Waiver Demonstration. *Health Affairs*. 2020;39(4):639-648. doi:10.1377/hlthaff.2019.01617
31. California Department of Health Care Services. Whole Person Care (WPC) Monthly Cumulative Unique Enrollees Report April 2020 to March 2021. https://www.dhcs.ca.gov/services/Documents/MCQMD/APR20-MAR21-WPC-Monthly-Cumulative-Chart.pdf
32. California Department of Health Care Services. Whole Person Care Program Medi-Cal 2020 Waiver Initiative. Published 2016. https://www.dhcs.ca.gov/provgovpart/Documents/WPCProgramOverview.pdf
33. Pourat N, Chuang E, Chen X, et al. Interim Evaluation of California's Whole Person Care (WPC) Program. Published 2019. Accessed December 13, 2020. https://healthpolicy.ucla.edu/publications/Documents/PDF/2020/wholepersoncare-report-jan2020.pdf
34. McCullough JM, Speer M, Magnan S, Fielding JE, Kindig D, Teutsch SM. Reduction in US Health Care Spending Required to Meet the Institute of Medicine's 2030 Target. *Am J Public Health*. 2020;110(12):1735-1740. doi:10.2105/AJPH.2020.305793
35. Anderson GF, Hussey P, Petrosyan V. It's Still The Prices, Stupid: Why The US Spends So Much On Health Care, And A Tribute To Uwe Reinhardt. *Health Affairs*. 2019;38(1):87-95. doi:10.1377/hlthaff.2018.05144
36. Hartman M, Martin AB, Benson J, Catlin A. National Health Care Spending In 2018: Growth Driven By Accelerations In Medicare And Private Insurance Spending. *Health Affairs*. 2019;39(1):8-17. doi:10.1377/hlthaff.2019.01451

37. Anderson GF, Ballreich J, Bleich S, et al. Attributes common to programs that successfully treat high-need, high-cost individuals. *Am J Manag Care*. 2015;21(11):e597-600.

38. Peck LR. Using Cluster Analysis in Program Evaluation. *Eval Rev*. 2005;29(2):178-196. doi:10.1177/0193841X04266335

39. Vuik SI, Mayer EK, Darzi A. Patient Segmentation Analysis Offers Significant Benefits For Integrated Care And Support. *Health Affairs*. 2016;35(5):769-775. doi:10.1377/hlthaff.2015.1311

40. Rinehart DJ, Oronce C, Durfee MJ, et al. Identifying subgroups of adult super-utilizers in an urban safety-net system using latent class analysis: Implications for clinical practice. *Med Care*. 2018;56(1):e1-e9. doi:10.1097/MLR.0000000000000628

41. Grant RW, McCloskey J, Hatfield M, et al. Use of Latent Class Analysis and k-Means Clustering to Identify Complex Patient Profiles. *JAMA Network Open*. 2020;3(12):e2029068. doi:10.1001/jamanetworkopen.2020.29068

42. Low LL, Yan S, Kwan YH, Tan CS, Thumboo J. Assessing the validity of a data driven segmentation approach: A 4 year longitudinal study of healthcare utilization and mortality. *PLoS One*. 2018;13(4):e0195243. doi:10.1371/journal.pone.0195243

43. Ng SCW, Kwan YH, Yan S, Tan CS, Low LL. The heterogeneous health state profiles of high-risk healthcare utilizers and their longitudinal hospital readmission and mortality patterns. *BMC Health Serv Res*. 2019;19(1):931. doi:10.1186/s12913-019-4769-7

44. Nnoaham KE, Cann KF. Can cluster analyses of linked healthcare data identify unique population segments in a general practice-registered population? *BMC Public Health*. Published online 2020. doi:10.1186/s12889-020-08930-z

45. Vuik SI, Mayer E, Darzi A. A quantitative evidence base for population health: applying utilization-based cluster analysis to segment a patient population. *Popul Health Metrics*. 2016;14(1):44. doi:10.1186/s12963-016-0115-z

