The effect of social risk and social support on pain severity and nonpharmacologic therapy utilization under Oregon Medicaid’s Back and Neck Pain policy

Morgan Justice

Health Systems and Policy Dissertation

OHSU-PSU School of Public Health

4 August 2025

Contents

Chapter 1: Problem Statement

1.0 Introduction

Chronic pain is one of the most common reasons adults seek medical care in the United States.[1–4] It is defined by epidemiologists as pain that lasts for at least three months as this characterization has been determined to be a reasonable metric for pain persisting past the normal time for tissue healing.[5] Prevalence estimates vary, but approximately 20% of US adults are living with chronic pain, with higher rates among certain subgroups, including those who have lower socio-economic status, older adults, women, rural residents, and those on public health insurance.[1] Chronic pain has substantial personal, societal, and economic costs including increased dependence on opioids, poor mental health, and contributes an estimated $560 billion each year in direct medical costs, lost productivity, and disability program-costs.[4] Chronic pain is the leading cause of disability in the US and treatment is rarely effective at substantially reducing or ameliorating the pain itself even when functional improvements are achieved.[6–8]

Chronic pain is a complex condition and is best understood through the biopsychosocial framework.[3] Psychological and social factors are often at least as important as underlying biological factors, greatly influencing the physical manifestations and treatment response to chronic pain. Among those influences, psychosocial conditions, such as depression, pain catastrophizing, and fear avoidance beliefs, are the most potent predictors of chronic pain and chronic pain-related disability, though most variation in explaining these outcomes remains unmeasured.[9] Nevertheless, the majority of readily available and insurance-covered treatment options have focused on somewhat narrow biomedical remediation via opioid therapies, steroid and other epidural injections, and spinal surgeries. Recently, there has been a shift to considering a whole person approach, incorporating psychological-based approaches as well as additional non-pharmacologic physical and biology-based approaches.[3,7,10–13]

There are many types of chronic pain, including fibromyalgia, chronic pain due to trauma, general chronic pain syndrome, chronic neck pain, and chronic back pain. Of these, chronic low back pain is the most prevalent and the leading cause of disability worldwide.[9] Chronic back pain is a nociceptive condition, meaning it is not possible in most cases to identify a specific source of the pain. [9] However, chronic back pain can be exacerbated by psychosocial conditions, such as anxiety or depression,[9,14] and by working conditions that require repetitive manual labor with little opportunity for modification.[9] Those with a lower socioeconomic status (SES) are overrepresented in jobs requiring manual labor, which can exacerbate existing inequities related to chronic pain outcomes and further increase poverty if people are forced out of the workforce due to their pain.[9,15]

While treatment options for chronic pain increasingly address psychosocial contributors, social contributors are not as well understood. Better understanding social contributors to chronic pain may offer insight into the origins of inequities in chronic pain outcomes and may help to explain unmeasured variation in chronic pain outcomes. Focusing on the social mechanisms of inequity in pain outcomes or access to treatment can inform policy interventions aimed at increasing health equity.[16]

Health equity is defined as the absence of avoidable or remediable differences in health among groups of people with different levels of advantages or disadvantages.[17] The definition of health equity assumes that the differences are avoidable, therefore, public policy is one avenue to pursue remediation.[17] Medicaid policies, specifically, deserve attention because certain Medicaid policies have the potential to improve health equity at the population level through creating accessible, high quality, and low-cost care for a large population of low-income individuals who often face health inequities. Additionally, the structure and organization of Medicaid policies differ by state, leading to the ability to compare the implementation and effects across various states. However, by focusing within the traditional boundaries of healthcare policy and the healthcare system (e.g., access to medical care), certain Medicaid policies may not address upstream, social determinants of health, or effectively address health outcomes.

In this dissertation I focused on the Oregon Back and Neck Pain policy, a Medicaid payer strategy introduced in 2016, which sought to increase access to nonpharmacologic treatment (NPT) services while minimizing the use of opioid treatment. [18] The policy consisted of two guidelines: reimbursing providers for NPT while simultaneously requiring the de-prescribing of opioids.[19] While financing NPT for pain is a critical policy lever for extending access to treatments for chronic pain, the policy does not explicitly contain additional levers to increase equity among the most socially at risk.

The Oregon Back and Neck Pain policy focuses on back and neck pain and does not address the many other types of chronic pain. In this dissertation, I limited my focus to chronic back and neck pain, though the majority of the literature is on chronic back pain. In the following sections, I describe existing treatment options for chronic pain, how chronic pain rose to the national agenda and led to the Oregon Back and Neck Pain policy, inequities in chronic pain outcomes, and a conceptual model of health equity concepts. I then present the theoretical foundation for the research, the research question and aims, and finally, the purpose and significance of this work.

1.1 Treatment Options for Chronic Pain

1.1.0 Opioids and Other Biomedical Treatments

Over the past several decades, the primary method for treating chronic pain in the US has been through a narrow focus on biomedical treatments, such as epidural injections, surgeries, prescription opioids, and other drugs such as non-steroidal anti-inflammatory drugs (NSAIDs). Among the most common and controversial of pain-related care has been opioid treatment.[20,21] This is the result of several factors. First, chronic pain is primarily treated by primary care physicians (PCPs), where appointment times have been shortened over time leaving opioids as a relatively quick solution for treatment.[22,23] Additionally, physicians faced mounting pressure to avoid undertreatment of chronic pain at a time when the identification and prevalence of chronic pain was increasing in the US population. [1,10,12,13] Opioids are inexpensive and generally covered under most insurance plans resulting in a treatment option that has high accessibility for most patients.[23] The liberalization of laws governing opioids across states and aggressive pharmaceutical marketing also contributed to the increased availability of and prescribing of opioids.[24,25] Finally, opioids were believed to be the most efficacious way to reduce or manage pain, despite the extremely limited evidence of their efficacy.[20,21,26,27]

As opioid use for the treatment of chronic pain escalated, limitations in its efficacy and adverse effects became evident.[12,13] At the same time, opioid dependence and addiction greatly increased, leading to the current opioid epidemic.[10–13] Opioid addiction, overdose, and deaths catalyzed physicians, researchers, and policy-makers to recognize the significant risks and concerns about using opioids as the first line treatment for chronic pain. This has led to the proliferation of research and policy development on NPT for chronic pain.[3,4]

1.1.1 Non-pharmacologic Treatments

The National Academies of Science[28] and National Pain Strategy (NPS)[29] reports recommend that the management of chronic pain be integrated, multimodal, interdisciplinary, evidence-based, and tailored to individual patient needs. Psychosocial needs, in addition to biological factors, are the strongest predictors of pain chronicity and pain-related disability,[3,30–32] thus deserving consideration when determining appropriate treatment.[3,26,29] NPTs for chronic pain include exercise and physical therapy, mind-body practices (e.g., Tai Chi, yoga), psychological therapies (e.g., cognitive behavioral therapy [CBT], acceptance and commitment therapy, and relaxation techniques), mindfulness practices, acupuncture, osteopathic medicine, spinal manipulation therapy, and various physical modalities (e.g., traction, superficial heat or cold, bracing, transcutaneous electrical nerve stimulation). NPTs shift the focus from prioritizing pain reduction to improving functioning and quality of life.[3,26] The choice of NPT is driven both by availability and the type and severity of chronic pain. In addition to each of these therapies, many of those suffering from chronic pain report relief with anti-inflammatory and related dietary practices although research support for such approaches is nascent.[3,33]

Although embraced by many patients and their PCPs alike, this shift away from opioids and towards NPT poses a major challenge for PCPs who are overseeing and coordinating the care of patients with chronic pain. Challenges include serving diverse populations with varying levels of access to and comfort with NPT, lack of reimbursement strategies to support NPTs, and lack of availability of evidence-based treatment options;[3,28] however, there is little evidence that opioids and other biomedical treatments are as effective or have a sustained impact when compared to NPT for chronic pain in achieving sustained functional improvements for patients with chronic pain.[20,27] The magnitude of the problem of chronic pain, opioid use, and the lack of availability of evidence-based resources requires multiple sectors (e.g., policy, research, and health systems) to come together to seek solutions to guide clinical and policy decision-making.

1.2 Policies Aimed at Addressing Chronic Pain Treatment

By the mid-2010s, many national organizations and task forces, including the NIH National Pain Strategy task force, National Academy of Medicine, the CDC, The Joint Commission, the FDA, and the American College of Physicians all released guidelines, statements, or recommendations indicating that evidence-based, comprehensive pain treatment options should be implemented. They also acknowledged that the reliance on opioid therapy as the primary method of treatment did not remedy the problem of chronic pain, but rather exacerbated it as well as created other problems like increased mortality risk, addiction, and disability.[26] In 2016, the National Academy for State Health Policy showed that only 12 states had implemented Medicaid policy changes to encourage the use of NPT.[34] Among Medicaid, Medicare, and commercial insurance plans, Heyward et al. found that most plans covered chiropractic, physical therapy, and occupational therapy, but most did not provide coverage for acupuncture or other NPT treatments such as evidence-based pain-specific psychotherapy approaches.[35]

In response to these national recommendations, the State of Oregon enacted a Medicaid payer strategy, the Oregon Back and Neck Pain policy, through the Oregon Health Plan (OHP) in 2016. This policy was designed to enhance access to safe, evidence-based NPT options, including pain-specific psychotherapy approaches,[18] while restricting reimbursement for opioids for back and neck pain and increasing required safety measures when opioids were prescribed.[19] The policy was made up of two guidelines aimed at: (1) reducing initiation of or encouraging tapering opioid therapy and (2) increasing the availability and use of NPT for chronic back and neck pain through provider reimbursement for previously uncovered NPT options. The primary goal of the policy was not cost-savings, but rather more effective management of chronic back and neck pain via a broad set of NPT treatments among the Medicaid population.[36]

The policy suggested stratifying patients into three pain-related disability risk categories – low-, medium-, or high-risk – based on patient responses to the STarT Back Assessment Tool which asks patients about pain-related functioning and concerns.[37] The STarT Back Assessment Tool is a validated assessment used to determine risk level for poor functional prognosis based on psychosocial indicators.[37] This risk stratification encouraged Oregon's coordinated care organizations (CCOs) to target more intensive NPT services to those patients with the greatest need, though CCOs were not required to implement the policy in this way. For those considered low-risk, the policy allowed for pharmacotherapy limited to NSAIDs, acetaminophen, or muscle relaxants and NPT options limited to four or fewer visits per year of osteopathic or chiropractic manipulative therapy, acupuncture, and/or physical or occupational therapy. For those in the medium- and high-risk categories, they were allowed NSAIDs, acetaminophen, muscle relaxants and additionally opioid medications *if* not used as a first line treatment option and prescribed with evidence of a referral to one or more of the NPT options. The policy originally limited opioid prescriptions to no more than a 90-day supply and restricted epidural steroid injections. The medium- and high-risk groups were allowed opioid pharmacotherapy if used in conjunction with up to 30 visits per year of any combination of the following NPTs: cognitive behavioral therapy, rehabilitative therapy, osteopathic or chiropractic manipulative therapy, acupuncture, yoga, massage, supervised exercise therapy, and/or intensive interdisciplinary rehabilitation.

Table 1. Oregon Back and Neck Pain Policy: Recommended Stratification using STarT Back Tool^

Low-risk	**Medium- and High-risk**
Pharmacotherapy: Limited to NSAIDs, acetaminophen, or muscle relaxants	Pharmacotherapy: NSAIDs, acetaminophen, or muscle relaxants plus opioid medications if used in conjunction with NPT
Non-pharmacotherapy: ≤ 4 visits per year Osteopathic or chiropractic manipulative therapy, acupuncture, and/or physical or occupational therapy	Non-pharmacotherapy: ≤ 30 visits per year Cognitive behavioral therapy, rehabilitative therapy, osteopathic or chiropractic manipulative therapy, acupuncture, yoga, massage, supervised exercise

	therapy, and/or intensive interdisciplinary rehabilitation

ˆNot reimbursed: Opioids used as a first line treatment option, opioids not prescribed in conjunction with NPT, opioids prescribed for >90 day supply, or epidural injections.

In 2018, the Health Evidence Review Commission (HERC) was presented with a proposal to amend the policy to expand coverage beyond back and neck pain to include five additional types of pain: chronic pain due to trauma, chronic postprocedural pain, chronic pain syndrome, other chronic pain, and fibromyalgia. In 2019, the HERC decided not to include the additional five types of chronic pain, leaving the policy limited to chronic back and neck pain.[38] They also formally voted to remove the opioid tapering requirement from the policy, saying that the decision to taper off opioids should be made between the provider and patient on an individualized basis.[39] They cited public pressure and an external review of the evidence that had been conducted to understand the effectiveness of opioid therapy in the treatment of chronic pain.

While the goals of the policy followed best practices, the policy itself did not contain specific implementation guidelines, resulting in varied implementation of the policy across Oregon CCOs. Based on conversations with the PI of the parent study on which this dissertation is based, described below, challenges included opioid tapering being complicated by prior Oregon Medicaid policies that dictated opioid prescribing, epidural steroid injections never fully being restricted, lack of understanding or knowledge of the STarT Back assessment tool resulting in no rigorous risk stratification, among others.[40]

1.3 Inequities in Chronic Pain

Racial, ethnic, social economic status (SES), language proficiency, education, and geographic inequities in reported pain, response, and access to treatment are well documented throughout the literature, but evidence on the *mechanisms* underlying these inequities is lacking.[41–43] Patients living in poverty; Black, Indigenous, and other people of color (BIPOC); women; and the elderly are more likely to report more severe pain and pain-related disability than other patients.[44–46] In addition to having worse pain outcomes, people living in poverty, BIPOC, and the elderly also have higher rates of psychiatric and clinical comorbidities and psychological distress which are important mediators in pain-related outcomes.[45–48] Beyond biological and psychosocial contributors to pain, BIPOC people and people of any race living in poverty are more likely to be un- or underinsured, delay seeking care, experience care in a fragmented or uncoordinated way, and have worse treatment outcomes.[49] They are also more likely to work in professions that require repetitive physical movements which can lead to or further exacerbate chronic back pain.[9]

In a study of NPT use before and after the implementation of the Oregon Back and Neck Pain policy, Choo et al.[50] found that while there was a 23% increase in overall utilization of NPT, Black, American Indian/Alaskan Native, and Hispanic patients were less likely than white patients to access NPT. Additionally, those living in urban areas and the elderly were more likely to access NPT compared to those who lived in rural areas or were younger.[50] These results indicate that there are disparities in the level of access afforded by the policy, but do not explore potential mechanisms that may be driving the inequities.

Social inequities are important not only in considering access to and utilization of pain treatments, but also because these inequities act as stressors that can exacerbate psychosocial conditions, many of which have been shown to lead to increased pain severity and reduced functioning.[30] Increased pain severity or disability can then lead to further un- or under-employment, emotional distress, and reduced mobility, creating a positive feedback loop that could lead to more inequities.[9] While the literature thoroughly documents that there are racial, ethnic, and SES inequities in chronic pain (and a separate body of literature explains the role of psychosocial conditions in exacerbating chronic pain), a gap exists in theoretically and empirically linking the ways that social inequities may be associated with chronic pain.

1.4 Social Determinants, Demographics, and Social Risk

As research on the effects of our social environments on health has expanded, so too has the lexicon of terms used. In this dissertation, I use the terms political determinants of health, social determinants of health, social risk, and demographics as defined below.

The WHO defines the social determinants of health as the conditions in which people are born, grow, pray, play, and work, and they are also shaped by the wider policies and systems in a society.[51] One of the broadest forces shaping our social determinants is policy. Michael Marmot, one of the first to write about social determinants of health, approached his research through the lens of public policy, elucidating how policy shaped the social conditions in which people are born and age.[52] The "political determinants of health", those forces that shape the conditions of daily life, are perhaps the most upstream determinant that affect the distribution of access to housing, secure financial futures, healthy and affordable foods, environmental conditions that ensure safe water and air, as well as other forces that interact with genetic predispositions to diseases and conditions.[53] These political determinants of health are the broader level of structures, processes, and outputs that interact and mutually reinforce each other to either advance health equity or exacerbate health inequity.[53]

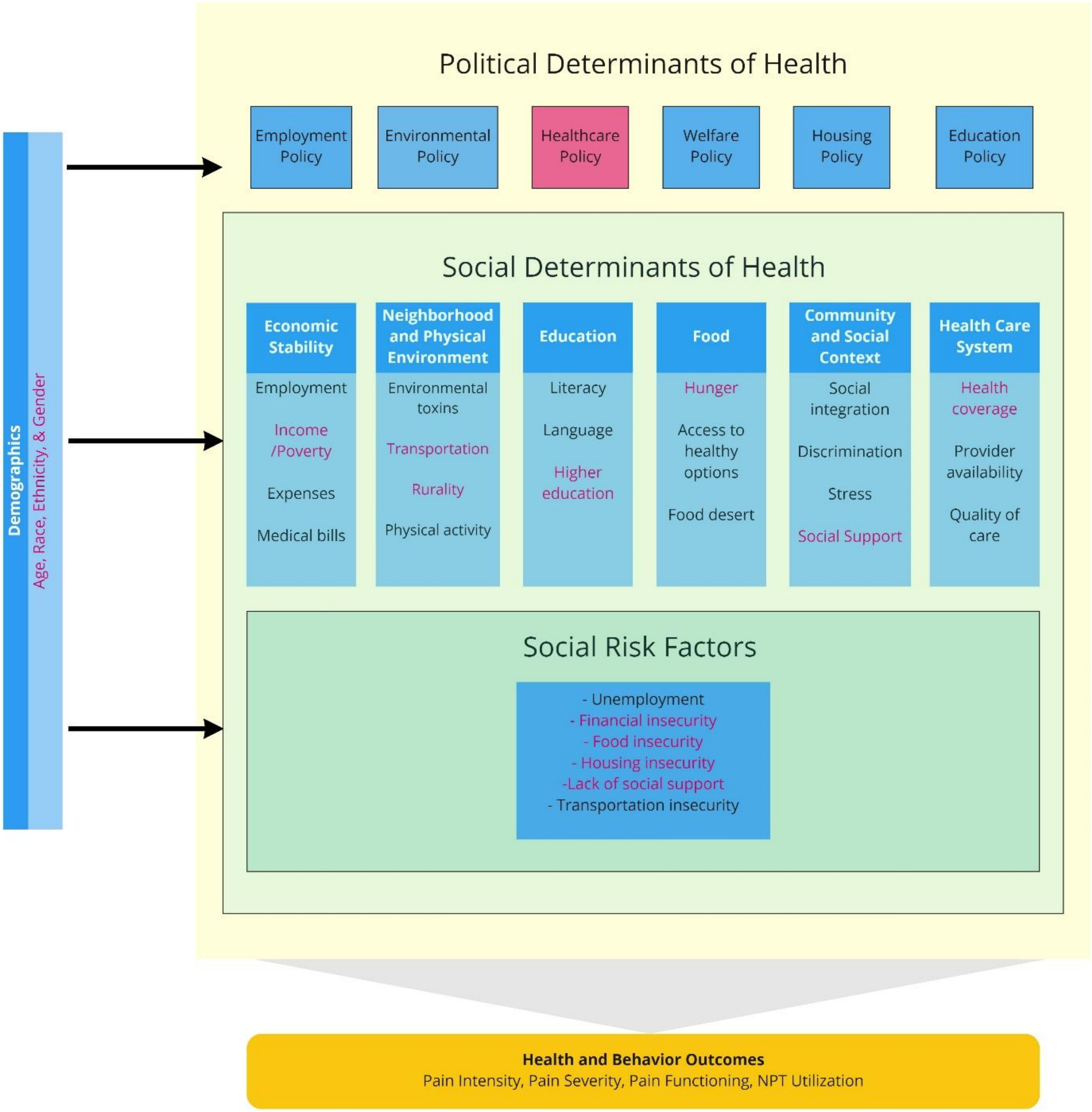
Social determinants of health are structural and environmental conditions in which people live and work; are influenced by policy decisions, or the political determinants of health; and have an impact on health. Social determinants of health operate in society at multiple levels, i.e., they can be individually or geographically-based, and shape more downstream individual social factors, such as social isolation, income, transportation security, and food security. Social determinants of health affect everyone and can have negative or protective effects on health.[51,54]

Social risk can be thought of as individual-level adverse effects of social determinants of health that are associated with poor health and can vary across demographic characteristics, such as age, race, ethnicity, and gender.[54] Alderwick and Gottlieb argue that making a distinction between the social determinants of health and social risk factors is important because identifying social risk factors can help health systems develop targeted interventions to address them.[54] Many social risk factors are actionable and modifiable from a health system perspective, whereas broader social determinants of health are not and require policy change. A few social risk factors, like education and un- or underemployment are not easily or directly modifiable by the health system but are nevertheless downstream effects of larger social or political determinants of health. Additionally, they argue that the term “risk factor” is currently used to describe any individual-level clinical exposure that increases the chances of poor health outcomes, therefore, the same logic should be extended to social exposures which also act as risk factors for health outcomes.[54]

Finally, demographic factors describe the non-modifiable characteristics of individuals, such as age, race, ethnicity, and gender. In research, demographic factors are typically the characteristics used to describe inequities, but are not themselves the causes of inequities. Policies often disproportionately advantage or disadvantage certain groups of people, which in turn affects the way their social determinants of health are structured, and results in differential social and geographic risk factors across groups.

Figure 1 illustrates each of these relationships based on a modified social-ecological framework,[55] with concepts relevant to this dissertation in red text.