46. Vuik SI, Mayer E, Darzi A. Enhancing risk stratification for use in integrated care: a cluster analysis of high-risk patients in a retrospective cohort study. *BMJ Open*. 2016;6(12):e012903. doi:10.1136/bmjopen-2016-012903

47. Yan S, Seng BJJ, Kwan YH, et al. Identifying heterogeneous health profiles of primary care utilizers and their differential healthcare utilization and mortality – a retrospective cohort study. *BMC Fam Pract*. 2019;20(1):54. doi:10.1186/s12875-019-0939-2

48. Nuti SV, Doupe P, Villanueva B, Scarpa J, Bruzelius E, Baum A. Characterizing Subgroups of High-Need, High-Cost Patients Based on Their Clinical Conditions: a Machine Learning-Based Analysis of Medicaid Claims Data. *J GEN INTERN MED*. 2019;34(8):1406-1408. doi:10.1007/s11606-019-04941-8

49. Whitson HE, Johnson KS, Sloane R, et al. Identifying Patterns of Multimorbidity in Older Americans: Application of Latent Class Analysis. *Journal of the American Geriatrics Society*. 2016;64(8):1668-1673. doi:https://doi.org/10.1111/jgs.14201

50. Davis AC, Shen E, Shah NR, et al. Segmentation of High-Cost Adults in an Integrated Healthcare System Based on Empirical Clustering of Acute and Chronic Conditions. *J GEN INTERN MED*. 2018;33(12):2171-2179. doi:10.1007/s11606-018-4626-0

51. Birmingham LE, Cheruvu VK, Frey JA, Stiffler KA, VanGeest J. Distinct subgroups of emergency department frequent users: A latent class analysis. *The American Journal of Emergency Medicine*. 2020;38(1):83-88. doi:10.1016/j.ajem.2019.04.029

52. Yan S, Kwan YH, Tan CS, Thumboo J, Low LL. A systematic review of the clinical application of data-driven population segmentation analysis. *BMC Med Res Methodol*. 2018;18(1):121. doi:10.1186/s12874-018-0584-9

53. Patel E, Kushwaha DS. Clustering Cloud Workloads: K-Means vs Gaussian Mixture Model. *Procedia Computer Science*. 2020;171:158-167. doi:10.1016/j.procs.2020.04.017

54. Pham DT, Dimov SS, Nguyen CD. Selection of K in K-means clustering: *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*. Published online August 11, 2016. doi:10.1243/095440605X8298

55. Magidson J, Vermunt J. Latent class models for clustering: A comparison with K-means. Canadian J Mark Res. *Professional Marketing Research Society*. 2002;20:36-43.

56. RStudio, Inc. *RStudio: Integrated Development for R.* https://rstudio.com/

57. Muthen & Muthen. *Mplus*. https://www.statmodel.com/

58. Centers for Medicare & Medicaid Services. *Chronic Conditions Data Warehouse Condition Categories*.; 2021. https://www2.ccwdata.org/web/guest/condition-categories

59. Asparouhov T, Muthen B. *Random Starting Values and Multistage Optimization*.; 2019. Accessed November 28, 2021. https://www.statmodel.com/download/StartsUpdate.pdf

60. Crowe AV, Howse M, Bell GM, Henry JA. Substance abuse and the kidney. *QJM: An International Journal of Medicine*. 2000;93(3):147-152. doi:10.1093/qjmed/93.3.147

61. Davern TJ. Drug-Induced Liver Disease. *Clinics in Liver Disease*. 2012;16(2):231-245. doi:10.1016/j.cld.2012.03.002

62. Grafe CJ, Horth RZ, Clayton N, Dunn A, Forsythe N. How to Classify Super-Utilizers: A Methodological Review of Super-Utilizer Criteria Applied to the Utah Medicaid Population,

2016–2017. *Population Health Management*. 2020;23(2):165-173. doi:10.1089/pop.2019.0076

63. Jiang HJ, Weiss AJ, Barrett ML. Characteristics of Emergency Department Visits for Super-Utilizers by Payer, 2014: Statistical Brief #221. In: *Healthcare Cost and Utilization Project (HCUP) Statistical Briefs*. Agency for Healthcare Research and Quality (US); 2006. Accessed February 10, 2022. http://www.ncbi.nlm.nih.gov/books/NBK442038/
64. Kaltenborn Z, Paul K, Kirsch JD, et al. Super fragmented: a nationally representative cross-sectional study exploring the fragmentation of inpatient care among super-utilizers. *BMC Health Services Research*. 2021;21(1):338. doi:10.1186/s12913-021-06323-5
65. Nylund-Gibson K, Choi AY. Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science*. 2018;4(4):440-461. doi:10.1037/tps0000176
66. Limon FJ, Lamson AL, Hodgson J, Bowler M, Saeed S. Screening for Depression in Latino Immigrants: A Systematic Review of Depression Screening Instruments Translated into Spanish. *J Immigrant Minority Health*. 2016;18(4):787-798. doi:10.1007/s10903-015-0321-y
67. Weller BE, Bowen NK, Faubert SJ. Latent Class Analysis: A Guide to Best Practice. *Journal of Black Psychology*. 2020;46(4):287-311. doi:10.1177/0095798420930932
68. Hwang SW, Bugeja AL. Barriers to appropriate diabetes management among homeless people in Toronto. *CMAJ*. 2000;163(2):161-165.
69. Kanzaria HK, Niedzwiecki MJ, Montoy JC, Raven MC, Hsia RY. Persistent Frequent Emergency Department Use: Core Group Exhibits Extreme Levels Of Use For More Than A Decade. *Health Affairs*. 2017;36(10):1720-1728. doi:10.1377/hlthaff.2017.0658

70. Ng SHX, Rahman N, Ang IYH, et al. Characterization of high healthcare utilizer groups using administrative data from an electronic medical record database. *BMC Health Services Research*. 2019;19(1):452. doi:10.1186/s12913-019-4239-2

71. Zhang Y, Khullar D, Wu Y, Casalino LP, Kaushal R. Identifying Patients with Persistent Preventable Utilization Offers an Opportunity to Reduce Unnecessary Spending. *J GEN INTERN MED*. 2020;35(12):3534-3541. doi:10.1007/s11606-020-06068-7

72. Bauer DJ. Observations on the Use of Growth Mixture Models in Psychological Research. *Multivariate Behavioral Research*. 2007;42(4):757-786. doi:10.1080/00273170701710338

73. Frankfurt S, Frazier P, Syed M, Jung KR. Using Group-Based Trajectory and Growth Mixture Modeling to Identify Classes of Change Trajectories. *The Counseling Psychologist*. 2016;44(5):622-660. doi:10.1177/0011000016658097

74. Harring JR, Hodis FA. Mixture Modeling: Applications in Educational Psychology. *Educational Psychologist*. 2016;51(3-4):354-367. doi:10.1080/00461520.2016.1207176

75. Lanza ST, Cooper BR. Latent Class Analysis for Developmental Research. *Child Development Perspectives*. 2016;10(1):59-64. doi:https://doi.org/10.1111/cdep.12163

76. Musliner KL, Munk-Olsen T, Eaton WW, Zandi PP. Heterogeneity in long-term trajectories of depressive symptoms: Patterns, predictors and outcomes. *Journal of Affective Disorders*. 2016;192:199-211. doi:10.1016/j.jad.2015.12.030

77. Nagin DS, Odgers CL. Group-Based Trajectory Modeling in Clinical Research. *Annual Review of Clinical Psychology*. 2010;6(1):109-138. doi:10.1146/annurev.clinpsy.121208.131413