Figure 1. Modified Social-Ecological Model for Political and Social Determinants of Health, Social Risk, and Demographics



1.5 Problem Statement

The early 2000s marked the "Decade of Pain Control and Research"[56] and the subsequent years have seen an increase in chronic pain research and related policy initiatives. This includes research identifying psychosocial conditions as major predictors of chronic pain outcomes and a shift in treatment options away from pharmacotherapies toward NPT treatments.[3,28] Research has also exposed vast racial and ethnic inequities in chronic pain outcomes; however, policy and research have failed to move beyond quantifying inequities to understanding and addressing modifiable mechanisms that may be driving the inequities.[42] Research has shown that socioeconomic status is a major predictor of chronic pain, with those who have the lowest socioeconomic status experiencing worse pain-related health outcomes than those with higher socioeconomic status, however, more research is needed to understand additional risk factors that may act as mediators to the relationship between psychosocial conditions and chronic pain. Additionally, there is an important gap in understanding whether social risk and psychosocial factors have a bidirectional relationship when examining chronic pain outcomes; however, this question is beyond the scope of this dissertation.

While other states have allowed for Medicaid to reimburse for NPT, the Oregon Back and Neck Pain policy is the only policy in the United States that both has targeted restrictions on reimbursing less safe biomedical pain treatments including long term opioid treatment and has included reimbursement for a broad set of evidence-based NPT services. Further, the policy was formulated in a manner that encouraged the use of risk stratification to match the types and amounts of services to the evidence base suggesting who is most likely to benefit from such treatment and allow a way for CCOs to manage the costs of expanding reimbursable NPT for back and neck pain. However, implementation of the policy varied substantially between CCOs and expanding coverage to NPT services alone may not be enough to increase equity in outcomes for those with increased social risk. For example, the policy did not include any provisions to help overcome social and other barriers this population may face, including food insecurity, housing insecurity, financial insecurity, transportation insecurity, health system implementation and referral to NPT services, availability of NPT providers in a given area. Understanding how social risks affects chronic pain-related outcomes can serve to inform future state policies, clinical implementation strategies, and health services interventions aimed at increasing equity in treatment for people living with chronic pain.

1.6 Research Question and Aims

This dissertation sought to answer the following question: *How do social risks affect the effectiveness of the Oregon Back and Neck Pain policy on use of NPT and chronic pain-related outcomes among eligible Medicaid enrollees at federally qualified health centers?*

I answered this research question with three distinct aims. In all three aims, I utilized a sample of individuals from Oregon, where the Oregon Back and Neck Pain policy was implemented, and California, where a similar policy was not in place, but which faced similar pressure to change their approach to pain treatment (e.g., restricting opioid treatment), allowing for comparison across states. Data on this sample come from the Back on Track (BoT) study and were collected via surveys administered at five evenly spaced timepoints over a 12-month interval. More information about the sample and data sources are described in subsequent sections. The modeling and analytic approach used in this dissertation was a multi-group (MG) finite mixture model (FMM). The aims of the dissertation were

Aim 1: Characterize patterns of NPT utilization over 12-months across states with and without the Oregon Back and Neck Pain Policy (Oregon v. California).

Aim 2: Examine the effects of social risks, socio-demographic characteristics, and clinical characteristics **on patterns of self-reported use of nonpharmacological therapy (NPT)** over 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

Aim 3: Examine the effects of social risks, socio-demographic characteristics, and clinical characteristics **on change in pain-related outcomes** between baseline and 6-months and 6-months to 12-months across states with and without the Oregon Back and Neck Pain policy.

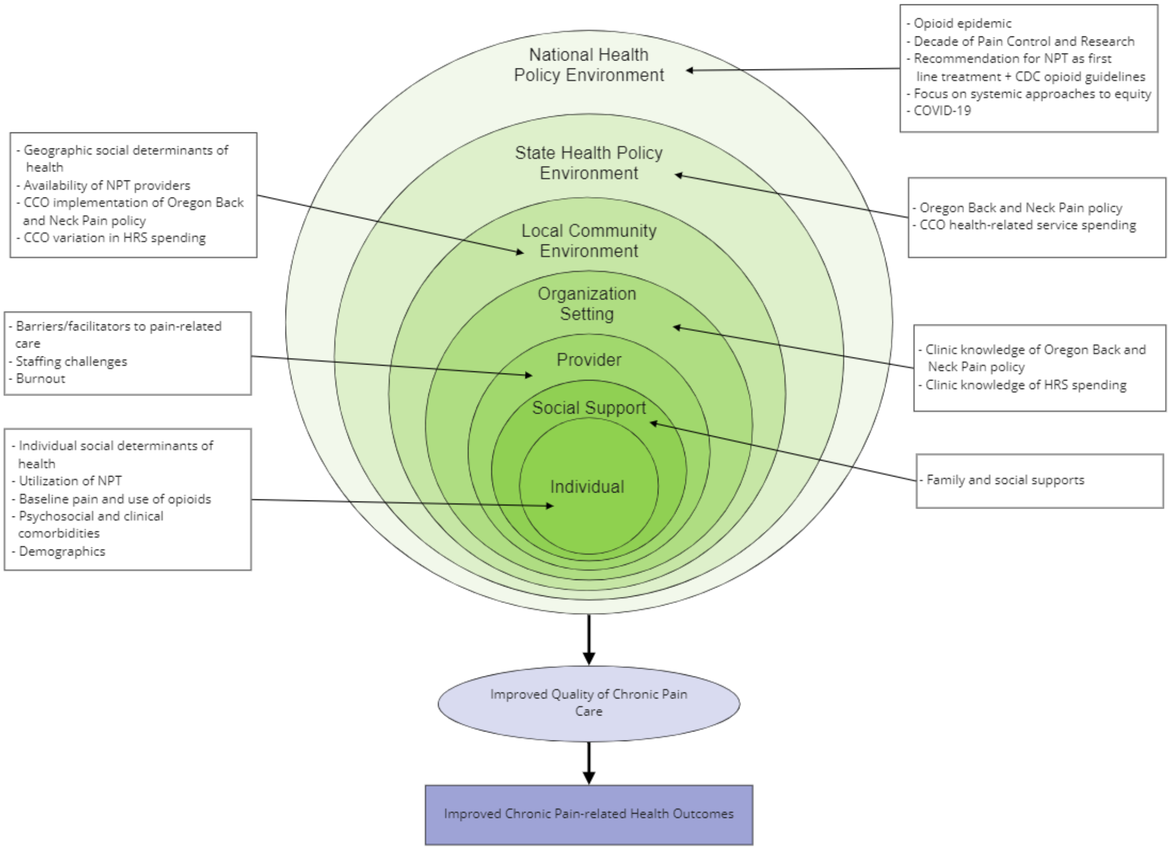
1.7 Theoretical Approaches

This dissertation was guided by one major theory and two complementary applied frameworks. The major theory used is the Ecosocial Theory of Disease Distribution (ecosocial theory, in short). Nancy Krieger first introduced ecosocial theory in 1994 and has subsequently expanded it over the last three decades.[57–61] Ecosocial theory is used to describe and explain causal relationships in disease distribution and production by focusing on the ways in which individuals exist in spheres of multi-level influence that often become embodied and influence our health outcomes. Ecosocial theory allows for understanding the ways in which policies, discrimination, and poverty become embodied and their effects cumulate over time to change populations' exposure, susceptibility, and resistance to disease. Krieger includes government as a central feature in the ecosocial theory, as the primary force that has agency and accountability for how structural factors act as determinants of health. This dissertation will explore how the Oregon Back and Neck

Pain policy and social determinants of health intersect to effect chronic pain outcomes for a population of Medicaid enrollees in federally qualified health centers (FQHCs).

To do this, I used two complementary frameworks. First, I used the Multi-level Influences on Quality of Care conceptual model put forth by Clauser and colleagues.[62,63] The Multi-level Influences on Quality of Care for Chronic Pain (Figure 2) is a modified social ecological model that was originally created to describe the multi-level influences on cancer care and is intended to show that multiple levels exert influence on the quality of care that a patient receives in a healthcare system and that quality of care translates into health outcomes. This model is appropriate to use in this dissertation because the Oregon Back and Neck Pain policy and the health-related service spending initiative, described in Chapter 2, are multi-level policy interventions targeting the patient and other core levels of influence, each with an intent on impacting the quality of care a patient receives and, ultimately, on health outcomes.

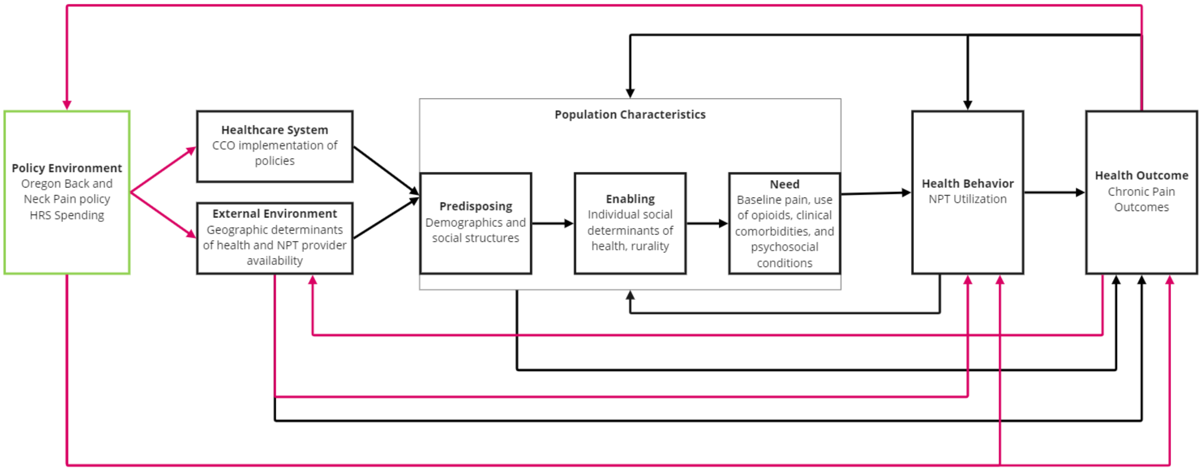
Figure 2. Multi-level Influences on Quality of Chronic Pain Care[ˆ]



ˆAuthor's adaptation of the Multi-Level Influences on Quality of Care model.[62,63]

The final conceptual model used in this dissertation is based on Aday and Andersen's Behavioral Model of Health Care Utilization[64] which has been used many times over the last 50 years in health services research to understand societal and individual determinants of health services utilization. In 2000, Gelberg, Andersen, and Leake[65] applied a new version of the Behavioral Model to a population experiencing homelessness and called it The Behavioral Model for Vulnerable Populations. The value of this updated model is that it allows for the social determinants of health to be included along the pathway that explains or predicts health utilization and health outcomes, though it does not account for upstream social determinants in the external environment. This dissertation will expand on The Behavioral Model for Vulnerable Populations to add a Policy Environment and geographic determinants of health and provider availability as part of the External Environment in addition to the individual Population Characteristics to guide the design, variable selection, and hypotheses generated in this dissertation (Figure 4) for both NPT service utilization and chronic pain outcomes. More detail about each theory and framework and how they are applied in this dissertation is presented in Chapter 2.

Figure 3. Behavioral Model of Health Services Utilization for Marginalized Populationsˆ



ˆAuthor's adaptation of the Behavioral Model of Health Services Utilization for Vulnerable Populations.[65]

1.8 Purpose and Significance

The purpose of this dissertation was to inform more equitable federal and state policies seeking to improve outcomes for people living with chronic pain by better understanding the role of social risks within a biopsychosocial framework. In 2012, Meghani et al.[66] and Campbell et al.[42] argued that we know that racial and ethnic disparities in pain outcomes and treatment effectiveness exist, but we know much less about the mechanisms at play that create those disparities. In other words, it is time to move from identifying problems of health disparities toward exploring and enacting evidence-based solutions that increase health equity.

This dissertation was aimed at understanding the policy-amenable health system, community, and individual social risks that may lead to poorer outcomes of care and inequitable access to NPT services. Other mechanisms driving disparities that are not a focus of this dissertation include aspects of provider bias that systematically underdiagnose pain because of the incorrect belief that BIPOC patients have a higher pain tolerance or under-prescribe pain treatment because the provider may lack trust that BIPOC patients will adhere to medication guidelines.[67] While understanding and improving the individual provider response and patient-provider relationship is critical to advancing health equity, I will not explicitly investigate how provider bias may influence the outcomes because the focus of this dissertation is on broader social contexts that are susceptible to policy interventions.

The Oregon Back and Neck Pain policy is the first in the United States to extend Medicaid benefits to such a wide range of NPT services and punctuated the policy landscape due to its novel use of recent evidence-based treatment for chronic pain and the goal of the policy aimed at increasing access and improving outcomes rather than focusing solely on cost-savings. Now, we have a window of opportunity to contribute to the evidence base for equitable chronic pain policy that is created by the following three elements emerging at once: a proliferation of state policies aimed at increasing access to NPT services, including psychosocial approaches, over traditional biomedical treatments; a national and state politic that is moving rapidly toward progressive, equity-oriented approaches to chronic pain management; and a chronic pain problem that is creating substantial personal and economic burden on the country. The confluence of policies, politics, and problems are what John Kingdon termed “the three streams” that, when they converge, create a short window of opportunity for change.[68] This is the time to further our understanding of whether the Oregon Back and Neck Pain policy worked differently for different groups of people so that social risks can be better accounted for in the biopsychosocial framework of chronic pain and in future state policies.

Chapter 2: Literature Review

2.0 Introduction: Burden of Chronic Pain

Chronic pain is a common and complex problem affecting millions of people in the United States and globally. Though often resulting from an acute injury, chronic pain is a unique condition with specific psychological, behavioral, biological, and social risk factors associated with it. From a population health perspective, it is important to understand the prevalence and determinants of chronic pain so that policymakers, healthcare leaders, and public health researchers know how to treat and manage pain for those most affected.

Chronic pain is one of the most common reasons adults seek medical care in the United States.[1–4] Chronic pain is defined by epidemiologists as pain that lasts for at least three months as this characterization has been determined to be a reasonable metric for pain persisting past the normal time for tissue healing.[5] Chronic pain can be due to cancer or non-cancerous causes. The focus of this dissertation will be on chronic non-cancer back and neck pain.

Chronic pain has substantial personal, societal, and economic costs including increased dependence on opioids, poor mental health, lost productivity, and disability program-costs.[4] Chronic pain contributes an estimated $560 billion each year in direct medical costs.[4] Chronic pain is the leading cause of disability in the US and globally and treatment is rarely effective at substantially reducing or ameliorating the pain itself even when functional improvements are achieved.[6–8] Chronic pain contributes more to years with lived disability than other common mental health and physical conditions combined.[69] Chronic pain contributes an estimated 10.1 million years annually lived with disability compared to 9 million for diabetes, hearing loss, chronic obstructive pulmonary disorder, stokes, Alzheimer's disease and related dementias, asthma, opioid use disorder, and alcohol use disorder combined.[69]

Prevalence estimates vary, but approximately 20% of US adults are living with disabling chronic pain at any given time, with higher rates among certain subgroups, including those who have lower socio-economic status, older adults, women, rural residents, and those on public health insurance.[1] The prevalence of chronic pain has been growing over time and disparities in prevalence are increasing, according to one study analyzing National Health Interview Survey data from 2002-2018.[70] Chronic back pain is the most common type of pain and the prevalence of back pain increased by about 15% and neck pain increased by 16% between 2002 and 2018.[70] For those whose income was less than twice the poverty level, their level of back or neck pain increased between 34-39% compared to 9% for those whose income was four times the poverty level.[70]

This chapter reviews the relevant literature to orient readers of this dissertation to the general burden of chronic pain in the United States; the biopsychosocial model through which chronic pain is best understood; biological, psychological, behavioral and social drivers of chronic pain and associated disparities; key aspects of the national policy landscape of chronic pain and the opioid epidemic; chronic pain treatment option efficacy, effectiveness, and risk of harm; the Oregon Back and Neck Pain policy; the history of Oregon innovations in health policy; CCOs and health-related service spending; gaps in the literature; and finally, the theoretical underpinnings that inform the subsequent design, hypotheses, and methods.

2.1 The Biopsychosocial Model of Pain

Chronic pain is a complex condition, influenced by many different factors, and is best understood through the biopsychosocial framework.[3,30] The biopsychosocial framework is an antidote to the biomedical reductionist framing that suggests that the mind and body are two separate parts of the body that do not interact. Instead, the biopsychosocial model provides a framework whereby biological, psychosocial, social, and other factors intersect rather than treating each as a discrete medical condition.

In 1965, Melzack and Wall introduced the Gate Control Theory of Pain, which was the first theory to show that psychosocial factors played a significant role in the perception of pain.[71] Based on the Gate Control Theory, the biopsychosocial framework was first developed by Engel in 1977 via the Conceptual Model of Illness and later expanded upon by Loeser in the Conceptual Model of Pain.[30] Prior to the development of the biopsychosocial model of illness and pain, pain that did not have clear physiological origin was not treated as “real” pain as the biomedical model of pain dominated current thinking, thereby reducing the broader role of psychological and social aspects in the etiology and maintenance of chronic pain.[30]

The current dominant theory supporting the biopsychosocial model is the neuromatrix theory of pain put forth by Melzack in 2001, which proposes that the experience of pain is influenced by a number of centers in the brain’s neural network.[72] The theory posits that pain is influenced by stress, which can be created by the pain itself or other external causes. Pain is also influenced by how an individual experiences the sensation of pain, how the individual thinks about pain and their ability to do anything about it, how the individual responds to pain through movement or behavior change, and finally how the individual feels about the pain.[72] Biological, psychological, and social inputs each play a significant role in determining who develops chronic pain and how an individual experiences it.

The biopsychosocial model allowed pain to be viewed as a dynamic interaction between biological, psychological, and social factors that is also a subjective experience involving emotional responses and behaviors that are affected by those emotional responses. Each part of the biopsychosocial model is part of the whole and interacts across levels, supporting the idea first put forth by Waddell in 1987[73] that pain cannot be fully understood, treated, or managed without first understanding the whole person who is exposed to the nociception, or the detection of painful stimuli, that may have caused the initial acute pain. As I will discuss later, there are many more social aspects that affect pain, the experience of pain, and the comorbid psychological conditions than other biological or psychological influences in the model.[30]

2.1.1 Psychosocial and Behavioral Factors

The biopsychosocial model is particularly useful for understanding chronic pain because, as Gatchel[31] argues, there is no field where "psychiatric and medical pathologies intersect more prominently than in pain disorders." Though evidence is continually being generated about which psychosocial conditions precede or predict the development of chronic pain, which ones exacerbate chronic pain, and which ones are exacerbated by chronic pain, there is a substantial body of evidence detailing the comorbidity of chronic pain and psychosocial conditions.[74,75] Between 30-60% of people who report chronic pain also report psychosocial conditions, such as anxiety or depression.[14,74,76,77] Both anxiety and depression are positively predictive of pain and pain-related disability.[14,78] In one of the first longitudinal clinical trials on pain and depression, Stepped Care for Affective disorders and Musculoskeletal Pain (SCAMP), Kroenke and colleagues found that there is a bidirectional and possibly causal relationship between depression and pain, wherein depression was a strong predictor of pain and pain was a strong predictor of depression.[76] A growing body of literature supports the causal and bidirectional relationship between pain and depression.[14,75,76]

In another longitudinal trial, Stepped Care to Optimize Pain care Effectiveness (SCOPE), Kroenke and colleagues assessed the SPADE cluster of symptoms (the Sleep disturbance, Pain, Anxiety, Depression, and low Energy/fatigue), which are the five most common co-occurring chronic conditions in the general population. They found that 90% of patients reported multiple conditions among the SPADE symptom cluster. The most commonly reported co-occurring condition with pain was sleep disturbance, which can exacerbate psychological distress and increase pain.[79] Additionally, they found that a reduction in the overall cluster symptom severity, measured by a composite score, resulted in an improvement in multiple functional outcomes related to pain.[79] This further highlights the idea that psychosocial and pain conditions interact synergistically rather than being experienced by people with these conditions as discrete medical conditions.

In addition to depression and anxiety, pain catastrophizing[32,80–82] is shown to be the strongest predictor of chronic pain and chronic pain-related disability, though most variation in explaining these outcomes remains unmeasured.[9] Pain catastrophizing is generally defined as an exaggerated negative mentality towards actual or anticipated pain and may be a construct made up of three different dimensions: magnification of the pain or risk of pain, rumination, and helplessness to do anything to prevent or improve pain.[83–85] Catastrophizing is related to anxiety and is an independent predictor of depression in people living with chronic pain,[86,87] underscoring the importance of the interdependency of conditions illustrated in the biopsychosocial model.

Several behavioral factors are associated with chronic pain. People who smoke tobacco, particularly those who are heavy smokers, reported higher levels of pain intensity than non-smokers.[88] Alcohol has a complicated relationship with chronic pain. It is often used by those with chronic pain to "self-medicate," though the analgesic properties are short-lived and heavy alcohol users build up a tolerance, requiring them to consume more to feel any effect.[88] Some research has indicated that alcohol withdrawal can lead to increased pain sensitivity, reducing the incentive for those with chronic pain to quit drinking.[88,89] The role of nutrition in the development or management of chronic pain is complicated and understudied. It is possible that the gut microbiome and inflammatory processes play a role in chronic pain etiology; management and targeted dietary interventions may be one way to improve pain management. One systematic review of 23 articles found that nutrition was significantly associated with reducing pain severity and intensity, but all articles were considered low-quality.[90] As described later in this chapter, physical activity and exercise, such as yoga, tai chi, and water aerobics, are shown to be positively associated with improvement in physical functioning, decreases in pain severity, and few adverse effects.[3,88]

2.1.2 Biological Factors

Pain has historically been understood and treated as a primarily biomedical condition.[30] That is, clinicians and researchers have sought ways to understand the biological underpinnings of pain so that a medical intervention can be applied to rid the body of pain altogether. While research and clinical treatment of pain is steadily moving toward a more whole person, biopsychosocial approach, there are some key biological factors that can determine when someone will develop chronic pain or chronic pain-related disability.

Pain is the body's alarm system to let us know when injury occurs. In many cases, it is a useful and transient condition resulting from an injury. This type of short-lived pain that has a known origin is referred to as acute pain. Having acute pain or chronic pain at another site in the body is the strongest clinical predictor of developing future chronic pain because the painful stimuli in other parts of the body alter the brain in such a way that leaves the individual vulnerable to developing chronic pain.[88,91] Effectively preventing or managing acute pain is one of the most important ways to prevent the incidence of chronic pain.[88]

Another important clinical risk factor for people with chronic pain is having multiple other chronic comorbid conditions, such as neck or back disorders, mental health conditions, or cancer.[92] Approximately 88% of people with chronic pain have an additional chronic diagnosis, which complicates treatment protocols for those with chronic pain because multiple conditions need to be managed simultaneously so that effective pain control options are likely reduced due to the competing needs of treatment for varied conditions.[92] While having multiple comorbid conditions is not a predictor of later developing chronic pain, chronic pain is an independent risk factor for all-cause mortality among those who have multiple comorbid conditions.[93]

Obesity, defined as a BMI greater than 30, is often related to having other comorbid conditions and is an independent predictor of chronic pain.[88] While there is limited evidence that weight loss improves chronic pain, multiple studies have shown that the likelihood of reporting chronic pain increased substantially as BMI increased.[94,95] Compared to people with a BMI less than 30, considered a healthy BMI, those with a BMI 30-34 had a relative rate of pain 68% higher; those with a BMI 35-39 had a relative rate 136% higher; and those with a BMI >40 had a relative rate 254% higher.[94] When controlling for other comorbid conditions, the rates are reduced but are still significantly higher for those who are obese compared to those who are not.[94] Not only is obesity a predictor of chronic pain and related to other health issues like cardiovascular disease, diabetes, and hypertension, but it is also bidirectionally related to psychosocial conditions that are known to independently predict chronic pain, such as depression and anxiety.[95]

Beyond clinical risk factors, identifying underlying genetic and biological mechanisms responsible for chronic pain is a continually growing field. The relationship between chronic pain and genetics is complicated because genes act at multiple levels to influence how an individual experiences pain, including emotional, behavioral, and biological processes.[96] While neither a single gene nor a broader genetic phenotype has been identified, there is research ongoing designed to understand what biomarkers are associated with pain. Sustained increases in stress hormones or inflammatory cells, and decreases in immune cells have been shown to be associated with chronic pain, but the mechanisms underlying these associations are not robustly understood, though epigenetics is one pathway research is exploring.[96,97]

2.1.3 Social Factors

The least studied contributing factors to chronic pain are social and geographic factors that are associated with developing, maintaining, or exacerbating chronic pain and chronic pain-related disability. These factors may contribute to chronic pain outcomes in a variety of ways, including being associated with more stressful life events[4,9,70,88,98,99] and psychosocial conditions that are known to be related to chronic pain,[4,100–103] causing inequitable access to pain management,[44,49,101,104] leading to people living in environments that expose them to more chronic stressors,[70,88,99–101,104–107] and contributing to biological, clinical, or behavioral conditions associated with chronic pain.[4] Often, these social and geographic factors are correlated with demographic characteristics, such as age, race, immigrant status, sexuality, or gender, leading to disparity in levels of chronic pain and pain-related disability between groups.[4,41,42,88,108]

Generally, older populations experience more chronic pain than younger populations, though the relationship can be complicated by independently predictive comorbid conditions that are more common in older adults.[88] Women report chronic pain more frequently, experience higher levels of pain intensity and pain-related disability, and are more likely to seek treatment than men.[88] Reasons for these gender differences are largely unknown.

Racial and ethnic disparities in chronic pain are well-documented.[41,42] Chronic pain and pain-related disability are more common among populations of color than white populations; however, the mechanisms for disparity are understudied.[41,108] Studies have shown that when adjusted for income, employment, and adverse life events, the relationship between race, ethnicity, and pain were attenuated.[88] In one study of pain differences across Black, white, and Hispanic participants, race and ethnicity no longer predicted chronic pain when income, education, employment, and education were accounted for.[45] However, in other studies, race has remained an important predictor of chronic pain, even when socioeconomic status is included, highlighting that there is unexplained variation in the relationship between race, ethnicity, and chronic pain outcomes that have not yet been accounted for.[108] Through mechanisms of structural racism such as historical redlining, discriminatory hiring practices, and poorer access to quality education, populations of color are more likely to have lower levels of socioeconomic status,[45] live in poverty,[45] have had adverse life events, have higher levels of medical comorbidities, and higher levels of depression and anxiety, each of which have been shown to be associated with poorer chronic pain outcomes.[4]

Socioeconomic status (SES), including SES markers such as income, education, and neighborhood, is inversely associated with experiencing chronic pain, pain severity, and pain-related disability.[70,88,105] Poverty, in particular, is one of the most well-known drivers of health inequity across a broad range of outcomes.[106,107] Poverty is associated with higher rates of depression and anxiety,[100] exposure to chronic stressors, inadequate living conditions, lack of healthy foods, physically-demanding labor, trauma and adverse childhood events (ACEs), and lack of access to health insurance.[104] In one study, those with an annual income of $25,000 or less were 71% more likely to have chronic-pain-related disability than those with a higher income.[45] Each of these contributes to increased levels of chronic pain or poor access to pain management therapies.[104]

Employment and occupation are associated with both poverty and chronic pain. Those who are un- or under-employed often report higher levels of chronic pain and pain-related disability than those who are employed, though this relationship may be bidirectional.[9,70,88] Chronic pain is not only prevalent among those who are unemployed, but also unemployment can be caused by chronic pain due to disability and associated limitations that limit the kind of work people can do. People who are unemployed or otherwise have a low socioeconomic status also often do not have access to health insurance, which prevents or delays them from seeking treatment or causes care to be experienced in an uncoordinated or fragmented way, leading to worse health outcomes.[44,49,101] Additionally, those working in occupations requiring manual labor or repetitive physical movements report high levels of chronic pain because this type of work can lead to or further exacerbate chronic pain, particularly chronic back pain.[9,70,88]

Poverty is associated with various psychosocial stressors that contribute to chronic pain and other psychosocial conditions, namely depression and anxiety.[100–102] Though the literature on the relationship between poverty stressors, psychosocial conditions, and pain is nascent, one study sought to understand the relationship between financial hardship, daily financial worry, and daily pain severity.[103] The sample consisted of 250 women with osteoarthritis, fibromyalgia, or both who were asked to keep a daily diary of their financial concerns and their pain levels. As expected, economic hardship was associated with increased daily financial worries, but importantly, days where financial worry was present were significantly associated with higher levels of pain severity.[103]

Food insecurity is another type of chronic stressor experienced by many, including people in poverty. Men and colleagues found in two large samples of Canadians 12 years of age and older in 2015 and 2018, that food insecurity was a stronger predictor of chronic pain, pain severity, and pain-induced functional limitations than income or education.[98] Compared to food-secure individuals, those who were marginally food-insecure were 31% times more likely to experience chronic pain; those who were moderately food-insecure were 89% more likely; and those who were severely food-insecure were 329% more likely to report experiencing chronic pain.[98] Food insecurity was also associated with an increased risk in using prescription opioids in the same samples.[98] Whether this association is related to nutritional deficits that food-insecure individuals may have, daily stress of not having enough to eat, or both is unknown.[33,98] The authors included covariates known to be associated with pain, though some measures, such as availability or utilization of pain management services, were not directly available and proxies had to be used.

Housing insecurity is another chronic stressor that affects many, including those living in poverty. The stress of not knowing whether one can afford rent month-to-month or the stress of being houseless, though, is understudied in relation to chronic pain outcomes. While little is known about how housing insecurity is related to chronic pain, geographic factors have been shown to be associated with chronic pain outcomes. Neighborhood factors that are associated with chronic pain often are highly correlated with measures of poverty. Environmental stressors, such as exposure to crime, housing status, neglected buildings, overflowing trash, and other conditions of impoverishment have been shown to be associated with increased psychosocial distress and are associated with increases in chronic pain.[99,101] Living in neighborhoods without sidewalks, parks, or playgrounds creates barriers to physical activity, which is known to impact the prevention or experience of chronic pain.[101] Finally, where someone lives can hinder access to high quality healthcare and pain management therapies, including primary care where the majority of pain is treated or to other providers, such as massage, acupuncture, or physical therapy practitioners.[101]

2.1.4 Biopsychosocial Summary

Psychosocial stressors that result from poverty include housing insecurity, financial insecurity, food insecurity, unsafe neighborhood conditions, living in neighborhoods without access to care or opportunities for physical activity, and general impoverished conditions and have been found to be associated with chronic pain outcomes, though research in most of these areas is limited. These social and geographic conditions can act as psychosocial stressors because they may impact the ability to feel like one has control over the basic needs of their life, let alone the ability to feel that they are in control of their own pain experience.[101,109] The ability to feel like one has agency to control their pain is an important psychosocial predictor of chronic pain outcomes.[109] These psychosocial stressors may also exacerbate catastrophizing and the related condition of anxiety, which are also known to be important predictors of chronic pain outcomes.[32,87] At least one study has shown that psychosocial conditions like depression and catastrophizing are more predictive of pain outcomes than poverty, education, or demographic variables[102] which highlights the need to understand how social and geographic conditions interact with psychosocial stressors and chronic pain.

There are many factors associated with the development or severity of chronic pain. Psychological, social, and geographic factors are often at least as important as underlying biological factors, greatly influencing the physical manifestations and treatment response to chronic pain. The contribution of these factors is important to understand so that the development of chronic pain can be prevented, and treatments can be effectively targeted and tailored to reduce pain severity and increase functioning. Some factors are amenable to medical or social intervention, while others can inform the assessment, management, and prognosis of chronic pain at an individual or societal level.

Demographic and social factors are often not directly amenable to medical intervention but can inform population-health strategies for prevention or management of chronic pain or provide context for individual-level assessment and treatment. Inequities between groups based on demographic characteristics are a result of systemic policies that have disproportionately benefited certain groups over others, leaving poor, rural, or communities of color with inequitable and poorer health outcomes and little access to high quality healthcare. One way to address disparity and increase health equity is to use policies to redistribute resources and access to historically marginalized communities.

2.2 Pain on the National Agenda

For more than 100 years, a pendulum has swung between liberal use of opioids in treating chronic pain to restrictive prescribing of opioids.[110] This has been felt most acutely in the last 30 years. In 1995, Oxycontin, a drug very similar to heroin that is primarily made up of oxycodone, was introduced on the market as the first-ever non-addictive narcotic.[110] It was aggressively marketed as such by Purdue Pharma directly to physicians in areas of the country where manual labor was the main economic activity and, as such, chronic pain was highly prevalent.[56,111] Up to this point, opioids were not thought to be the primary method with which to treat chronic pain due to their addictive properties. During the following years, Purdue Pharma worked tirelessly to influence policymakers and healthcare professionals' perspectives on opioid prescribing. Pain was termed the "fifth vital sign," doctors and healthcare systems were evaluated on their ability to keep pain low or eradicate it altogether, and patients began advocating for their right to be free of pain, with the best way to achieve this through OxyContin.[110] Treating pain with long-term opioids became the norm and, because OxyContin was actually highly addictive, this spurred the opioid epidemic that continues to ravage the country today.[110] The opioid epidemic began with the belief that opioids were the safest and most effective way to treat pain. Today the opioid epidemic continues with record-breaking overdose deaths reported in 2020.[112] While policymakers and healthcare leaders now recognize the addictive properties of opioids and have sought ways to regulate prescribing, the introduction and proliferation of fentanyl and other synthetic opioids continues to fuel opioid overdoses and deaths.[112]

Simultaneously to the rise of OxyContin and the opioid epidemic, the United States Congress declared the decade beginning in 2000 as "The Decade of Pain Control and Research."[56] This was officially promulgated via the *Pain Relief Promotion Act* wherein Congress acknowledged that "inadequate treatment of pain, especially for chronic diseases and conditions, irreversible diseases such as cancer, and end-of-life care, is a serious public health problem." The Act also stated that physicians "should not hesitate to dispense or distribute controlled substance when medically indicated for these conditions," however it did not limit or alter any of the provisions in the *Controlled Substances Act*, which regulates controlled substances and limits the dispensing and distribution of those substances for legitimate medical purposes.[56] The *Pain Relief and Promotion Act* centers the problem as one of balancing the competing demands of adequate analgesic pain management with strict regulation of these drugs to prevent abuse. This idea came to be known as the Doctrine of Balance.[56]

During the 2000s, 2010s, and into today, many national organizations have been involved in issuing new guidelines for the safe prescribing of opioids for pain management as well as generating evidence that non-pharmacological approaches are safe and effective treatment options for chronic pain and should be used as a first line treatment. Some of these organizations and initiatives that have been influential in the movement to find effective and safe pain management treatments include the Institute of Medicine's report on Relieving Pain in America in 2011,[4] the subsequent founding of the National Pain Strategy and their report on a comprehensive population strategy for pain,[29] the National Academies of Science, Engineering and Mathematics meeting in 2018 to discuss safe and effecting nonpharmacological treatments for pain,[28] the Centers for Disease Control and Prevention (CDC) 2016 opioid prescribing guidelines,[113] and the Helping End Addiction Long-term (HEAL) Initiative, which emerged from Congress as a way to address the opioid epidemic that was affecting many of their constituents and effectively broke down silos among NIH divisions so that researchers in pain and researchers in substance use disorders could coordinate priorities and resources.[114]

The CDC issued guidelines in 2016 to help guide primary care practitioners in prescribing opioids for chronic pain.[113] These guidelines address when to start or continue opioids for chronic pain, how to select the appropriate opioid and length of treatment, and how to assess risk of or address addiction or overdose. These guidelines were accompanied by a growing body of evidence that opioids were not as effective at reducing pain severity or improving functioning as previously believed, and they had already proven to carry a substantial risk of harm to individuals and society.[20,21]

2.3 Treatment for Chronic Pain

2.3.1 Pharmacologic and Other Biomedical Treatments

Until recently, the primary way of understanding and treating chronic pain has been through a biomedical model of care where the goal of care has been to identify the source of pain and treat to eliminate pain altogether.[28,30] Methods of treatment under a biomedical model include opioids, other drugs, invasive medical procedures, and epidural steroid injections as first-line treatment options. Epidural injections have been shown to be effective for short-term and long-term pain relief, but most studies have not evaluated functioning.[115] Pharmacologic treatments for chronic pain include opioids and other types of drugs, including antidepressants, anticonvulsants, non-steroidal anti-inflammatory drugs (NSAIDs), and acetaminophen.[21,27] Among these, opioids are a central concern for the public, healthcare systems, and policymakers alike because of the opioid epidemic that an overreliance on prescription opioids spurred beginning in the late 1990s.

Opioid prescriptions increased four-fold from 2000-2010 and the United States remains the largest per-capita consumer of opioids in the world.[28,116] Reasons for the US consistently being the largest consumer of opioids internationally are multi-faceted. First, as described above, opioids have been used for years as the first-line treatment for millions of Americans who have chronic pain.[28] The US approach to pain management has primarily been through a biomedical model of care rather than using non-pharmacological approaches that have been shown to be efficacious in reducing pain and improving function. Second, the incentive and reimbursement structures of the US healthcare system reflect the preference for biomedical care over non-pharmacological care, with insurance plans that have historically made opioids more affordable and easily accessed over other treatments and incentive structures that prioritize shorter, more efficient appointments over longer, visits that may result in better quality pain management.[28] Third, the US has loose marketing policies compared to the rest of the world and decentralized oversight of prescription monitoring.[28] One of the most prominent examples of the impact marketing had on the opioid epidemic was with OxyContin.[56,110,111]

Despite the reliance on opioids as a first-line pain treatment, the evidence for the effectiveness of opioids to relieve pain or improve functioning is limited. The Agency for Healthcare Research and Quality (AHRQ) conducted a series of three comparative effectiveness systematic reviews on treatment of chronic pain.[3,21,27] One of the reviews focused on opioid efficacy, comparison of opioids to placebo or non-opioid treatment, and harms associated with opioid use at three time intervals: short-term follow-up (1 to <6 months), intermediate-term (6 to <12 months), and long-term (≥12 months).[21] Outcomes included pain levels, function, quality of life, and harms. The review included 115 randomized control trials (RCTs), 40 observational studies, and seven studies of diagnostic accuracy of opioid risk prediction instruments on a population of adults with various types of chronic pain.[21] The review found that there was a small effect on improvement of pain and functioning in the short-term for opioids compared to placebo interventions.[21] There was no evidence available for the superiority of opioids compared to placebo in the intermediate- or long-term. For opioids compared to nonopioids, opioids plus nonopioids compared to nonopioids, and opioids plus nonopioids compared to opioids alone, there was no effect or no evidence available for improvement in pain or functioning at all time points.[21] This finding is consistent with a systematic review conducted by Busse and colleagues in 2018[20] which found that compared to placebo, opioids have a statistically significant, but small effect on pain and functioning for people with chronic noncancer pain. In some cases, results have shown that the use of opioids worsens pain and functioning.[117,118]

The AHRQ systematic review found that opioids compared to placebo or nonopioids were associated with multiple adverse events (AEs), including discontinuation of a trial due to AEs, nausea, vomiting, constipation, dizziness, headache, somnolence, and pruritis.[21] Opioids were also associated with serious AEs, including hospitalizations. Additionally, opioids were found to be associated with an increased risk for abuse, dependence or addiction; overdose; and all-cause mortality.[21]

For low back pain, there is limited evidence that certain antidepressants have a short-term (1 to <6 months) effect on pain, but there isn't evidence of intermediate or long-term impact on pain and no evidence that antidepressants improve functioning for people with low back pain.[27] There is some moderate evidence that some antidepressants have a large increased risk for certain adverse effects like nausea, vomiting, sedation, or withdrawal from studies due to AEs.[27]

2.3.2 NonPharmacologic Treatments (NPTs)

In the late 2010s, many national organizations put forth reports calling for the use of evidence-based NPT as the first line of treatment for chronic pain, including those issued by the IOM, CDC, NASEM, AHRQ and the National Pain Strategy. They recommend that the management of chronic pain be integrated, multimodal, interdisciplinary, evidence-based, and tailored to individual patient needs.[3,4,28] Psychosocial needs, in addition to biological factors, are the strongest predictors of pain chronicity and pain-related disability,[3,30–32] thus deserving consideration when determining appropriate treatment for pain management.[3,26,29] NPTs are primarily targeted at addressing functioning rather than alleviating pain directly.

NPTs for chronic pain include exercise and physical therapy, mind-body practices (e.g., Tai Chi, yoga), psychological therapies (e.g., cognitive behavioral therapy [CBT], acceptance and commitment therapy, and relaxation techniques), mindfulness practices, acupuncture, osteopathic medicine, spinal manipulation therapy, and various physical modalities (e.g., traction, superficial heat or cold, bracing, transcutaneous electrical nerve stimulation). NPTs shift the focus from prioritizing pain reduction to improving functioning and quality of life.[3,26] The choice of NPT is driven both by availability and the type and severity of chronic pain. In addition to each of these therapies, many of those suffering from chronic pain report relief with anti-inflammatory and related dietary practices although research support for such approaches is nascent.[3,33]

In 2020, the AHRQ updated their 2018 report[6] on recommendations for non-invasive NPT for 5 types of chronic pain as part of the series of reports devoted to the treatment of chronic pain described in the previous section.[3] The review included predefined search terms limited to RCTs reporting results at least 1-month post-intervention. The review included 233 RCTs and assessed strength of evidence (SOE) for three time intervals: short term (1 to <6 months from treatment completion), intermediate term (6 months to <12 months), and long term (>12 months). Thirty-six percent of the trials included were small (N<70), resulted in small effect sizes, had limited evidence for effect after 12 months, and compared against usual care, attention control, or placebo interventions. Only one trial for chronic back pain included pharmacotherapy as a comparator.[3]

The following types of NPT were shown to relieve pain or improve functioning for at least one month following treatment for people with chronic low back pain compared to usual care: exercise, psychological therapy/CBT, spinal manipulation, low-level laser therapy, massage, mindfulness-based stress reduction, yoga, acupuncture, and multidisciplinary rehabilitation (MDR). [3]

CBT was the only NPT that showed consistent, though small, effects on relieving pain and improving functioning across all time-points.[3] Exercise showed small to moderate effects on relieving pain at all time points and a small effect on improving functioning in the short-term.[3] Acupuncture showed small, sustained effects in the short- and long-term for relieving pain and a small effect on improving functioning in the short-term.[3] Manual therapies, such as massage and spinal manipulation, showed small effects on functioning and pain in the short- and intermediate-term. Mindfulness practices showed no effect on functioning but small effects on pain up to 12-months. Yoga had moderate short-term and small intermediate effects on functioning with small short-term and moderate intermediate effects on pain. Finally, multidisciplinary rehabilitation showed small effects up to 12-months on both pain and functioning.[3] Other than trials for CBT, acupuncture, or exercise, most did not assess the impact on pain or functioning after 12-months. If they did, they did not find an effect, e.g., mindfulness practices, multidisciplinary rehab.[3]

The types of NPT that have been shown to be most effective varies by type of chronic pain, though the majority of trials are focused on those with chronic back pain. Those with chronic neck pain showed improvements with exercise, low-level laser, mind-body practices, massage, and acupuncture compared to usual care.[3] The majority of trials included in the AHRQ review for chronic neck pain were acupuncture trials. Acupuncture showed small effects on function up to 12-months and no improvement in pain at any timepoint. Exercise was the next most common intervention for chronic neck pain among those included in the AHRQ review. Exercise showed a small long-term effect on functioning but no effect at any other time point or at all for pain. Massage showed moderate effects for relieving pain and small effects for improving functioning in the short-term. Low-level laser therapy showed moderate effects in the short-term for both pain and functioning. Finally, mindfulness practices showed small effects up to 12-months for functioning and did not assess pain at any timepoint.[3]

While the evidence on effect of NPT for chronic back and neck pain is mostly small, evidence shows that noninvasive NPT is a safe approach to pain management.[3] Across all trials, adverse events and serious adverse events were extremely rare. The most common harm reported was increased pain in massage, spinal manipulation, and MBSR trials.[3] Serious adverse events, e.g., deaths or hospitalizations, among patients participating in a NPT trial is rare and among those that reported a serious adverse event, all were found to be unrelated to treatment.[119] Importantly, NPT is not associated with mortality, overdose, addiction, or any other negative outcome.[3] While evidence may be limited, just as it is for opioids, NPT is a safer option for pain management and this review underscores why many national organizations are calling for NPT to be the first-line treatment for people with chronic pain.