78. Ben-Assuli O, Padman R, Shabtai I. Exploring trajectories of emergency department visits using a laboratory-based indicator of serious illness. *Health Informatics J*. 2020;26(1):205-217. doi:10.1177/1460458218824751

79. Daoust R, Paquet J, Cournoyer A, et al. Acute Pain Resolution After an Emergency Department Visit: A 14-Day Trajectory Analysis. *Annals of Emergency Medicine*. 2019;74(2):224-232. doi:10.1016/j.annemergmed.2019.01.019

80. De Rubeis V, Andreacchi AT, Sharpe I, Griffith LE, Keown-Stoneman CDG, Anderson LN. Group-based trajectory modeling of body mass index and body size over the life course: A scoping review. *Obesity Science & Practice*. 2021;7(1):100-128. doi:10.1002/osp4.456

81. Hebert JJ, Abraham E, Wedderkopp N, et al. Patients undergoing surgery for lumbar spinal stenosis experience unique courses of pain and disability: A group-based trajectory analysis. *PLOS ONE*. 2019;14(11):e0224200. doi:10.1371/journal.pone.0224200

82. Knight EP, Shea K, Rosenfeld AG, Schmiege S, Hsu CH, DeVon HA. Symptom Trajectories Following an Emergency Department Visit for Potential Acute Coronary Syndrome. *Nurs Res*. 2016;65(4):268-278. doi:10.1097/NNR.0000000000000167

83. Mattsson M, Maher GM, Boland F, Fitzgerald AP, Murray DM, Biesma R. Group-based trajectory modelling for BMI trajectories in childhood: A systematic review. *Obesity Reviews*. 2019;20(7):998-1015. doi:10.1111/obr.12842

84. Shen Y, Chen D, Huang X, et al. Novel phenotypes of coronavirus disease: a temperature-based trajectory model. *Annals of Intensive Care*. 2021;11(1):121. doi:10.1186/s13613-021-00907-4

85. Franklin JM, Shrank WH, Pakes J, et al. Group-based Trajectory Models: A New Approach to Classifying and Predicting Long-Term Medication Adherence. *Medical Care*. 2013;51(9):789-796.

86. Librero J, Sanfélix-Gimeno G, Peiró S. Medication Adherence Patterns after Hospitalization for Coronary Heart Disease. A Population-Based Study Using Electronic Records and Group-Based Trajectory Models. *PLOS ONE*. 2016;11(8):e0161381. doi:10.1371/journal.pone.0161381

87. Vadhariya A, Fleming ML, Johnson ML, et al. Group-Based Trajectory Models to Identify Sociodemographic and Clinical Predictors of Adherence Patterns to Statin Therapy Among Older Adults. *Am Health Drug Benefits*. 2019;12(4):202-211.

88. Chien TY, Lee ML, Wu WL, Ting HW. Exploration of Medical Trajectories of Stroke Patients Based on Group-Based Trajectory Modeling. *International Journal of Environmental Research and Public Health*. 2019;16(18):3472. doi:10.3390/ijerph16183472

89. Davis MA, Nallamothu BK, Banerjee M, Bynum JPW. Identification Of Four Unique Spending Patterns Among Older Adults In The Last Year Of Life Challenges Standard Assumptions. *Health Affairs*. 2016;35(7):1316-1323. doi:10.1377/hlthaff.2015.1419

90. Hansen AV, Mortensen LH, Trompet S, Westendorp R. Health care expenditure in the last five years of life is driven by morbidity, not age: A national study of spending trajectories in Danish decedents over age 65. *PLOS ONE*. 2020;15(12):e0244061. doi:10.1371/journal.pone.0244061

91. Jiang J, Click B, Anderson AM, et al. Group-Based Trajectory Modeling of Healthcare Financial Charges in Inflammatory Bowel Disease: A Comprehensive Phenotype. *Clin Transl Gastroenterol*. 2016;7(7):e181. doi:10.1038/ctg.2016.39

92. O'Hare AM, Hailpern SM, Wachterman M, et al. Hospice Use And End-Of-Life Spending Trajectories In Medicare Beneficiaries On Hemodialysis. *Health Affairs*. 2018;37(6):980-987. doi:10.1377/hlthaff.2017.1181

93. Wodchis WP, Arthurs E, Khan AI, Gandhi S, MacKinnon M, Sussman J. Cost Trajectories for Cancer Patients. *Current Oncology*. 2016;23(s1):64-75. doi:10.3747/co.23.2995

94. Wong ES, Yoon J, Piegari RI, Rosland AMM, Fihn SD, Chang ET. Identifying Latent Subgroups of High-Risk Patients Using Risk Score Trajectories. *J GEN INTERN MED*. 2018;33(12):2120-2126. doi:10.1007/s11606-018-4653-x

95. Ankuda CK, Ornstein KA, Kelley AS. Assessing health care use trajectories after the onset of functional disability: application of a Group-Based Trajectory Model. *The Journals of Gerontology: Series B*. Published online January 16, 2022:gbab233. doi:10.1093/geronb/gbab233

96. Srivastava A, Cai X, Mehta R, et al. Hospitalization Trajectories and Risks of ESKD and Death in Individuals With CKD. *Kidney International Reports*. 2021;6(6):1592-1602. doi:10.1016/j.ekir.2021.03.883

97. Nguena Nguefack HL, Pagé MG, Katz J, et al. Trajectory Modelling Techniques Useful to Epidemiological Research: A Comparative Narrative Review of Approaches. *Clin Epidemiol*. 2020;12:1205-1222. doi:10.2147/CLEP.S265287

98. Berlin KS, Parra GR, Williams NA. An Introduction to Latent Variable Mixture Modeling (Part 2): Longitudinal Latent Class Growth Analysis and Growth Mixture Models. *Journal of Pediatric Psychology*. 2014;39(2):188-203. doi:10.1093/jpepsy/jst085

99. Jung T, Wickrama K a. S. An Introduction to Latent Class Growth Analysis and Growth Mixture Modeling. *Social and Personality Psychology Compass*. 2008;2(1):302-317. doi:10.1111/j.1751-9004.2007.00054.x

100. Ram N, Grimm KJ. Methods and Measures: Growth mixture modeling: A method for identifying differences in longitudinal change among unobserved groups. *International Journal of Behavioral Development*. 2009;33(6):565-576. doi:10.1177/0165025409343765

101. Wang M, Bodner TE. Growth Mixture Modeling: Identifying and Predicting Unobserved Subpopulations With Longitudinal Data. *Organizational Research Methods*. 2007;10(4):635-656. doi:10.1177/1094428106289397

102. Grimm KJ, Ram N, Estabrook R. Nonlinear Structured Growth Mixture Models in Mplus and OpenMx. *Multivariate Behavioral Research*. 2010;45(6):887-909. doi:10.1080/00273171.2010.531230

103. Grimm KJ, Ram N, Hamagami F. Nonlinear Growth Curves in Developmental Research. *Child Development*. 2011;82(5):1357-1371. doi:10.1111/j.1467-8624.2011.01630.x

104. Grimm KJ, Stegmann G. Modeling change trajectories with count and zero-inflated outcomes: Challenges and recommendations. *Addictive Behaviors*. 2019;94:4-15. doi:10.1016/j.addbeh.2018.09.016

105. Sterba SK. Understanding Linkages Among Mixture Models. *Multivariate Behavioral Research*. 2013;48(6):775-815. doi:10.1080/00273171.2013.827564

106. Soloski KL, Durtschi JA. Identifying Different Ways People Change: A Latent Basis Growth Mixture Model Example Identifying Nonlinear Trajectories of Binge Drinking. *Journal of Marital and Family Therapy*. 2020;46(4):638-660. doi:10.1111/jmft.12382