2.3.3 Generating Evidence for NPT

More evidence is needed, particularly as it pertains to marginalized populations, to better understand how NPT impacts pain severity and functioning. However, generating evidence for NPT services is challenging for the following reasons:[28]

1. Pain is a multifactorial condition that fluctuates based on emotional distress, activity level, among other things. Patients may have multiple comorbidities for which they are receiving other treatment that is unmeasured in the trials. This makes it difficult to isolate the treatment effect of the intervention.
2. Pain can vary from day to day and week to week.
3. Most trials only assess one intervention rather than multimodal treatment as recommended.

4. Even among trials of the same intervention, there is variation in the frequency and duration of treatment.
5. The specific tools used to assess pain and functioning vary across studies.
6. There are barriers to carrying out trials in a way that creates generalizable information, including NPT not being widely available in all areas of the US, e.g., rural; people needing transportation to get to treatment; people without the ability to take regular time off work to go to treatment often do not participate in trials.

While there are gaps in the evidence surrounding NPT treatments, particularly around the effectiveness of NPT to provide sustained pain relief and among marginalized populations in particular, the evidence for sustained effect is better than the evidence available for pharmacologic and other biomedical treatments. NPT treatments are shown to be safer than opioids, though NPT is not shown to relieve pain as well as analgesics, like opioids. However, NPT treatments show modest but consistent effects in functioning. Using the evidence currently available that indicates NPT is a safe and effective method for managing chronic pain, Oregon sought to expand access of NPT to their Medicaid population.

2.4 Oregon Medicaid’s Back and Neck Pain Policy

In 2016 the Oregon Health Plan (OHP) introduced the Oregon Back and Neck Pain policy in response to these national recommendations to limit opioid prescribing and increase access to NPT as a first line treatment for chronic pain. The goal of this policy was to discourage use of biomedical treatments that have limited efficacy and pose significant patient safety risks by expanding access to safe, effective NPT services for those enrolled in

Oregon's Medicaid program. The Oregon Back and Neck Pain policy is a Medicaid payer strategy and was written in response to national recommendations that NPT services, not opioids, should be the first line of treatment for individuals experiencing chronic back and neck pain. This policy was designed to enhance access to safe, evidence-based NPT options, including pain-specific psychotherapy approaches,[18] while restricting reimbursement for opioids for back and neck pain and increasing required safety measures when opioids were prescribed.[19] Medicaid is a potentially ideal lever for addressing health inequities because many Medicaid enrollees face disparities in chronic pain outcomes and access to treatment related to underlying social risks such as poverty, lack of transportation, or food insecurity. By making NPT services covered and reimbursable by Medicaid, Oregon was potentially expanding access to safer and more effective pain management for a large portion of the state's population.

The policy was made up of two guidelines aimed at: (1) reducing initiation of or encouraging tapering opioid therapy and (2) increasing the availability and use of NPT for chronic back and neck pain through provider reimbursement for previously uncovered NPT options. The primary goal of the policy was not cost-savings, but rather more effective management of chronic back and neck pain via a broad set of NPT treatments among the Medicaid population.[36]

The policy suggested stratifying patients into three pain-related disability risk categories – low-, medium-, or high-risk – based on patient responses to the STarT Back Assessment Tool which asks patients about pain-related functioning and concerns.[37] The STarT Back Assessment Tool is a validated assessment used to determine risk level for poor functional prognosis based on a combination of physical and psychosocial factors among individuals with low back pain of any duration (i.e., acute or chronic).[37,120] It was developed to guide primary care providers in determining treatment pathways for patients with low back pain.[120]

This risk stratification encouraged Oregon's coordinated care organizations (CCOs) to target more intensive NPT services to those patients with the greatest need, though CCOs were not required to implement the policy in this way. For those considered low-risk, the policy allowed for pharmacotherapy limited to NSAIDs, acetaminophen, or muscle relaxants and NPT options limited to four or fewer visits per year of osteopathic or chiropractic manipulative therapy, acupuncture, and/or physical or occupational therapy. For those in the medium- and high-risk categories, they were allowed NSAIDs, acetaminophen, muscle relaxants and additionally opioid medications *if* not used as a first line treatment option and prescribed with evidence of a referral to one or more of the NPT options. The policy originally limited opioid prescriptions to no more than a 90-day supply and restricted epidural steroid injections. The medium- and high-risk groups were allowed up to 30 visits per year of any combination of the following NPTs: cognitive behavioral therapy, rehabilitative therapy, osteopathic or chiropractic manipulative therapy, acupuncture, yoga, massage, supervised exercise therapy, and/or intensive interdisciplinary rehabilitation.

Table 1. Oregon Back and Neck Pain Policy: Recommended Stratification using STarT Back Tool^

Low-risk	**Medium- and High-risk**

Pharmacotherapy: Limited to NSAIDs, acetaminophen, or muscle relaxants	Pharmacotherapy: NSAIDs, acetaminophen, or muscle relaxants plus opioid medications if used in conjunction with NPT
Non-pharmacotherapy: ≤ 4 visits per year Osteopathic or chiropractic manipulative therapy, acupuncture, and/or physical or occupational therapy	Non-pharmacotherapy: ≤ 30 visits per year Cognitive behavioral therapy, rehabilitative therapy, osteopathic or chiropractic manipulative therapy, acupuncture, yoga, massage, supervised exercise therapy, and/or intensive interdisciplinary rehabilitation

[^] Not reimbursed: Opioids used as a first line treatment option, opioids not prescribed in conjunction with NPT, opioids prescribed for >90 day supply, or epidural injections.

In 2018, the Health Evidence Review Commission (HERC) was presented with a proposal to amend the policy to expand coverage beyond back and neck pain to include five additional types of pain: chronic pain due to trauma, chronic postprocedural pain, chronic pain syndrome, other chronic pain, and fibromyalgia. In 2019, the HERC decided not to include the additional five types of chronic pain, leaving the policy limited to chronic back and neck pain.[38] They also formally voted to remove the opioid tapering requirement from the policy, saying that the decision to taper off opioids should be made between the provider and patient on an individualized basis.[39] They cited public pressure and an external review of the evidence that had been conducted to understand the effectiveness of opioid therapy in the treatment of chronic pain.

While the goals of the policy followed best practices, the policy itself did not contain specific implementation guidelines for the CCOs to use, resulting in varied implementation of the policy across Oregon CCOs. Based on conversations with the parent study on which this dissertation is based, described below, challenges included opioid tapering being complicated by prior Oregon Medicaid policies that dictated opioid prescribing, epidural steroid injections never fully being restricted, lack of understanding or knowledge of the STarT Back assessment tool resulting in no rigorous risk stratification, among other.[40]

Two main studies, a study by Choo and colleagues[50] and the Back on Track study by DeBar, sought to evaluate the effect of the Oregon Back and Neck Pain policy on NPT service utilization in Oregon and one of those studies additionally included chronic pain outcomes. Choo et al.[50] evaluated the changes in NPT use before and after the implementation of the Oregon Back and Neck Pain policy guidelines as well as the relationship between the changes and demographic characteristics. While there was a 23% increase in overall utilization of NPT, Black, American Indian/Alaskan Native, and Hispanic patients were less likely to access NPT compared to white patients. Additionally, those living in urban areas and the elderly were more likely to access NPT compared to those who lived in rural areas or were younger.[50] The results from Choo et al.'s evaluation of the impact of the Oregon Back and Neck Pain policy guidelines on utilization indicates that there are disparities in the level of access afforded by the policy. However, their research does not explain what mechanisms were at play that may be driving the disparities.

The Back on Track study was designed to address the comparative effectiveness of different payer or health system strategies that aim to prevent unsafe opioid prescribing. Back on Track used a quasi-experimental design to compare changes in utilization and pain outcomes between Oregon and California, a state that did not implement a Medicaid strategy to expand access to NPT services. The study collected data on enrollees at five timepoints over 12 months between November 2019 and November 2020 on two cohorts. One cohort is people who were chronic opioid users and another cohort of “new starts,” people who did not have evidence of chronic opioid use at the time of study enrollment. Though the Oregon Back and Neck Pain policy impacted all Medicaid enrollees in Oregon, data from the Back on Track study are from federally-qualified health centers (FQHCs). Historically, FQHC patients are more likely than other Medicaid enrollees to have limited access to pain-related services. Results are forthcoming for this study. This dissertation used data from the Back on Track study from both cohorts across Oregon and California.

2.5 Oregon Health Policy Innovation Landscape

The following sections provide background information on innovation in Oregon under the OHP and how social determinants of health are prioritized through spending in the CCOs.

2.5.1 The Triple Aim and Oregon CCOs

The social determinants of health have been increasingly discussed in health system and policymaking circles since the early 2010s when the Patient Protection and Affordable Care Act (ACA) was introduced and passed into law. The Triple Aim[121] of improving the experience of care, improving the health of populations, and reducing per capita costs of healthcare were the three pillars of the ACA, which was the first national policy to embody these aims. The ACA ushered in millions of previously un- or under-insured individuals into the insurance risk pools, many of whom are both medically and socially complex patients. This presented new challenges such as how to appropriately set quality metrics across health systems serving populations that make achieving those metrics more difficult than other health systems, how to reduce per capita costs without penalizing health systems serving socially complex patients, and how to ensure access to care was equitable across populations. To achieve population health equity, improve care, and reduce costs, health systems, payors, and policymakers needed to understand and account for the vast social conditions that are drivers of health.

2.5.2 Oregon's Innovation with the Oregon Health Plan

Well before Berwick and colleagues[121] published their seminal paper on the Triple Aim in 2008, Oregon was a leader in experimenting with socially progressive healthcare policies that held the essence of the Triple Aim. In the early 1990s, the Oregon Health Plan (OHP), Oregon's Medicaid program, was used to expand coverage to Oregonians who were living at or below the federal poverty line (FPL) while simultaneously reducing healthcare costs.[122] The state legislature did this through what widely became known as "rationing" care. In 1989, the Oregon Health Services Commission was established and this commission prepared a list of 709 health services and diagnoses that were ranked relative to their societal benefit, rather than relative to their individual benefit. The goal of this was to increase coverage to un- and under-insured Oregonians while controlling costs by limiting high expense and low benefit services. The "line" was drawn originally at 587 so anything above the line was covered by Medicaid and anything below the line was not. In the beginning, there was a backlash across the state and nationally to the concept of rationing care.[122] In practice, though, the list of Medicaid services became a set of basic benefits packages and was ultimately heralded by advocates, policymakers, and healthcare systems as achieving greater coverage and expanded care options for

Oregonians.[123] Setting the line, though, did not result in substantial cost-savings as hoped for.[123]

Another component of the early 1990s OHP was the required enrollment for all Medicaid members into managed care organizations (MCOs).[122] Much of Oregon's Medicaid population had already been covered by MCOs so the transition to coverage requirement was not as difficult as it may have been in other states. Under MCOs, the capitation payments were made large enough to cover the cost of care so that providers, hospitals, and MCOs supported funding for Medicaid and were incentivized to accept Medicaid patients, thereby increasing access to high quality care. In 1997, the per member per month rate was $130, one of the highest in the country, though still below that of Medicare or private insurance.[122] Under MCOs, the financial risk is transferred to MCOs, so services that fell below the line were not necessarily restricted. Instead, the MCO and capitated payment structure allowed greater flexibility to approve necessary treatments that fell below the coverage line. MCOs, along with a substantial cigarette tax instituted at the same time, accounted for the majority of cost-savings under the OHP.[123]

In a telephone survey of nondisabled adults who were either enrolled in OHP or were food stamp (now, SNAP) recipients on private insurance or uninsured, Mitchell and colleagues[124] found that OHP was associated with a higher percentage of enrollees having a usual source of care than food stamp recipients. Those enrolled in OHP reported higher use of dental care and prescription drug use, but also reported a higher rate of unmet need for prescription drugs, mostly due to having conditions below the line that prevented drugs from being covered.[124] OHP enrollees were as satisfied with their care as food stamp enrollees on private insurance and there was no evidence that rationing substantially restricted access to services.[124]

The early OHP, though a success by many measures, was not without its problems. The expansion of OHP and the requirement for Medicaid members to be enrolled in MCOs substantially reduced the rate of reimbursement for FQHC and safety net clinics and reduced previously earmarked dollars for safety net hospitals that served large proportions of uninsured Oregonians.[125] Many safety net providers were not part of MCOs, leaving safety net providers with sicker, more complex patients and fewer dollars.[125] In the early days of OHP, the capitation payment was a flat rate and did not account for risk-adjustment. Though risk-adjustment is central to determining payments now, this originally disadvantaged MCOs serving more medically and socially complex patients.

The second phase of OHP began in 2003 where the plan was split into two plans: OHP Plus and OHP Standard.[126,127] OHP Plus covered those who were categorically eligible for Medicaid, which includes (up to specific income thresholds) children and pregnant women, the disabled, and families enrolled in Temporary Assistance to Needy Families (TANF). OHP Standard is a Medicaid expansion program designed to cover those not categorically eligible for Medicaid.[126,127] In addition to splitting the plan into two parts, OHP began instituting premiums for low-income families meeting certain income thresholds. While these premiums were low, they were still too expensive for most families to afford leaving many people uninsured again. Additionally, due to budgetary shortfalls, OHP Standard was closed to new enrollments in 2004. By 2007, OHP had lost 75% of its enrollment.[126]

To try to address this drastic increase in the uninsured population, the Oregon legislature decided to reopen OHP Standard for enrollment in 2008. They had a budget to allow 10,000 new enrollees, though anticipated that demand would be much higher. To try to account for the high demand in a way that was fair, Oregon applied for a waiver from CMS to implement a lottery system whereby people could sign-up with low-entry requirements (e.g., basic demographic information) and be entered for a chance to be selected.[127] If selected, they were required to verify eligibility and submit the proper paperwork to be enrolled in OHP Standard. This unique approach allowed researchers to study the impacts of expansion of public health insurance on health care utilization, health outcomes, and financial impact on individuals using a randomized controlled design. One year after applicants were randomly assigned to either be enrolled in OHP Standard or not, those enrolled were about 25% more likely to have health insurance, have statistically significantly higher health care utilization, have lower out-of-pocket medical costs and debt, and have better self-reported physical and mental health than those not selected for OHP Standard.[127]

From its inception, OHP has been innovative and prioritized how to expand access to the greatest number of individuals as possible in Oregon. As an attempt to expand coverage and control costs, OHP introduced the coordinated care organization, which would go on to become a successful national model for delivering coordinated care using population health approaches.

2.5.3 Oregon's Coordinated Care Organizations

In 2012, CMS approved a waiver that established 16 coordinated care organizations (CCOs) across the state of Oregon. The waiver was to allow CCOs to operate under global budgets and the state promised that they would reduce the Medicaid per capita spending growth rate from 5.4% to 3.4% over 3 years and sustain it.[128,129] With the approval of the waiver, CMS invested $1.9 billion dollars over 5 years. Each region of the state was covered by at least one CCO and each CCO had several clinics for which it was responsible.

The CCO model grew out of the previous model of managed care organizations (MCOs), but differed in several key ways. First, CCOs integrated physical, behavioral, and dental health care and coordinated certain social services in the community for their members.[128,129] This allowed for the expansion of mental health care and addiction treatment across the state. Second, CCOs operated under global budgets which allowed the CCO to move away from the MCO fee-for-service (FFS) model and vertically integrate provider and payor.[128,129] Global budgets meant that the CCO had to meet certain quality metrics to receive their full payments or risk losing money and much of this risk was transferred to providers. However, using performance on quality of care metrics rather than a fee-for-service model also allowed providers to deliver the treatment that would ensure their patients reached optimal health rather than being restricted by OHP's prioritized list. Additionally, progress on metrics were tracked and reported transparently to the state which led to more accountability for the CCOs. Third, unlike their MCO predecessor and the related Accountable Care Organizations (ACOs), CCOs had an administrative layer that acted as an intermediary and contracting agent between the state and providers.[128,129]

Finally, the governance structure of CCOs differs from the original MCO model. CCOs are required to have a community advisory council (CAC) that is made up of local officials, community members, and a majority of people the CCO serves. In addition, the CCO board must contain at least one CAC member and they must engage seniors, people with disabilities, communities of color, individuals who use behavioral health services, and providers when making decisions so that more stakeholders than just payers are represented.[128,129]

Oregon was successful in reducing the Medicaid growth rate and sustaining it at 3.4%, meeting their requirement under the CMS waiver.[130] McConnell and colleagues[131] compared Oregon's CCO performance with different models in Colorado and Washington state. When compared to Colorado, a state that had a very similar, though less expensive, Accountable Care Organization model, expenditures declined in both states and there was no statistically significant difference between the two. However, when compared to Washington, Oregon had a 7 percent relative reduction of expenditures across evaluation and management, imaging, procedures, text, and inpatient facility care, though most of the reduction was driven by reduced inpatient utilization. Oregon also showed reductions in avoidable hospitalizations, but additionally showed reductions in primary care utilization.[131]

2.5.4 CCOs and Health Disparities

One of the priorities of the CCOs was to eliminate health disparities and with the changes from the previous MCO model, they were uniquely situated to help address the social determinants of health of their members that contribute to those disparities in health outcomes.[132] CCOs sought to reduce disparities through several specific ways. First, CCOs were each required to develop and implement transformation plans that were geared toward reducing disparities in their member populations. These plans included ensuring their organization abilities and staffing were adequate to serve a linguistically and culturally diverse community, hiring new staff dedicated to increasing health equity, updating cultural competency policies, and analyzing data in ways that would unearth disparities in quality metrics between racial and ethnic populations.[132]

The second way CCOs sought to eliminate health disparities was by forming regional Health Equity Coalitions that provided guidance to the CCOs. The coalitions supported diverse representation reflective of the communities served by the CCO on the CAC. Finally, the coalitions advocated for services in neighborhoods where people of color lived to ensure CCOs were equitably investing in all communities.[132]

The third component in the CCO strategy to eliminate health disparities was to expand the use of community health workers (CHWs).[132] Community health workers are lay members of the community who may or may not work within a healthcare setting, but who often share characteristics with the communities they serve, e.g., linguistic, racial, ethnic, socioeconomic. They can act in many capacities, including offering interpretation services, providing culturally appropriate health education, helping people navigate the healthcare system to get care they need, coaching individuals on healthy behaviors, acting as community advocate to the healthcare system, or providing some basic services like taking vital signs. The CHWs serve as a bridge between members and their local CCO.

McConnell and colleagues[132] evaluated the impact of CCOs on Black-white and American Indian-white health disparities. Prior to the implementation of CCOs in 2012, large disparities between the groups existed. After implementation, several key metrics had a narrower gap but disparities persisted. After CCO implementation, there was a 36% reduction in the disparity for primary care visits, though other studies have shown that primary care visits reduced overall, so it is not clear whether this is a reduction in disparity or a result of overall reduced primary care utilization. There was a reduction in Black-white disparity for three of four access to care, but a key measure of emergency department utilization was unchanged. Higher rates of ED utilization persist among Black and American Indian populations compared to white populations.[132]

As discussed earlier, quantifying disparities is insufficient to be able to increase health equity. To increase health equity, researchers and policymakers must understand the factors that are contributing to these disparities and seek interventions to address them. Medicaid policy is potentially an ideal mechanism to address social determinants of health to improve health outcomes because Medicaid provides coverage for over 86 million people as of January 2022[133] and this population is much more likely to have higher social risks compared to a commercially insured population.[134] Because Medicaid policy is written by the states and states contract with CCOs, MCOs, and ACOs, there is an opportunity to embed incentives or requirements to address social determinants of health through value-based payment structures.[134] Finally, there may be internal motivation by CCOs to address social determinants of health if doing so allows them to reduce spending on medical services and capture a larger share of capitation payments.[134]

2.5.5 Flexible Service Spending

The Medicaid policy in Oregon that sought to require CCOs to help address the social determinants of health of their enrollees was through a category of spending called Health-Related Services (HRS).[134] CCOs were allowed to spend a portion of their budgets on services not covered by traditional billing or encounter codes, but that were thought to be related to the health of the population. Typically, these were social services and spending could be directed at the community or individual levels. HRS was originally known as Flexible Service Spending from 2012-2017 and was inconsistently used because there was lack of clarity about what exactly fell under “flexible services”.[134] In 2017, Oregon issued a rule clarification along with their Medicaid Waiver 1115 that defined a new category of spending on social determinants of health called “Health-Related Services” that included flexible services.[134] HRS was defined as cost-effective services offered as an adjunct to medical services, and community benefit initiatives, defined as community-level interventions focused on improving population health and health care quality. In 2017, Medicaid also changed calculations for medical loss ratios, a concern raised by earlier adopters of flexible service spending, so that if interventions delivered as part of HRS reduced the medical services that people needed their capitation rates were not affected by this.[134] The goal was to ensure there was not a perverse incentive to avoid addressing the social determinants of health.

Part of the prioritization of HRS spending involved conducting community health assessments and discussing priorities based on those assessments with the CACs of each CCO.[134] Once priorities were defined, CCOs entered into formal agreements or contracts with community-based organizations who would receive investments under HRS. CCOs also were required to report detailed information on HRS spending publicly.

During the first three years of the new waiver, 2017-2020, HRS spending increased by 120%, from $7.2 million in 2016 to $16.2 million in 2019.[135] However, spending varied widely among CCOs, ranging from an average of $0.04 per member to $10.30. Some of the variation can be accounted for in CCOs being in different phases of developing processes to support spending on HRS and another source of variation may be due to CCOs spending on social determinants of health was coming out of other budget categories like quality incentives or prior year profits.[135]

The majority of the HRS spending was devoted to community benefit initiatives. This made up 57% of total HRS spending across CCOs.[135] Nearly half of the community benefit spending was not categorized, but among the half that was, categories included housing, training and education, food security, and support for capacity building in community-based organizations. Individual services comprised 24% of HRS spending and those categories were more defined than community benefit initiatives.[135] Spending on individual services included primary training, education, transportation, and case management with a smaller proportion devoted to food, social supports, home services, housing, and others.

CCO spending on HRS was flexible and not uniform across regions.[135] Smaller CCOs or CCOs in rural areas lack the same networks of community-based organizations that larger, more urban CCOs can leverage. This can potentially lead to differential impact of HRS for CCO populations because there may not be as much capacity in small, rural areas to carry out HRS initiatives. Additionally, the COVID-19 pandemic placed additional strain on the social service and health care sectors. Oregon released 2020 quality incentives early to help alleviate some of this pressure.[135] This release allowed CCOs to quickly channel resources to partners who could help with emergency housing, food, and other needs, which was in higher demand both because of the pandemic, but also because of the unusually aggressive fire season that affected much of Oregon in summer 2020. Finally, in response to the racial justice uprisings in summer 2020 and the need to make HRS initiatives more widely available, some CCOs sought to build new partnerships with community-based organizations that served communities of color and created websites to allow members to directly request assistance.[135]

2.6 Gaps in the Literature

This dissertation addressed three critical gaps in the literature.

Gap 1: Effectiveness of NPT services among socially and economically disadvantaged populations.

Strong evidence on the effectiveness of NPT services for long-term functioning and pain relief does not exist, even among socially advantaged populations.[3,28] The available evidence indicates that NPT services are as safe or safer than biomedical approaches, but the quality of the evidence is modest at best, mostly focused on short-term outcomes, and rarely includes subgroup analyses.[3,28] Generating evidence on treatments for chronic pain is challenging and few studies have sought to focus on what works among the most disadvantaged groups. Given the disparities that exist in chronic pain and utilization outcomes, generating evidence about the effectiveness of NPT services among those experiencing disparities is critical. By evaluating how a policy designed to increase access to NPT services among Medicaid enrollees at FQHCs affected chronic pain outcomes, this dissertation contributed to addressing this gap in the literature, though more rigorous clinical trials will be needed to examine effectiveness.

Gap 2: How social risks influence chronic pain outcomes and health services utilization.

Disparities in chronic pain outcomes are well-documented across many different groups, including those living in poverty, minoritized racial and ethnic populations, rural people, older people, among others.[41,42,44,88] Identifying disparities is important, but identifying the source of those disparities is a crucial next step in determining how to increase health equity.[66] The social determinants of health are one potential source of disparities in chronic pain outcomes and treatment utilization. Indeed, we know that social determinants of health operate at multiple levels of influence and can influence health outcomes and health services access across a broad range of conditions.[53,105–107] Social factors are key drivers in the biopsychosocial model of pain,[30] yet, the relationship between chronic pain, social determinants of health, and other psychosocial factors is complicated and understudied. Social factors not only affect pain and functioning, other psychosocial comorbidities known to predict chronic pain, but also act to enable or hinder utilization of pain management treatment options. This dissertation contributed to the literature on the biopsychosocial model of chronic pain and pain management utilization by identifying specific social determinants of health, at the geographic and/or individual levels, that are predictive of chronic pain outcomes and NPT service utilization so that future health policy and health system interventions may take these social determinants of health into account when seeking to increase health equity among chronic pain populations.

Gap 3: How Medicaid policy may be used to increase health equity.

While scientists are seeking to understand these complex interactions between chronic pain and biopsychosocial factors, policymakers are moving forward to try to address pressing issues affecting people today through multi-level policy interventions that seek to affect change for the individual, health system, clinics, providers, and within the community. Often, multiple policies are enacted simultaneously with differing goals, e.g., to impact the quality of chronic pain care and to address social determinants of health. Evaluating how one Medicaid policy[18,19] that seeks to impact chronic pain by increasing access to NPT services is critical to understanding the overall impact on populations. This dissertation sought to address this gap by assessing how access to NPT services impacted Medicaid enrollees while accounting for various social determinants of health with varying levels of social determinants of health.

2.7 Theoretical Frameworks

One primary theory and two complementary frameworks guided this dissertation and informed the design, key variables, and hypotheses that will be described in further detail in Chapter 3.

2.7.1 Ecosocial Theory

This dissertation was guided by the Ecosocial Theory of Disease Distribution (ecosocial theory, in short). Krieger first introduced ecosocial theory in 1994 and has subsequently expanded it over the last three decades.[57–61] Ecosocial theory was used to describe and explain causal relationships in disease distribution and production. [57–61] Ecosocial theory is used to describe and explain causal relationships in disease distribution and production. Specifically, the theory contains four constructs – embodiment; pathways to embodiment; the cumulative interplay of exposure, susceptibility, and resistance; and agency and accountability – that must be considered in concert to understand the multi-level relationships between social factors and disease development. *Embodiment* is the process of the body being in synergistic relationship with the ecosystem in which it exists. This core concept is intended to capture the ways in which "nature" and "nurture" are not separate, opposing stances, but rather that the interaction between the two can phenotypically alter populations. Embodiment is continual and the process is influenced by political, social, communal, and environmental forces. In her later work, Krieger introduces the concept *embodying (in)justice* as a way to denote how historical and contemporary exposures to justice or injustice reside in the body and have effects on the health of populations.[61] The *pathways to embodiment* capture the multitude of ways through which embodiment occurs by making explicit the various factors that exert force on the body. *Cumulative interplay* describes how patterns of disease occur within a multi-level context and how people in different socio-economic positions experience different exposures, susceptibilities, and resistances to risk factors that lead to disease. Finally, Krieger regards government as central to the process of embodiment because of the power it holds in controlling health and wealth in societies. This is reflected in her fourth construct of *agency and accountability* where she argues that the government and policy-making institutions are responsible for the production of disease through policies that perpetuate inequity, power structures, and discrimination. The ecosocial theory is multi-level and considers history or time as well as processes and power to be central constructs helping to explain differential outcomes. Each construct on its own is important but they all must be considered in concert to understand the mechanisms at play – the how and why – in determining health disparities and finding solutions to increase health equity.

Ecosocial theory guided this dissertation because the lived experiences of racism, sexism, and poverty, both historically across generations and contemporarily in present day, are *embodied* in the populations experiencing chronic pain. The *pathways to this embodiment* are ongoing and create a *cumulative interplay* across time. The pathways to embodiment include access or lack of access to healthy foods, nearby healthcare, education, social supports, adequate housing, healthy physical activity, and well-paying, safe jobs, to name a few. These pathways can act as stressors, mediating the relationship between exposures, psychosocial conditions, and outcomes. Finally, in addition to *pathways to embodiment*, I consider *agency and accountability* in how the Oregon Back and Neck Pain policy and the health-related service spending initiative was used to potentially increase health equity by expanding access to NPT services and addressing social determinants of health at multiple levels. The relationship between healthcare systems and marginalized populations, including populations of color and people of any race living in poverty, is justifiably fraught. For generations, healthcare systems have harmed these populations in the name of medicine, resulting in a lack of trust from these communities. Understanding what effect the policies that sought to address disparities and mechanisms of disparities (e.g., financial insecurity, medically underserved communities, food insecurity) had on health outcomes and healthcare access is important to inform future policies and health system interventions.

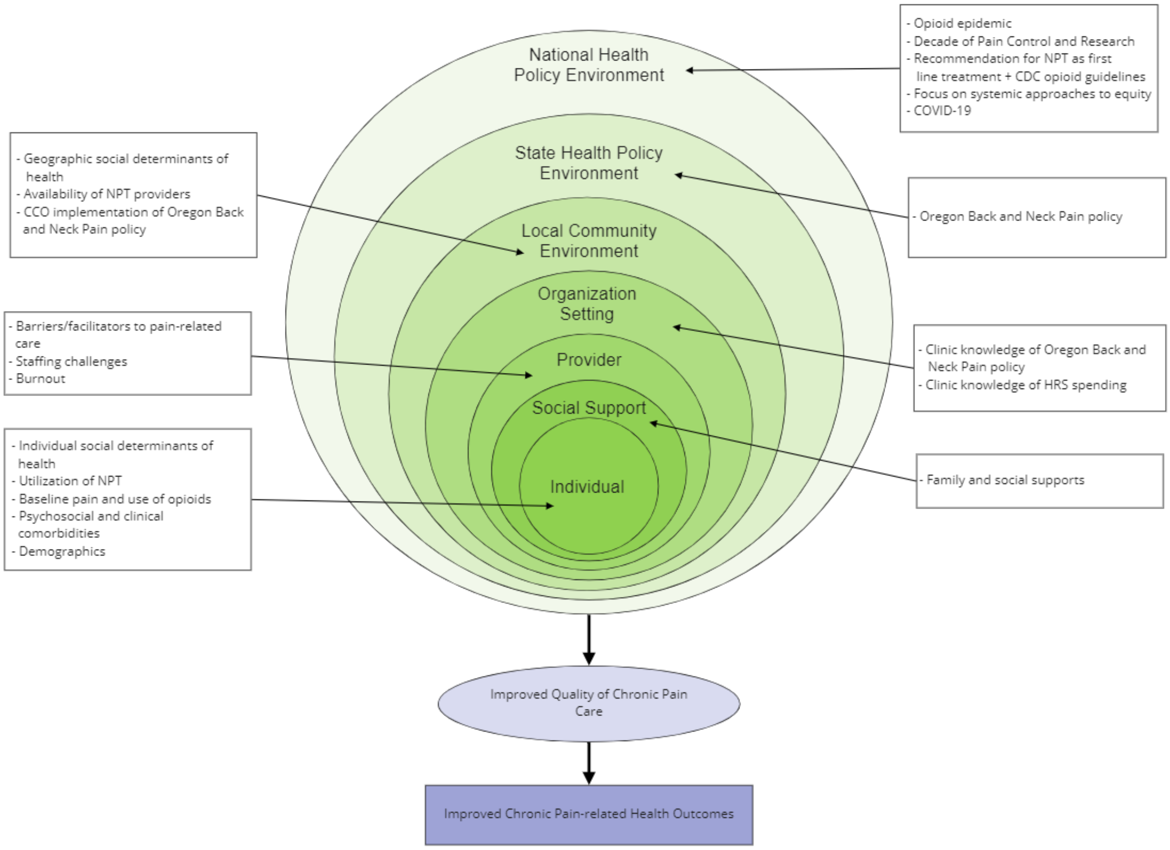
2.7.2 Social Ecological or Multi-level Influences on Quality of Care Framework

The social ecological framework, introduced by Bronfenbrenner in the 1970s,[136] depicts five levels of environment with the individual in the middle. The five levels originally used, from outermost to innermost, are the chronosystem, macrosystem, exosystem, mesosystem, and microsystem. The levels are interconnected and what happens in one level influences the next level, with each level exerting cumulative influence on the center, or individual.[136] The social ecological framework is a useful conceptual model to use with the ecosocial theory because it can depict the interrelated nature of the national, state, community, health system, and individual spheres that influence a person's health over time. It is used often to describe how complex or multi-level healthcare system or policy interventions, social determinants of health, and individual behaviors or clinical profiles impact the outcome of interest.

This dissertation used the Multi-level Influences on Quality of Care conceptual model put forth by Clauser and colleagues[62,63]This dissertation will use the Multi-level Influences on Quality of Care conceptual model put forth by Clauser and colleagues[62,63] to guide the design, variable selection, and hypotheses of all three aims. The Multi-level Influences on Quality of Care for Chronic Pain (Figure 1) is a modified social ecological model that was originally created to describe the multi-level influences on cancer care and is intended to show that multiple levels exert influence on the quality of care that a patient receives in a healthcare system and that quality of care translates into health outcomes.[62,63] Specifically, the Clauser at al. model is concerned with which spheres multi-level interventions impact and the impact on quality of care and health outcomes. A multi-level intervention is defined as any intervention that targets the patient and at least two additional levels of influence, e.g., health system and providers.[62] The levels of influence used in the original model are the national health policy environment, the state health policy environments, local community environment, organization and/or practice setting, provider/team, family and social supports, and the individual patient.

This model was appropriate to use in this dissertation because the Oregon Back and Neck Pain policy is a multi-level policy interventions targeting the patient and other core levels of influence, each with an intent on impacting the quality of care a patient receives and, ultimately, on health outcomes.

Figure 1. Multi-level Influences on Quality of Chronic Pain Care^

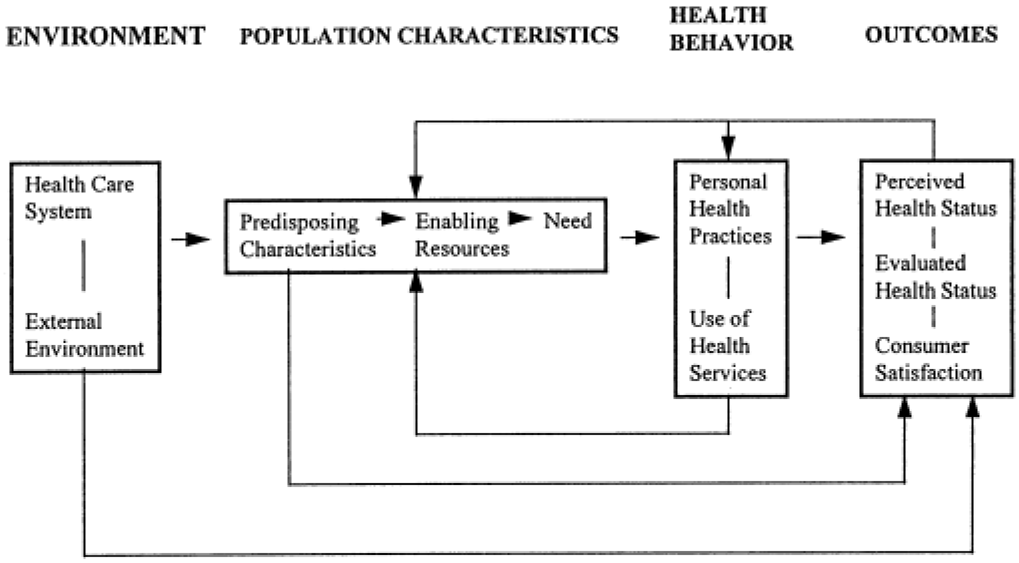


^Author's adaptation of the Multi-Level Influences on Quality of Care model.[62,63]

2.7.3 The Behavioral Model of Health Care Utilization for Vulnerable Populations

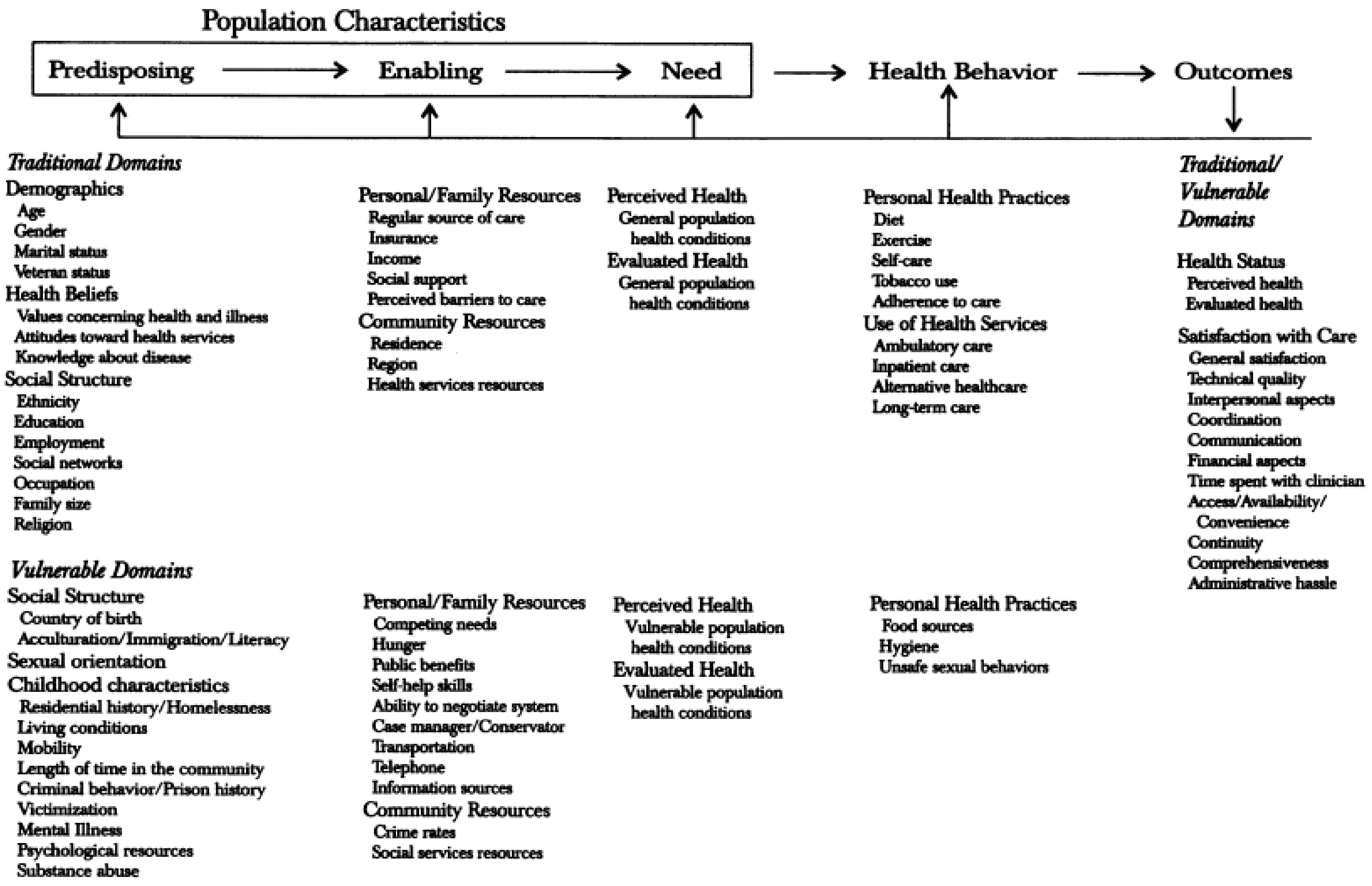
The final conceptual model used in this dissertation was based off Aday and Andersen's Behavioral Model of Health Care Utilization[64] (Figure 2) which has been used many times over the last 50 years in health services research to understand societal and individual determinants of health services utilization. The model was originally proposed in the 1960s to both predict and explain how predisposing characteristics, enabling or hindering resources, and patient need influenced the use of health services.[64] The model was updated several times to reflect growing understanding of the multiple levels of influence that impact utilization and how utilization impacts health outcomes.[137] In 1974, the model was updated to include the role of the health care system and health policy and their impact on how populations utilize health services.[64] The model was updated in the early 1990s to incorporate the role of the external environment, e.g., political, environmental, and economic contexts, in predicting or explaining utilization. At this time, the model also expanded beyond just a model of utilization, but also incorporated health status as an outcome with behavioral utilization measures used as a predictor. In 1995, Andersen put forth a version of the model includes dynamic feedback loops to indicate the multi-directional and multi-level influence that health behaviors and health outcomes have on predispositions, enabling or hindering resources and health practices.[137]

Figure 2. Phase 4 of Andersen's Behavioral Model of Health Services Utilization[137]



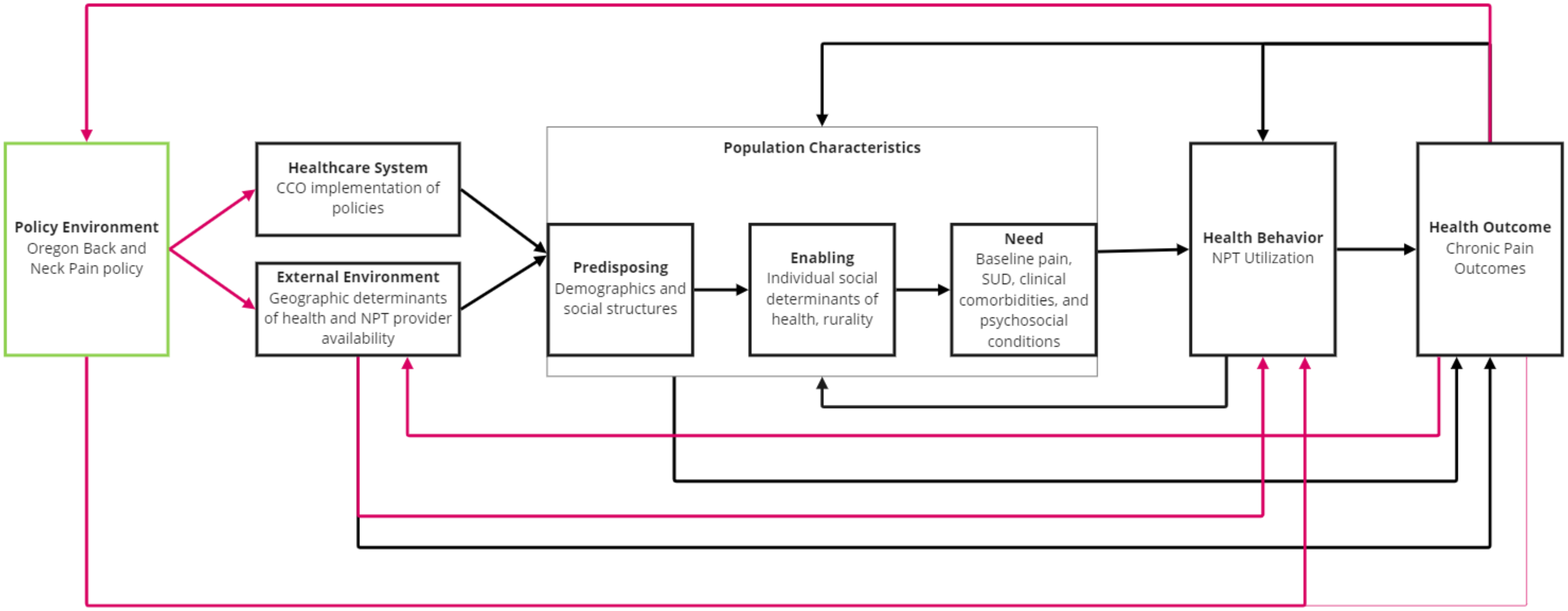
In 2000, Gelberg, Andersen, and Leake[65] applied a new version of the Behavioral Model to a population experiencing homelessness and called it The Behavioral Model for Vulnerable Populations (Figure 3). They argue that the original Behavioral Model needed to include specific domains that are relevant to populations who are disadvantaged within society, so they updated the model to include Vulnerable Domains for each model characteristic. [65] The value of this updated model is that it allows for the social determinants of health to be included along the pathway that explains or predicts health utilization and health outcomes, though it does not account for upstream social determinants in the external environment.