107. Green JA. Too many zeros and/or highly skewed? A tutorial on modelling health behaviour as count data with Poisson and negative binomial regression. *Health Psychology and Behavioral Medicine*. 2021;9(1):436-455. doi:10.1080/21642850.2021.1920416

108. Chuang E, O'Masta B, Albertson EM, Haley LA, Lu C, Pourat N. *Whole Person Care Improves Care Coordination for Many Californians*. UCLA Center for Health Policy Research; 2019. https://healthpolicy.ucla.edu/publications/Documents/PDF/2019/wholepersoncare-policybrief-sep2019.pdf

109. Knighton AJ, Stephenson B, Savitz LA. Measuring the Effect of Social Determinants on Patient Outcomes: A Systematic Literature Review. *Journal of Health Care for the Poor and Underserved*. 2018;29(1):81-106. doi:10.1353/hpu.2018.0009

110. Sterling S, Chi F, Weisner C, et al. Association of behavioral health factors and social determinants of health with high and persistently high healthcare costs. *Preventive Medicine Reports*. 2018;11:154-159. doi:10.1016/j.pmedr.2018.06.017

111. Gelberg L, Andersen RM, Leake BD. The behavioral model for vulnerable populations: Application to medical care use and outcomes for homeless people. *Health Serv Res*. 2000;34(6):1273-1302.

112. Gottlieb LM, Wing H, Adler NE. A Systematic Review of Interventions on Patients' Social and Economic Needs. *American Journal of Preventive Medicine*. 2017;53(5):719-729. doi:10.1016/j.amepre.2017.05.011

113. Gottlieb LM, Garcia K, Wing H, Manchanda R. Clinical interventions addressing nonmedical health determinants in Medicaid managed care. *Am J Manag Care*. 2016;22(5):370-376.

114. Albertson EM, Chuang E, O'Masta B, Miake-Lye I, Haley LA, Pourat N. Systematic Review of Care Coordination Interventions Linking Health and Social Services for High-Utilizing Patient Populations. *Population Health Management*. 2022;25(1):73-85. doi:10.1089/pop.2021.0057

115. Fichtenberg C, Delva J, Minyard K, Gottlieb LM. Health And Human Services Integration: Generating Sustained Health And Equity Improvements. *Health Affairs*. 2020;39(4):567-573. doi:10.1377/hlthaff.2019.01594

116. Petchel S, Gelmon S, Goldberg B. The Organizational Risks Of Cross-Sector Partnerships: A Comparison Of Health And Human Services Perspectives. *Health Affairs*. 2020;39(4):574-581. doi:10.1377/hlthaff.2019.01553

117. Berkowitz SA, Brown P, Brotman DJ, et al. Case Study: Johns Hopkins Community Health Partnership: A model for transformation. *Healthcare*. 2016;4(4):264-270. doi:10.1016/j.hjdsi.2016.09.001

118. Frank JW, Linder JA, Becker WC, Fiellin DA, Wang EA. Increased hospital and emergency department utilization by individuals with recent criminal justice involvement: Results of a national survey. *J GEN INTERN MED*. 2014;29(9):1226-1233. doi:10.1007/s11606-014-2877-y

119. Miller SC, Kinzbrunner B, Pettit P, Williams JR. How does the timing of hospice referral influence hospice care in the last days of life? *J Am Geriatr Soc*. 2003;51(6):798-806. doi:10.1046/j.1365-2389.2003.51253.x

120. Lantz PM. "Super-Utilizer" Interventions: What They Reveal About Evaluation Research, Wishful Thinking, and Health Equity. *The Milbank Quarterly*. 2020;98(1). doi:10.1111/1468-0009.12449

121. Linden A. Assessing regression to the mean effects in health care initiatives. *BMC Medical Research Methodology*. 2013;13(1):119. doi:10.1186/1471-2288-13-119