Figure 3. The Behavioral Model for Vulnerable Populations[65]



This dissertation expanded on The Behavioral Model for Vulnerable Populations to add a Policy Environment in addition to the individual Population Characteristics to guide the design, variable selection, and hypotheses generated in this dissertation (Figure 4) for both NPT service utilization and chronic pain outcomes. The addition of the Policy Environment as its own domain underscores the role of government, as described by Krieger, in shaping population characteristics as well as health behaviors and outcomes in the Behavioral Model. The two new arrows from Outcomes back to the Policy Environment and the External Environment, accounts for how health outcomes impact decisions policymakers make about issues affecting their constituents and how health outcomes affect portions of the External Environment, such as the level of poverty. Finally, the original model did not account for how the external environment directly impacts the health behaviors, but I have added this arrow to account for certain geographic characteristics, such as provider availability, that could impact utilization behaviors. The specifics of the variables, hypotheses, and design are detailed in Chapter 3

Figure 4. Behavioral Model of Health Services Utilization for Marginalized Populations^



^Author's adaptation of the Behavioral Model of Health Services Utilization for Vulnerable Populations.[65]

2.8 Conclusion

This chapter reviews the literature on the general burden of chronic pain in the United States; biopsychosocial model through which chronic pain is best understood; biological, psychological, behavioral and social drivers of chronic pain and associated disparities; key aspects of the national policy landscape of chronic pain and the opioid epidemic; chronic pain treatment option efficacy, effectiveness, and risk of harm; Oregon Back and Neck Pain policy; gaps in the literature; and finally, theoretical underpinnings that inform the subsequent design, hypotheses, and methods. Synthesis of this literature highlights critical gaps in the availability of evidence for the effectiveness of NPT among a socially and economically disadvantaged population, the role of social determinants of health in influencing chronic pain outcomes and health services utilization, and how Medicaid policy may be used to increase health equity. Using theories and frameworks designed to account for the role of social determinants of health by acknowledging the inter-related nature of the national policy environment, state policy environment, community, health system, and individual spheres of influence can help elucidate the pathways through which health equity may be increased. A comprehensive analysis of how chronic pain outcomes and health services utilization among Medicaid recipients receiving care at FQHCs are influenced by these spheres of influence is needed to understand the unique role that social determinants of health and Medicaid policies play in determining health and health services outcomes among socially and economically disadvantaged populations.

Chapter 3: Design and Methods

3.0 Methods

3.0.1Study Design and Settings

This analysis used secondary data from the Back on Track (BoT) study. BoT was led by a research team at Kaiser Permanente in partnership with OCHIN, a Health Resources and Administrative Services (HRSA)-designated non-profit network that provides, among other health information technology services, electronic health record (EHR) service for federally qualified health centers (FQHCs) and is a national leader in health information technology services for community health centers serving low-income individuals. OCHIN includes 186 FQHCs in Oregon and 105 FQHCs in California with >450 similar clinics across the country. BoT study participants were recruited through 81 participating OCHIN clinics.

BoT was a quasi-experimental study evaluating the Oregon Back and Neck Pain (OBNP) policy and included three substudies. This current study relied on data from a prospective cohort substudy that used patient surveys to evaluate changes in pain, functional outcomes, satisfaction, treatment-related adverse events, and use of policy-relevant pain-related treatment services among patients with a new episode of back and/or neck pain.

3.0.2 Data Collection and Sample

Participants were recruited between June 2018-May 2019, with survey data collected between June 2018 – June 2020. The sample was identified using criteria from the electronic health record (EHR), mailed recruitment materials, and screened for study eligibility over the phone. For those who screened eligible, they were consented and enrolled in the study.

In addition to no evidence of receiving long term opioid therapy (LTOT) in the previous 6 months, study eligibility required that enrolled individuals did not have evidence of a primary care visit with a back or neck pain diagnosis in the 90 days prior to the in-person primary care visit with a back and/or neck pain diagnosis. Thus, this was a cohort of patients who were beginning a new episode of care for back and/or neck pain without evidence of current or recent opioid treatment. The specific inclusion criteria for the sample are presented below in Table 3.1.

Table 3.1. Sample Eligibility Criteria

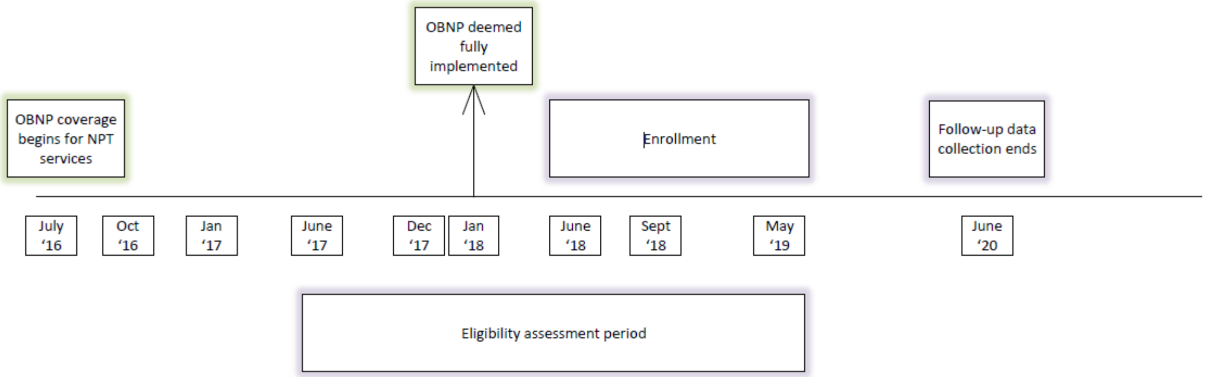
Eligibility Criteria (data source in parentheses)
18-64 years of age and currently enrolled in Medicaid (EHR)
Completed ≥1 in-person primary care visit from 6/1/2017-5/31/2019 with at least one of the back / neck pain diagnosis covered by the Oregon Back and Neck Pain policy ("eligible visit"; EHR)
No in-person visits that meet the above criteria for the "eligible visit" in the 90 days prior to the "eligible visit" (EHR) suggesting a "new episode" of care
No evidence of patient being prescribed opioids consistent with chronic opioid therapy in 90 days prior to recruitment (EHR)
Had an active mailing address (EHR)
No malignant cancer diagnosis or evidence of having received hospice or other end-of-life palliative care in year prior to recruitment (EHR)
Had an appointment at clinic for back or neck pain in past month (Eligibility screener)
Had NOT taken any opioid medications on a daily basis for two months or more during the three months prior to recruitment (Eligibility screener)

The sample was followed for 12 months post-enrollment and was administered assessments every three months (baseline, 3-months, 6-months, 9-months, and 12-months). The initial assessment will be referred to as "baseline" throughout the text, but occurred within one month of the new episode of care, thus capturing outcomes and care received after a new episode of back/neck pain was diagnosed. There were 1,690 people enrolled and eligible for all four follow-up assessments.

Participants represent 48 clinics across 12 coordinated care organizations (CCOs) in Oregon and 33 clinics across 7 managed care organizations (MCOs) in California. Oregon's CCOs[138] and California's Medicaid MCOs[139] both serve as pivotal structures in delivering Medicaid services, emphasizing integrated care and cost containment. Oregon's CCOs operate under a global budget model, integrating physical, behavioral, and dental health services, and are accountable for health outcomes within their communities.[140] Similarly, California's MCOs provide managed care services to Medi-Cal beneficiaries, focusing on coordinated care to improve quality and reduce costs.[139] Both states have implemented performance-based incentives to enhance care quality and have incorporated community-based organizations to address social determinants of health, reflecting a shared commitment to holistic, value-driven healthcare delivery.[141]

The assessment period for each participant and the total 12-month survey administration period occurred after the policy was deemed fully implemented and NPT services were being reimbursed by Centers for Medicare and Medicaid Services (CMS; July 2017). The advantage of this is the assessment period reflected how the policy operated when relatively mature with respect to provision of NPT services – from June 2018 through June 2020.

Figure 3.1. Sample Recruitment and Oregon Back and Neck Pain Policy (OBNP) Timeline



3.0.3 Data Sources

The survey assessed sociodemographic information, social risks, social support for pain management, use of policy-relevant NPT treatment services, pain intensity and interference, and clinical characteristics. The study also utilized EHR data to construct indices of rurality and federal poverty level (FPL) of those in the surrounding region, date of birth, mental health and substance use diagnoses, and to construct a comorbidity index of disease severity, the Charlson Comorbidity Index.[142]

3.0.3.1 Social Determinants of Health and Sociodemographic Measures

A description of the variables included in the Aims 2 and 3 analyses as predictors can be found in Table 3.2. Social risk was captured using three questions: medical financial insecurity in the previous 12 months (0=No, 1=Yes), food insecurity in the previous 12 months (0=No, 1=Yes), and housing insecurity in the upcoming 2 months (0=No, 1=Yes). Social support was measured by a single question asking whether the person has sought support from others in their life to manage their pain (0=No, 1=Yes). These variables reflect the measures of social determinants of health available in the data.

The sociodemographic variables included age (centered), sex (0=male, 1=female), race and ethnicity (1=non-Hispanic white, 2=non-Hispanic Black, Indigenous, or other people of color [BIPOC], and 3=Hispanic), education (1=less than high school, 2=high school, or 3=at least some college), individual federal poverty level (FPL) (0% FPL, 0.01%-99.99% FPL, 100%-149.9% FPL, and ≥150% FPL), and rurality based on clinic location (0=urban, 1=rural). The non-Hispanic BIPOC category includes multiple races due to small sample sizes in the individual racial categories. Age, sex, race and ethnicity, and rurality were determined based on information from the EHR and education was self-reported on the baseline survey.

3.0.3.2 Clinical Characteristics

The clinical characteristics of participants include the number of painful conditions (continuous), STarT Back Score (1=low risk, 2=medium risk, and 3=high risk), type of qualifying pain diagnosis (1=back pain, 2=neck pain, or 3=both), any diagnosed substance use condition (0=no substance use, 1=at least one substance use), any diagnosed mental health condition (0=no mental health condition, 1=at least one mental health condition), and the Charlson Comorbidity Index (continuous).

The policy suggested stratifying patients into three pain-related disability risk categories – low-, medium-, or high-risk – based on patient responses to the STarT Back Assessment Tool which asks patients about pain-related functioning and concerns.[37] The STarT Back Assessment Tool is a validated assessment used to determine risk level for poor functional prognosis based on psychosocial indicators and is intended to guide primary care providers in identifying appropriate care pathways for patients with low back pain.[37,120]

This risk stratification encouraged Oregon's CCOs to target more intensive NPT services to those patients with the greatest need, though CCOs were not required to implement the policy in this way. More information about this stratification tool is found in Chapter 2.

Pain conditions were defined based on the pain-related ICD-10 diagnosis corresponding to the non-malignant chronic pain condition clusters developed for the National Pain Strategy pain condition clusters.[143] Substance use conditions were defined as having at least one diagnosis in the year prior to enrollment for alcohol abuse, cannabis-related disorder, drug abuse, or opioid-related disorder. Mental health conditions were defined as having at least one diagnosis in the year prior to enrollment for anxiety, depression, PTSD, ADHD, bipolar disorder, or schizophrenia. Number of painful conditions, type of qualifying pain diagnosis, substance use, mental health, and the Charlson Comorbidity Index were determined based on information from the EHR and the STarT Back Score was based on baseline survey.

Table 3.2. Predictors Included in Analyses

Measure	**Brief Description of Measure**
Food Insecurity*	Binary: In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? No=0 Yes=1
Housing Insecurity*	Binary: Are you worried or concerned that in the next two months you may not have stable housing that you own, rent, or stay in as a part of a household? No=0 Yes=1
Medical Financial Insecurity*	Binary: In the last 12 months, have you needed to see a doctor but could not because of cost? No=0 Yes=1
Social Support for Pain Management*	Binary: Since your last clinic visit, have you used any of these strategies to manage your pain: seeking support from others in your life? No=0 Yes=1
Federal Poverty Level (FPL) Percentage#	Categorical: 0, 0% 1, 0.01%-99.99% 2, 100.0%-149.9% 3, ≥150.0%-199.9%
Age#	Continuous, centered
Female#	Binary: No=0 Yes=1
Race#	Categorical: White, non-Hispanic=1 BIPOC, non-Hispanic=2 Hispanic=3
Education level*	Categorical: 1=Less than high school; 2=High school graduate; 3=At least some college
Rural#	Binary: Urban=0 Rural=1
STarT Back score*	Categorical: Low risk=1 Medium risk=2 High risk=3
Type of Qualifying Pain Diagnosis#	Categorical: Back=1 Neck=2 Both=3

Number of additional pain conditions (in addition to back/neck pain) in baseline period[#]	Continuous Pain-related ICD-10 diagnosis corresponding to the non-malignant chronic pain condition clusters developed for the National Pain Strategy chronic pain condition clusters
Any psychosocial conditions in baseline period[#]	Binary: At least 1 diagnosis of the following: Anxiety Depression PTSD Other MH diagnosis
Any substance use disorder condition at baseline[#]	Binary: At least 1 diagnosis of the following: Alcohol abuse Cannabis-related disorder Drug abuse Opioid related disorder
Charlson Comorbidity Index[#]	Continuous: Burden of chronic disease based on 12 ICD-10 diagnostic categories. Higher score indicate more disease

[#]Source: Electronic health record (EHR); [*]Self-reported at baseline

3.0.4 Outcome Measures

3.0.4.1 NPT Service Utilization

Participants were asked about their NPT service utilization in the prior 3-months (for baseline, participants were asked about relevant health service utilization since their most recent clinic visit). Participants were asked about use of acupuncture, chiropractic, massage therapy, physical or occupation therapy, cognitive behavioral therapy (CBT) or acceptance and commitment therapy (ACT), psychotherapy, and yoga. For each type of service, they were asked the following series of questions: Have you used this service in the last 3-months (0=No, 1=Yes); if yes, why (1=to improve well-being/general health, 2=to manage back or neck pain, 3=to manage pain other than back or neck pain, 4=to manage a condition other than pain); overall, how often have you done this in the last 3 months (1=once, 2=a few times, 3=once a week or more, 4=daily or almost daily); and, did your health insurance pay for this service (1=yes, it paid the entire cost of the service and I paid nothing, 2=it paid some of the cost, but I paid for part of the service and/or a copay, 3=no, I paid the entire cost of the service, 4=no, the service was free, 5=don’t know). The full set of survey questions are available in Table 3.3.

Table 3.3. NPT Use Survey Questions

	Have you used this service in the last 3 months?	**If yes, why?** ***Check all that apply.***	**Overall, how often have you done this in the last 3 months?**	**Did your health insurance pay for this service?**
1. Acupuncture: Stimulation of specific points of the body, with thin needles	☐ Yes ☐ No → ***Go to question 12 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don't know
2. Chiropractic: Hands on adjustment of spine and joints to Improve alignment, function or pain	☐ Yes ☐ No → ***Go to question 13 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don't know
3. Massage Therapy: Hands on pressure, rubbing, or manipulation of muscles and soft tissue	☐ Yes ☐ No → ***Go to question 14 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don't know

	Have you used this service in the last 3 months?	**If yes, why?** ***Check all that apply.***	**Overall, how often have you done this in the last 3 months?**	**Did your health insurance pay for this service?**
4. Rehabilitation Therapies: Hands on treatment such as traction, TENS, ultrasound, or mobilization by a **Physical Therapist (PT) or Occupational Therapist (OT)** to treat pain or injury	☐ Yes ☐ No → ***Go to question 15 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don’t know
5. Cognitive Behavioral Therapy (CBT) or Acceptance and Commitment Therapy (ACT): One-on-one or group CBT or ACT by a psychologist or other mental health provider	☐ Yes ☐ No → ***Go to question 16 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don’t know
6. Psychotherapy: One-on-one or group talk therapy (not CBT or ACT) by a psychologist or other mental health provider	☐ Yes ☐ No → ***Go to question 17 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don’t know

	Have you used this service in the last 3 months?	If yes, why? *Check all that apply.*	Overall, how often have you done this in the last 3 months?	Did your health insurance pay for this service?
7. Yoga Group or Class: Practices that combine physical postures, breathing techniques, and meditation or relaxation	☐ Yes ☐ No → ***Go to question 18 below***	☐ To improve well-being / general health ☐ To manage back or neck pain ☐ To manage pain other than back or neck pain ☐ To manage a condition other than pain	☐ Once ☐ A few times ☐ Once a week or more ☐ Daily or almost daily ☐	☐ Yes, it paid the entire cost of the service and I paid nothing ☐ It paid some of the cost but I paid for part of the service and / or a co-pay ☐ No, I paid the entire cost of the service ☐ No, the service was free ☐ Don’t know

3.0.4.2 Brief Pain Inventory

The Brief Pain Inventory Short Form (BPI-SF) is a validated assessment that asks patients to report their average pain severity and pain-related impairments in functioning in key life domains that has been well-received for use by clinicians and their support staff in clinical practice settings and has been acceptable to patients in currently and recently NIH- and PCORI-funded studies.[144,145] The BPI-SF is scored as a pain intensity subscale (3 items),[145] pain-related interference (7 items), and a severity composite of the two subscales (see below for the survey questions).[144] See Table 3.4.

Table 3.4. Brief Pain Inventory Survey Questions

	0	1	2	3	4	5	6	7	8	9	10
	No pain/Does not interfere										Pain as bad as you can imagine/Completely interferes
1. What number best describes **how much pain you have right now**?											
2. What number best describes your **pain at its worst in the last week**?											
3. What number best describes your **pain on average in the last week**?											
The next questions ask about how much pain has **interfered** in your life **in the last week**.											
4. What number best describes how pain has interfered with your **general activity in the last week?**											
5. What number best describes how pain has interfered with your **mood in the last week?**											
6. What number best describes how pain has interfered with your **walking ability in the last week?**											
7. What number best describes how pain has interfered with your **normal work including both work outside the home and housework in the last week?**											
8. What number best describes how pain has interfered with your **relations with other people in the last week?**											
9. What number best describes how pain has interfered with your **sleep in the last week**?											
10. What number best describes how pain has interfered with your **enjoyment of life in the last week?**											

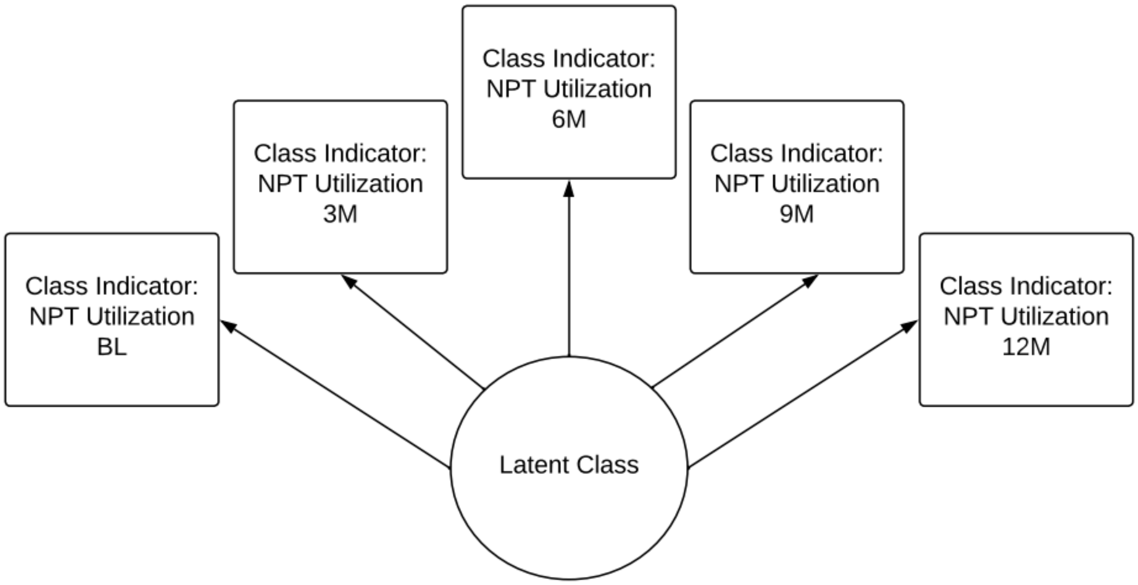
3.1 Analyses

3.1.1 Aims 1 and 2 Analysis

3.1.1.1 Latent Class Analysis Overview

Multiple group (MG) repeated measures latent class analysis (RMLCA) was used to examine the underlying patterns of NPT utilization across the 12-month survey period in Aims 1 and 2. RMLCA is considered a person-centered analytic approach where a series of observed responses on indicator variables are used to identify distinct, latent subgroups of individuals, called classes.[146] The class indicators are the observed responses to the NPT survey questions at each of the five timepoints (see Figure 3.2). RMLCA is particularly useful for pain management and NPT service use research because it identifies distinct patterns of individual trajectories over time, capturing the dynamic nature of pain and treatment experiences.[147,148] This method can distinguish underlying subgroups based on how patients utilize different NPT services, revealing heterogeneity in treatment preferences, frequency of use, and responses to pain interventions across multiple assessment periods.[148,149] By recognizing these subgroups, which are latent variables within the RMLCA model, policymakers, researchers and clinicians can better tailor interventions and resource allocation, ultimately improving patient outcomes by aligning policy mechanisms (e.g., availability of NPT services) more closely with individual needs and usage patterns.[150,151]

Figure 3.2. Latent Class Construct Components



3.1.1.2 Class Enumeration

The optimal number of latent classes or subgroups is determined by starting with a 1-class solution and incrementing the number of classes by one until the model is not identified.[146] The optimal number of classes is chosen by examining the sample size of the subgroups, classification probabilities, and model fit criteria including likelihood ratio chi-square, entropy, the Bayesian Information Criterion (BIC),[152] Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC),[153] and Approximate Weight of Evidence (AWE).[146] The rule for smallest class size is that any class with <10% of the population is too small and classification probabilities should be at least 0.8. Entropy ranges from 0 (the model does not fit the data) to 1 (the model perfectly fits the data). Higher entropy values are desirable, while lower BIC, AIC, CAIC, and AWE values indicate that a model fits the data better and indicates better certainty of assigning individuals to the latent classes or subgroups.[146] Additionally, for each additional class, the adjusted Lo-

Mendell Rubin likelihood ratio test (LMR)[154] and the bootstrapped likelihood ratio test (BLRT)[155] are used to compare against the K-1 class model to determine the best fitting model. The approximate Bayes factor (BF) and correct model probabilities (cMP) are used to compare the K class model against the K+1 class model to determine the best fitting model.[156] A significant value for the LMR and BLRT indicates that the K class model fits the data better than a K-1 class model while a larger BF value and value closer to 1 for the cMP indicates the K class model fits the data better than a K+1 class model. This process is called "class enumeration" and is used to identify a mixture model that yields empirically, highly-differentiated, and well-separated latent classes with members having a high degree of homogeneity in their responses on the class indicators. In addition to examining the empirical fit indices, there is also practical reflection required to ensure that the subset of candidate models selected for the final model makes sense subjectively. In this RMLCA, class enumeration was conducted separately in California and Oregon then in a combined sample to ensure the number of classes was consistent across states.

3.1.1.3 Repeated Measures Latent Class Indicators

In the RMLCA presented here, NPT utilization latent classes are modeled based on five indicators for the highest reported frequency of any type of NPT utilization at baseline, 3-months, 6-months, 9-months, and 12-months (see Table 3.5 and Figure 1). These categorical indicators were used to create subgroups with similar NPT utilization patterns. Each indicator represents the highest frequency of utilization of any NPT service used for back or neck pain and regardless of payment type reported during the prior 3-months at each time point (except baseline, where they were asked about use since their qualifying clinic visit; see Figure 1). Payment type was excluded from the indicator definition for two reasons: first, in the main study, BoT, qualitative data revealed that many CCOs and clinics provided NPT services that were not covered by CMS, but were nevertheless made available to participants at a low or no cost to them which is assumed to be an indirect policy effect of expanding access to NPT services via the OBNP. This is possible because of the flexible nature CCOs are afforded by the 1115 Waiver in how to spend their allocated funds for services that benefit their patients.[129,130] Secondly, empirically, the majority of participants (67-78%) reported at each timepoint that the service most frequently used was covered in part or in full by CMS, thereby reducing potential bias that payment type could be associated with how frequently participants are using NPT services (see Supplement 1).

Table 3.5. NPT Utilization Indicator Definition

Outcome	**Brief Description of Measure**
Use of NPT services	If used <u>any</u> of the following services in the past 3 months • Acupuncture • Chiropractic • Massage therapy • PT or OT • CBT/ACT • Other Psychotherapy • Yoga AND Reason: To manage back or neck pain Frequency: Never or once, a few times, once a week or more

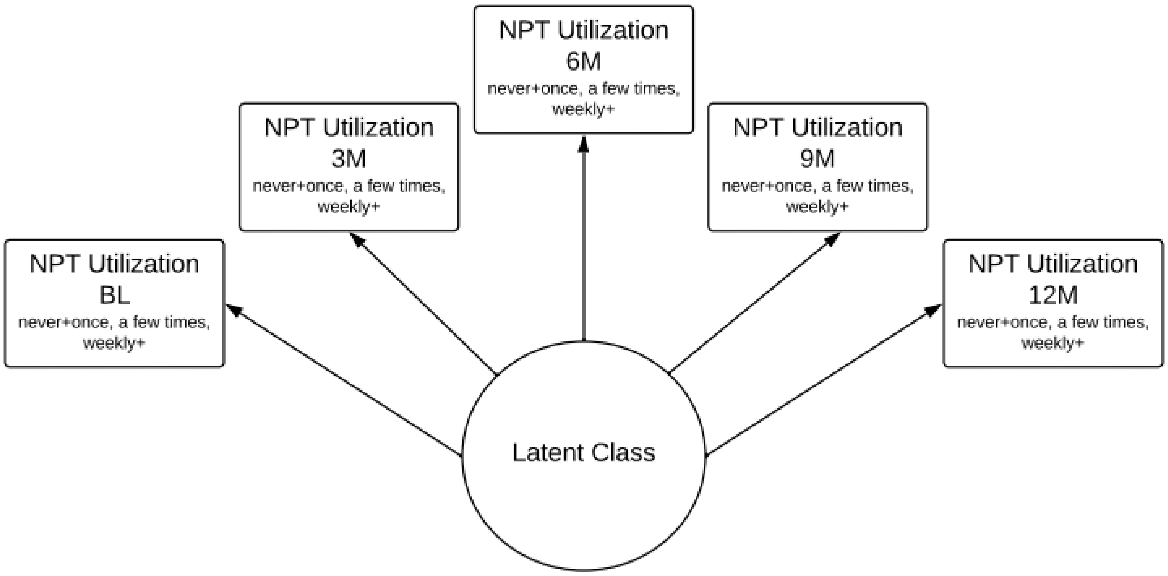
In the raw data, there are 5 frequency options when participants were asked how often they used each NPT service in the previous 3-months (or since their most recent clinic visit [14-28 days ago] at baseline): Never, once, a few times, weekly or almost weekly, daily or more. In the model tested in this dissertation, there are three frequency categories for each indicator: Never or once, a few times, and weekly or more. Those who reported that they did not use an NPT service (i.e., “never”) and those who reported they used a service once during the prior 3-months for the back/neck pain are combined into a single category, “never or once”. Those who reported they used an NPT service a few times during the prior 3-months for the back/neck pain are in their own category, and those who reported having used an NPT service at least weekly to daily are combined into a single category, “weekly+”.

The decision to collapse the “never” and the “once” categories is based on clinical justification that using a service “once” during the past 3-months may offer the same therapeutic benefit as never using the service at all. Participants may have only used a service once because a particular NPT service was not a good fit or participants judged the service to have no benefit (or that the service’s downsides did not outweigh the potential benefits). Therefore, the therapeutic benefit for those who only used a service once may not be different from those who never used a service at all. Additionally, those who reported using NPT once may represent a different kind of utilizer than someone who has used a service more than once during the previous 3-months (e.g., someone who is trying to find an NPT service that works for them may use that service only once). Those who reported using an NPT service weekly or daily are combined into a single category because among the types of services that were available, certain services like PT, acupuncture, chiropractic care, and CBT or other psychotherapy are unlikely to be offered daily whereas other services like yoga or massage could be used daily. So, combining the weekly and daily reflects a category that captures the most likely highest frequency of use for a given modality. Additionally, the sample size was small for those using a service daily which could lead to unstable class solutions.

A participant could have reported that they used more than one NPT service during the prior 3-months, though this was rare (see Supplement 1). In these cases, the highest frequency is used for that person's indicator, e.g., if a participant reported at 3-months that they used massage once and acupuncture weekly or more during the previous 3-months, that person's 3-months indicator value would be "weekly or more".

Figure 3.3 represents the final construction of the RMLCA model that includes five indicators representing the highest reported frequency of NPT use at each timepoint.

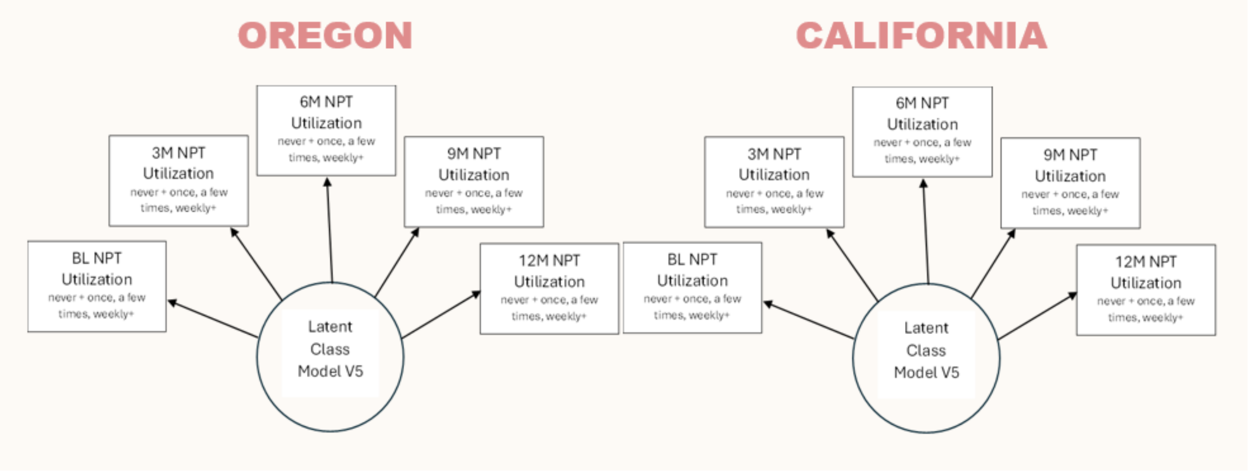
Figure 3.3. Repeated Measures Latent Class Model



3.1.1.5 Multiple Group Analysis

Finally, multiple group (MG) analysis was applied to the final RMLCA model to determine whether the latent classes/subgroups reflecting different patterns of NPT utilization differed between the states (see Figure 3.4). MG models are used primarily in moderation analyses with a grouping variable that will illustrate the group effect of interest.[157–160] Typically, when not using a MG model, this grouping variable is a fixed effect indicator and can be used to illustrate whether the outcome was different between groups on average. However, to assess indirect or moderating effects under the traditional approach, the binary indicator would need to be modeled as interaction terms which makes the analyses much more computationally complex, particularly when dealing with latent variables. MG modeling, on the other hand, allows for parameters to vary across groups if needed and does not require the creation of interaction terms, thereby reducing the computational complexity of the model.[157–160] Each model, e.g., logistic regression or latent growth model, is estimated simultaneously for each state and the results are independent.

Figure 3.4. Multiple Group Repeated Measures Latent Class Model



MG modeling allows for measurement invariance to be tested in each group to determine whether the latent classes are the same and, if measurement invariance holds, to examine how class prevalences and effect sizes differ between groups.[161] Testing for measurement invariance ensures that latent classes have the same meaning and interpretation across different groups. Establishing invariance confirms that observed differences between groups reflect true substantive differences rather than measurement artifacts or biases.[147] Additionally in multiple group models, regression models are estimated simultaneously in each group.[159] The grouping variable in this study was *state* and consists of two groups: Oregon (where the Oregon Neck and Back Pain policy was implemented) and California (where no similar policy was in place).

3.1.1.6 RMLCA and Descriptive Analyses for Aims 1 and 2

Descriptive summary statistics (i.e., frequency and percentages for categorical variables and mean and standard deviations (SD) for continuous variables) for participant baseline demographic characteristics, baseline clinical characteristics, and baseline outcomes overall and stratified by state are presented.

Latent class logistic regression was used to examine how observed covariates predicted membership in the latent classes in each of the states. A multiple group model was used and the logistic regressions for each state were estimated independently and simultaneously. Because LCA is based on the probability that an individual belongs to a certain class (rather than static assignment), the RMLCA measurement model and the regression model are estimated simultaneously.[161] The logistic regression model uses a logit link function[162] that produces a set of regression coefficients for each covariate and then these regression coefficients are then exponentiated to more interpretable odds ratios.[161]

To ensure the best solution for the model was found, random starts were set at 100 and bootstrap draws set to 1,000.[163] In Mplus, the random starts option is used to help avoid local maxima and ensure that the best (global) solution is found when estimating latent class models. Because these models involve complex likelihood estimations, using multiple sets of starting values increases the chances of identifying the solution with the highest log-likelihood (i.e., the best fitting model).[163,164] The estimator was full information maximum likelihood with robust standard errors which is the recommended estimator for categorical dependent variables.[165] All RMLCA analyses were conducted using Mplus version 8[164] and descriptive analyses were conducted using SAS 9.4.

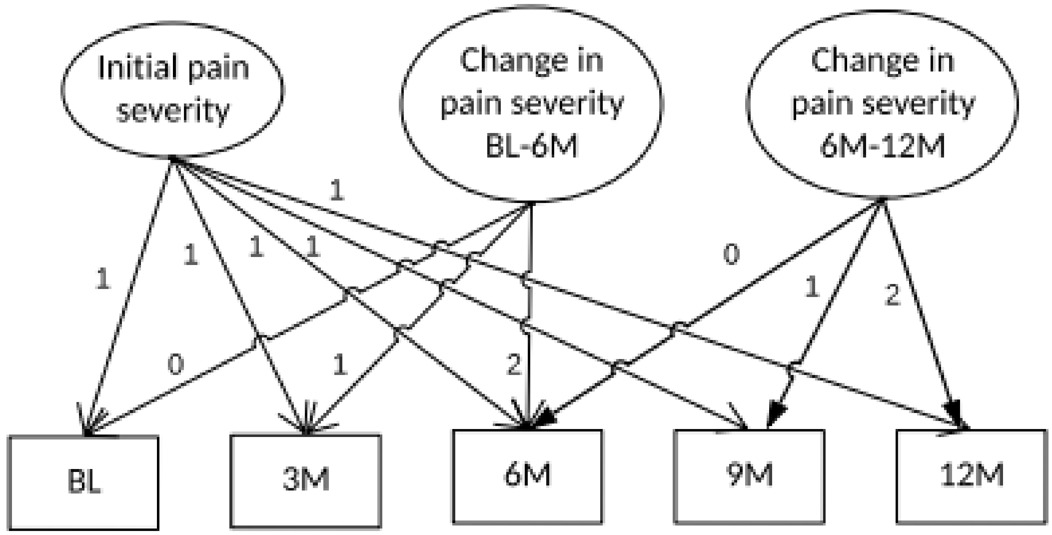
3.1.2 Aim 3 Analysis

3.1.2.1 Piecewise Latent Growth Model

Multiple group, piecewise latent growth modeling was used to analyze the change in pain severity via the BPI-SF between baseline and 6-months and between 6-months and 12-months. The period from baseline to 6-months corresponds to the time when participants in Oregon would have been receiving the majority of the NPT services they were newly eligible for under the OBNP because the OBNP limited the number of treatments available to people. Using a piecewise model allows for understanding how change in BPI score may correlate with the most active time period under the policy and to understand long-term changes in pain levels by assessing the period from 6-months to 12-months.

Latent growth modeling (LGM) is used to measure individual growth trajectories or change over time in terms of an underlying, latent process.[166,167,167] Rather than using more traditional approaches like hierarchical linear modeling where time is considered a level rather than an indicator of growth, LGM allows time to be a parameter that can be estimated. It also allows for the initial, baseline value (i.e., the intercept) to be analyzed. Latent growth modeling allows for the continuous outcome to be measured as the slope of the line, to account for and separate systematic versus random bias, and to adjust for the intercept of the pain score.[167,168] In the piecewise latent growth model, the outcomes will be two slopes of the change in pain score between baseline and 6-months and the second between 6-months and 12-months.[166–168] The slopes and the intercept are modeled as latent variables and the error terms, E, are covarying (see Figure 3.5)

Figure 3.5. Piecewise Latent Growth Model



3.1.2.2 Model Fit

Model fit is assessed using several fit indices produced by Mplus. Absolute fit indices measure how well the model reproduces the observed data and include the overall chi-square test, standardized root mean square residual (SRMR) with excellent fit represented with values ≤ 0.05,[169] and root mean square error of approximation (RMSEA) with good fit represented with values ≤ 0.06.[169,170] Relative fit indices compare the fit of a given model to a baseline (i.e., null) model. The relative fit indice reported here is the comparative fit index (CFI) with good fit represented with values ≥ 0.95.[171]

3.1.2.3 Covariates

To examine whether covariates predict individual differences in change over time, covariates were included as predictors of the slope factor in the latent growth model. This was accomplished by specifying regression paths from each covariate to the latent slope, allowing estimation of the extent to which each covariate accounted for variability in the rate of change across individuals. Statistically significant path coefficients were interpreted as evidence that the covariate was associated with the trajectory of change. Model fit indices were evaluated to ensure that inclusion of covariates did not substantially degrade overall model fit. In addition, covariates were also examined as predictors of the intercept factor to account for baseline differences in the outcome.

3.1.3 Missing Data

Missing data patterns were examined for each indicator variable for the Aim 1 and Aim 2 RMLCA and for the BPI-SF score in Aim 3 to determine the appropriate missing data mechanism. Chi-square tests (for categorical covariates) and independent samples t-tests (for continuous covariates) were used to assess whether missingness was related to observed covariates. Significant associations indicated that missingness was dependent on observed variables rather than on unobserved/unmeasured variables, supporting the assumption that data were missing at random (MAR).[172,173]

Given the MAR assumption, missing data were handled using full information maximum likelihood (FIML) estimation with the robust maximum likelihood estimator (MLR,) which is the recommended estimator for categorical dependent variables.[165] FIML uses all available data points to produce unbiased parameter estimates under MAR, making it an appropriate approach for repeated measures latent class analysis and latent growth modeling.[164,173,174] There were two individuals who were missing all survey data and five individuals who were missing NPT use data at all five timepoints and they were excluded from the analysis. The final analytic sample size was 1,683.

Chapter 4: Results

4.0 Results Overview

This chapter presents descriptive data on the sample characteristics and NPT utilization followed by results for the 3 aims of this dissertation. Descriptive results include the observed distribution of any NPT service use over the five timepoints and descriptive statistics of the samples within Oregon, California, and overall. Aim 1 results include the class enumeration, measurement invariance, unadjusted model probabilities for a 3-class solution, and state prevalence results. Aim 2 results include the final adjusted model fit, adjusted model probabilities, and logistic regression results for the multiple group repeated measures latent class analysis (RMLCA). Aim 3 results include the results for the piecewise latent growth model and regression analysis. Specific aims are described below.