122. Horn BP, Crandall CS, Binder DS, Sklar DP. What Happens to High-Cost Patients? An Analysis of the Trajectories of Billed Charges Over Time. *Population Health Management*. 2017;20(5):362-367. doi:10.1089/pop.2016.0149

123. Saeed S, Moodie EEM, Strumpf EC, Klein MB. Segmented generalized mixed effect models to evaluate health outcomes. *Int J Public Health*. 2018;63(4):547-551. doi:10.1007/s00038-018-1091-9

124. Turner SL, Karahalios A, Forbes AB, Taljaard M, Grimshaw JM, McKenzie JE. Comparison of six statistical methods for interrupted time series studies: empirical evaluation of 190 published series. *BMC Medical Research Methodology*. 2021;21(1):134. doi:10.1186/s12874-021-01306-w

125. Maura J, Weisman de Mamani A. Mental Health Disparities, Treatment Engagement, and Attrition Among Racial/Ethnic Minorities with Severe Mental Illness: A Review. *J Clin Psychol Med Settings*. 2017;24(3):187-210. doi:10.1007/s10880-017-9510-2

126. Mauvais-Jarvis F, Bairey Merz N, Barnes PJ, et al. Sex and gender: modifiers of health, disease, and medicine. *The Lancet*. 2020;396(10250):565-582. doi:10.1016/S0140-6736(20)31561-0

127. Clemans-Cope L, Wishner JB, Allen EH, Lallemand N, Epstein M, Spillman BC. Experiences of three states implementing the Medicaid health home model to address opioid use disorder—Case studies in Maryland, Rhode Island, and Vermont. *Journal of Substance Abuse Treatment*. 2017;83:27-35. doi:10.1016/j.jsat.2017.10.001

128. Kennedy-Hendricks A, Daumit GL, Choksy S, Linden S, McGinty EE. Measuring Variation Across Dimensions of Integrated Care: The Maryland Medicaid Health Home Model. *Adm Policy Ment Health*. 2018;45(6):888-899. doi:10.1007/s10488-018-0871-0

129. McGinty EE, Kennedy-Hendricks A, Linden S, Choksy S, Stone E, Daumit GL. An innovative model to coordinate healthcare and social services for people with serious mental illness: A mixed-methods case study of Maryland's Medicaid health home program. *General Hospital Psychiatry*. 2018;51:54-62. doi:10.1016/j.genhosppsych.2017.12.003

130. Linden A. Conducting Interrupted Time-series Analysis for Single- and Multiple-group Comparisons. *The Stata Journal*. 2015;15(2):480-500. doi:10.1177/1536867X1501500208

131. California Department of Health Care Services. CalAIM Enhanced Care Management and Community Supports Frequently Asked Questions (FAQ). Published online 2022. https://www.dhcs.ca.gov/Documents/MCQMD/ECM-Community-Supports-FAQ.pdf

132. Blewett LA, Owen RA. Accountable Care for the Poor and Underserved: Minnesota's Hennepin Health Model. *Am J Public Health*. 2015;105(4):622-624. doi:10.2105/AJPH.2014.302432

133. Sandberg SF, Erikson C, Owen R, et al. Hennepin Health: A Safety-Net Accountable Care Organization For The Expanded Medicaid Population. *Health Affairs*. 2014;33(11):1975-1984. doi:10.1377/hlthaff.2014.0648

134. Vickery KD, Shippee ND, Guzman-Corrales LM, et al. Changes in Quality of Life Among Enrollees in Hennepin Health: A Medicaid Expansion ACO. *Med Care Res Rev*. 2018;77(1):60-73. doi:10.1177/1077558718769457

135. California Department of Health Care Services. Enhanced Care Management (ECM). Published online 2021. https://www.dhcs.ca.gov/Documents/MCQMD/ECM-Key-Design-Implementation-Decisions-05252021.pdf