4.1 Specific Aims

Aim 1: Characterize patterns of NPT utilization over 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

Aim 2: Examine the effects of social risks, socio-demographic characteristics, and clinical characteristics on patterns of self-reported use of nonpharmacological therapy (NPT) over 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

Aim 3: Examine the effects of social risks, socio-demographic characteristics, and clinical characteristics on change in pain-related outcomes between baseline and 6-months and 6-months to 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

4.3 Descriptive Results

4.3.1 Sample Descriptives

Table 4.1 shows the baseline characteristics of the sample overall and by state (California and Oregon) and results of the chi-square or t-tests determining whether there were statistically significant differences in baseline characteristics for those in the two states. The average age was 42.8 years (SD 12.7). The sample was majority female (65% in Oregon and 61% in California) and white (55% in California and 77% in Oregon; p<0.0001). California had a higher percentage of non-Hispanic Black (17.5%) and Hispanic (19%) participants compared to Oregon (4% and 9.2%, respectively). Overall, 17% of the sample lived in rural locations, 46% had a high school education or less, and 66% were living below the FPL. FPL was associated with state, with 69% of California participants living below the FPL compared to 62% of Oregon participants (p<0.0001).

The majority of participants were at high risk of persistent disabling symptoms based on their STaRT Back scores (72.2%) and rates were similar across California and Oregon. Participants in California were more likely to have back pain (64.1%) or both back and neck pain (27.5%) than neck pain only (64.1%) when compared to participants in Oregon (p<0.01). Overall, 93.3% of participants met criteria for chronic pain with pain lasting 3 months or more and had an average of 1.8 (SD 1.3) painful conditions. Participants in Oregon were more likely to have at least one mental health condition (52.6%) compared to those in California (43.4%; p<0.001). Participants in Oregon (13.4%) were more likely than those in California (10.3%) to have a substance use condition, though this was not statistically significant. On average, participants had 1.2 (SD 1.5) medical comorbidities.

Rates were similar across states for medical financial insecurity, food insecurity, housing insecurity, and social support for pain management. Overall, 21.1% of the sample reported medical financial insecurity, 34.4% reported food insecurity, and 31.6% reported housing insecurity. Just over half the sample in each state reported having at least one social risk. Half of the sample reported having social support for their pain management during the last year. On the baseline assessment, Oregon participants reported having used at least one type of NPT service weekly or more (19.7%) sometime during the prior month between their qualifying clinic visit and study enrollment at a higher rate than California participants (14.7%) and this was statistically significant (p=0.02).

Table 4.1. Baseline Characteristics of the Sample, Overall and by State

	Overall	California	Oregon	P-value[7]
Socio-demographics				
Age,[1] mean (SD)	42.8 (12.7)	43.5 (12.9)	42.2 (12.6)	**0.05**
Female,[1] N (%)	1062 (62.9)	487 (60.6)	575 (65.1)	0.06
Race,[1] N (%)				**<.0001**
White, non-Hispanic	1124 (66.6)	442 (55.0)	682 (77.2)	
Black, non-Hispanic	175 (10.4)	141 (17.5)	34 (3.9)	
Hispanic	234 (13.9)	153 (19.0)	81 (9.2)	
Other	70 (4.2)	26 (3.2)	44 (5.0)	
Missing	85 (5.0)	42 (5.2)	43 (4.9)	
Rural,[2] N (%)	289 (17.1)	124 (15.4)	165 (18.7)	0.15
Missing	17 (1.0)	10 (1.2)	7 (0.8)	
Education,[1] N (%)				0.09
Less than high school	259 (15.3)	128 (15.9)	131 (14.8)	
High school	521 (30.9)	264 (32.8)	257 (29.1)	
College or more	889 (52.7)	400 (49.8)	489 (55.3)	
Missing	19 (1.1)	12 (1.5)	7 (0.8)	
FPL Percentage,[2] N (%)				**<.0001**
0%	417 (24.7)	182 (22.6)	235 (26.6)	
0.01%-99.99%	690 (40.9)	376 (46.8)	314 (35.5)	
100%-149.9%	287 (17.0)	100 (12.4)	187 (21.2)	
150%-199.9%	94 (5.6)	33 (4.1)	61 (6.9)	
>200%	83 (4.9)	29 (3.6)	54 (6.1)	
Missing	117 (6.9)	84 (10.5)	33 (3.7)	
Clinical Characteristics				

STarT Back Score,[1] N (%)				0.37
Low risk	126 (7.5)	63 (7.8)	63 (7.1)	
Medium risk	180 (10.7)	75 (9.3)	105 (11.9)	
High risk	1218 (72.2)	585 (72.8)	533 (71.6)	
Missing	164 (9.7)	81 (10.1)	83 (9.4)	
Back and Neck Pain,[2] N (%)				**<0.01**
Back pain	1069 (63.3)	515 (64.1)	554 (62.7)	
Neck pain	185 (11.0)	68 (8.5)	117 (13.2)	
Both	434 (25.7)	221 (27.5)	213 (24.1)	
Pain Duration ≥3 months,[1] N (%)	1574 (93.3)	751 (93.4)	823 (93.1)	0.75
Missing	11 (0.7)	4 (0.5)	7 (0.8)	
Number of pain conditions,[2,3] mean (SD)	1.8 (1.3)	1.8 (1.3)	1.8 (1.3)	0.47
Any mental health condition,[2,4] N (%)	814 (48.2)	349 (43.4)	465 (52.6)	**<0.0001**
Any substance use condition,[2,5] N (%)	201 (11.9)	83 (10.3)	118 (13.4)	0.06
Charlson Comorbidity Index,[2] mean (SD)	1.2 (1.5)	1.2 (1.5)	1.3 (1.5)	0.30
Social Risk and Social Support				
Medical Financial Insecurity,[1] N (%)	357 (21.1)	157 (19.5)	200 (22.6)	0.23
Missing	31 (1.8)	17 (2.1)	14 (1.6)	
Food Insecurity,[1] N (%)	581 (34.4)	293 (36.4)	288 (32.6)	0.22
Missing	36 (2.1)	18 (2.2)	18 (2.0)	
Housing Insecurity,[1] N (%)	533 (31.6)	266 (33.1)	267 (30.2)	0.42
Missing	53 (3.1)	26 (3.2)	27 (3.1)	
Social Support – Pain,[1] N (%)	847 (50.2)	394 (49.0)	453 (51.2)	0.34
Missing	25 (1.5)	15 (1.9)	10 (1.1)	
Social Risk, N (%)	921 (54.6)	447 (55.6)	474 (53.6)	0.46
Missing	51 (3.0)	27 (3.4)	24 (2.7)	
NPT Use				
NPT BL,[1,6] N (%)				**0.02**
Never	927 (54.9)	462 (57.5)	465 (52.6)	
Once	190 (11.3)	82 (10.2)	108 (12.2)	
A few times	191 (11.3)	96 (11.9)	95 (10.8)	
Once a week or more	237 (14.0)	90 (11.2)	147 (16.6)	
Daily or almost daily	55 (3.3)	28 (3.5)	27 (3.1)	
Missing	88 (5.2)	46 (5.7)	42 (4.8)	

[1] Self-reported at baseline

[2] Electronic health record (EHR)

[3] Pain conditions included: Limb/extremity pain, joint pain and non-systemic, non-inflammatory arthritic disorders; Fibromyalgia; Headache; Orofacial, ear, and temporomandibular disorder pain; Abdominal and bowel pain; Urogenital, pelvic and menstrual pain; Musculoskeletal chest pain; Neuropathy; Systemic disorders or diseases causing pain; General pain; Other painful conditions

[4] Mental health conditions included: Depression, anxiety, PTSD, ADHD, bipolar disorder, schizophrenia, other mental health conditions
[5] Substance use conditions included: Alcohol use disorder, cannabis use disorder, opioid use disorder, other drug use disorder
[6] Highest frequency among any service used for pain at baseline
[7] P-values from chi-square for binary/categorical variables and t-tests for continuous variables

4.3.2 Observed Distributions of NPT Utilization Across 12-months

The observed distribution for the combined, Oregon, and California samples are shown in Table 4.2. Overall, the majority of participants reported using any NPT service once or never at baseline (69.8%) and 18.2% reported weekly or more use at baseline. Weekly or more use of NPT services increased at 3-months (24.9%) and 6-months (23.1%) and then returned to near baseline levels at 12-months. Participants reported occasional utilization less frequently at baseline (11.9%) compared to all other timepoints. Most participants reported never or once using NPT services at all timepoints (ranging from 53.8% to 69.8%).

Table 4.2. Observed Proportions for NPT Frequency at Five Timepoints (Class Indicators) in California, Oregon, and the Combined Sample

	CA	OR	Comb
	Obs.	Obs.	Obs.
NPTBL			
Never + Once	0.718	0.681	0.698
A Few Times	0.127	0.113	0.119
Weekly+	0.156	0.207	0.182
NPT3M			
Never + Once	0.606	0.477	0.538
A Few Times	0.195	0.228	0.213
Weekly+	0.199	0.295	0.249
NPT6M			
Never + Once	0.594	0.581	0.587
A Few Times	0.200	0.165	0.182
Weekly+	0.206	0.254	0.231
NPT9M			
Never + Once	0.638	0.616	0.627
A Few Times	0.197	0.170	0.183
Weekly+	0.164	0.214	0.191
NPT12M			
Never + Once	0.644	0.677	0.662
A Few Times	0.188	0.144	0.165

Weekly+	0.168	0.179	0.174

4.4 Aim 1 Results

Aim 1: Characterize patterns of NPT utilization over 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

4.4.1 Class Enumeration

4.4.1.1 Class Enumeration: Oregon

The results of the class enumeration are presented in the following section. Class enumeration was conducted in the California and Oregon samples separately and then in the combined sample, testing whether a K+1 class solution fit the data better than the K class solution. The 1-class through 4-class models are presented below (Table 4.3). In Oregon, the 5-class model was not identified meaning there was insufficient data to find a stable solution. Model non-identification can occur for multiple reasons including having too few observations in the data relative to the number of parameters being estimated, the mode is overly complex (e.g., trying to extract 5 classes when only 3 meaningful ones exist), convergence issues, or when multiple sets of parameter estimates produce similar or identical likelihoods making it impossible to distinguish between them reliably. Overall, the 3-class model fit the data best compared to the other class solutions. The 2-class model had the lowest BIC (6140.692) and the best correct model probability (0.995), but no other fit criteria indicated the 2-class model as the optimal model. The 3-class model has the next lowest BIC (6151.324), which is the strongest predictor of model fit, and lowest AWE (6076.549). The Bayes Factor measures whether the 3-class model fits the data better than a 4-class model and indicates that the 3-class model is the best (2444199.584). The adjusted LMR is nearly significant (0.062) and the bootstrapped p-value is significant (<0.0001), indicating that the 3-class model is a better fit than the 2-class model. The 4-class model has the lowest AIC (5975.340) and CAIC (6058.995); however, the BIC, LMR p-value, and all other fit criteria do not indicate that it is the best fitting model. The entropy difference between the 3- and 4-class models is negligible (3-class E=0.64, 4-class E=0.68) and the 4-class model has 4 thresholds that approach extreme values leading to convergence issues. Finally, while the 4-class solution did have adequate sample size for the smallest class (N=123.1, 14%), the 3-class solution had a slightly larger smallest class (N=162, 18.4%) which made the classes more stable when used in further analyses.

The item response probabilities for the Oregon 3-class solution are presented in Table 4.4 and represent the probability of a participant responding to an item in a certain way based on their class membership. Class 1 is referred to as “high utilizers” as this subgroup of participants reported high utilization (i.e., weekly or more) at each of the five timepoints relative to their observed distribution. Class 2 is referred to as “occasional utilizers” as this subgroup utilized NPT services “a few times” across all timepoints with the biggest increase at 6-months (item response probability=0.748). Finally, class 3 are the “never utilizers” given their low or no utilization at all timepoints. The never utilizer class is the largest (52.9%) followed by the high utilizers (28.8%) and the occasional utilizers (18.4%).

4.4.1.2 Class Enumeration: California

In the California sample (Table 4.3), the model was not well-identified with a 5-class solution, so classes 1-4 were assessed for model fit. The 4-class solution had the best absolute fit based on the likelihood ratio chi-square (212.5; p=0.24) and entropy (0.682). However, the 3-class solution had better fit relative to the 2 and 4-class solutions (BIC=5251.8, CAIC=5162.7, AWE=5178.7). Additionally, the 3-class solution had Lo-Mendel Reuben p-value (0.02), boot-strapped p-value (<0.0001) indicating it fit better than a 2-class solution and the Bayes Factor (7,926,679,036) and correct model probability that indicated the 3-class model fit better than the 4-class model. The Bayes Factor and correct model probability statistics were not able to be calculated for the 4-class model because the 5-class model was not identified and therefore did not produce fit indices on which to compare. While entropy is lower in the 3-class model (0.667) than the 4-class model (0.682), the difference is small (difference=0.015) given that a perfect model fit would be equal to 1 and the worst model fit would be equal to 0.

While some fit criteria indicate that the 4-class model fits the data better, the 3-class model has more fit criteria indicating that it is the best model. Additionally, the rule for class size is that the smallest class should have at least 10% of the sample in it. The 4-class model smallest class was 5.7% (N=45.6). For these reasons, the 3-class model fits the California data best compared to the other class solutions.

The item response probabilities for the California 3-class solution are presented in Table 4.4 and represent the probability of a participant responding to an item in a certain way based on their class membership. Class 1 is referred to as “high utilizers” as this subgroup of participants reported high utilization (i.e., weekly or more) at each of the five timepoints relative to their observed distribution. Class 2 is referred to as “occasional utilizers” as this subgroup utilized NPT services “a few times” across all timepoints with increases at 3-months (item response probability=0.643) and 6-months (item response probability=0.679). Finally, class 3 is characterized by low or no utilization at all timepoints. Class 3 is referred to as the “never utilizers” given their low or no utilization at all time points. The never utilizer class is the largest (55.7%) followed by the high utilizers (25.9%) and the occasional utilizers (18.4%).

4.4.1.3 Class Enumeration: Combined Sample

In the combined sample, the 1-class through 5-class models are presented below. The model was not identified with a 6-class solution (Table 4.3). Results from the RMLCA suggested that a 3-class solution was the best fit for the combined data. Although the 5-class solution had the lowest AIC value (11047.70) and the highest entropy value (0.651), statistical significance for the adjusted LMRT decreased substantially beyond the 3-class solution and the BIC (11287.04), Adj-LMRT (<0.0001), BLRT (<0.0001), and BF (315762213.7) indicate the 3-class solution is the optimally fitting model for the data relative to the 4-class model. The 5-class solution also failed to converge for the BLRT and the 6-class solution was not identified. Finally, the 4- and 5-class solutions did not have adequate sample size in the smallest class (4-class: N=118.3, 7%; 5-class: N=152.2, 9%).

Table 4.3. Repeated Measures Latent Class Analysis Fit Indices for California, Oregon, and the Combined Sample

Model	LL	npar	LR x2[1]	df	p-value	AIC[1]	BIC[1]	CAIC[1]	AWE[1]	Adj LMR p-value[2]	Boot-strapped p-value[2]	BF (K,K+1)[3]	cmP(K)[4]	E[5]
California														
1-class	-2840.07	10	797.752	232	<0.0001	5700.131	5746.99	5719.168	5724.168	n/a	n/a	1.277E-100	2.9232E-108	n/a
2-class	-2573.28	21	349.168	221	**<0.0001**	5188.559	5286.962	5228.536	5239.036	**<0.0001**	**<0.0001**	2.28915E-08	2.28915E-08	0.673
3-class	-2518.92	32	240.438	210	0.0734	5101.829	**5251.777**	**5162.746**	**5178.746**	**0.0167**	**<0.0001**	**7926679036**	**0.999999977**	0.667
4-class	-2504.94	43	**212.48**	199	0.2438	**5095.872**	5297.364	5177.728	5199.228	0.4203	0.06	n/a	n/a	**0.682**
5-class	**Model not identified**													
Oregon														
1-class	-3257.63	10	756.686	232	<0.0001	6535.258	6583.08	6554.713	6559.713	n/a	n/a	8.64304E-97	8.60079E-97	n/a
2-class	-2999.13	21	364.335	221	<0.0001	6040.265	**6140.692**	6081.121	6091.621	**<0.0001**	<0.0001	203.5679794	**0.995111649**	0.641
3-class	-2967.15	32	300.363	210	**<0.0001**	**5998.294**	**6151.324**	**6060.549**	**6076.549**	**0.062**	**<0.0001**	**2744199.584**	0.004888351	0.640
4-class	-2944.67	43	255.409	199	0.0043	**5975.340**	6180.974	**6058.995**	6080.495	0.1802	<0.0001	n/a	n/a	**0.679**
5-class	**Model not identified**													
Combined Sample														
1-class	-6120.84	10	1132.92	232	<0.0001	12261.68	12315.97	12283.94	12288.94	n/a	n/a	4.9092E-207	3.7268E-224	n/a
2-class	-5604.94	21	507.745	221	<0.0001	11251.88	11365.88	11298.63	11309.13	<0.0001	<0.0001	7.59152E-18	7.59152E-18	0.646
3-class	-5524.67	32	347.194	210	**<0.0001**	11113.33	**11287.04**	**11184.57**	**11200.57**	**<0.0001**	**<0.0001**	**315762213.7**	**0.999999997**	0.634
4-class	-5503.38	43	304.624	199	<0.0001	11092.76	11326.18	11188.48	11209.98	0.2475	<0.0001	1513.984203	3.16694E-09	0.633
5-class	-5469.85	54	237.556	188	0.0083	**11047.70**	11340.83	**11167.90**	**11194.9**	0.2089	did not converge	0	n/a	**0.651**
6-class	**Model not identified**													

1 The lowest values indicate that a model fits the data better and indicates better certainty of assigning individuals to the latent classes or subgroups.[146]

2 The adjusted Lo-Mendell Rubin likelihood ratio test (LMR)[154] and the bootstrapped likelihood ratio test (BLRT)[155] is used to compare against the K-1 class model to determine the best fitting model. Significant values indicate that the K-class model is the best fitting model compared to the K-1 class model.

3 The approximate Bayes factor (BF) is used to compare the K class model against the K+1 class model to determine the best fitting model.[156] A larger BF value indicates the K class model fits the data better than a K+1 class model.

4 The correct model probabilities (cMP) is used to compare the K class model against the K+1 class model to determine the best fitting model.[156] A value closer to 1 for the cMP indicates the K class model fits the data better than a K+1 class model.

5 Entropy ranges from 0 (the model does not fit the data) to 1 (the model perfectly fits the data). Higher entropy values are desirable. [146]

The item response probabilities for the combined sample 3-class solution are presented in Table 4.4 and represent the probability of a participant responding to an item in a certain way based on their class membership. Similar to the individual state RMLCA results, the 3 classes for the combined data were characterized as “high utilizers, (27.3%)” “occasional utilizers, (18.5%)” and “never utilizers (54.1%).

Table 4.4. Item Response Probabilities for 3-class Solutions in California, Oregon, and the Combined Sample

	California			Oregon			Combined		
	High utilizers (25.9%)	**Occ. utilizers (18.4%)**	**Never utilizers (55.7%)**	**High utilizer (28.8%)**	**Occ. utilizers (18.4%)**	**Never utilizer (52.9%)**	**High utilizer (27.3%)**	**Occ. utilizers (18.5%)**	**Never utilizer (54.1%)**
NPTBL									
Never + Once	0.480	0.482	0.899	0.562	0.429	0.831	0.530	0.446	0.865
A Few Times	0.151	0.374	0.036	0.057	0.321	0.072	0.097	0.346	0.054
Weekly+	0.369	0.144	0.065	0.381	0.250	0.097	0.373	0.209	0.080
NPT3M									
Never + Once	0.330	0.192	0.877	0.184	0.226	0.722	0.258	0.206	0.794
A Few Times	0.112	0.643	0.083	0.205	0.449	0.166	0.157	0.535	0.130
Weekly+	0.557	0.165	0.040	0.611	0.325	0.112	0.584	0.259	0.076
NPT6M									
Never + Once	0.195	0.292	0.886	0.181	0.186	0.934	0.204	0.222	0.908
A Few Times	0.157	0.679	0.057	0.027	0.748	0.037	0.085	0.704	0.049
Weekly+	0.649	0.029	0.057	0.792	0.065	0.029	0.711	0.074	0.043
NPT9M									
Never + Once	0.187	0.380	0.954	0.240	0.257	0.945	0.213	0.315	0.951
A Few Times	0.255	0.549	0.041	0.225	0.487	0.030	0.218	0.538	0.038
Weekly+	0.558	0.071	0.005	0.534	0.255	0.025	0.569	0.147	0.011
NPT12M									
Never + Once	0.331	0.423	0.886	0.467	0.449	0.884	0.406	0.429	0.887
A Few Times	0.221	0.455	0.076	0.180	0.329	0.055	0.189	0.397	0.066
Weekly+	0.448	0.122	0.038	0.353	0.223	0.061	0.405	0.174	0.047

4.4.2 Measurement Invariance

After determining that the 3-class solution was the best solution in the samples individually and collectively, measurement invariance was tested between the states. First, a Wald test was used to determine whether classes were statistically significantly different from each other between states (i.e., testing whether the classes can be interpreted the same) and then each item threshold was tested individually (see Table 4.6). An item threshold value reflects how likely it is that someone in a particular class will endorse that value, e.g., how likely it is that someone in a high utilizer class would endorse never using an NPT service, and is used for measurement invariance testing. Thresholds are the log-odds of the item response probabilities presented in Table 4.4. If the threshold values are not statistically significantly different from each other, they can be set to be invariant (i.e., equal across groups) and interpreted the same. If thresholds are statistically significantly different, they must be allowed to freely vary. See Table 4.5 for an overview of the differences between item response probabilities and thresholds.

Table 4.5 Differences Between Item Response Probabilities and Thresholds

Concept	Refers to…	Scale	Level	Main Use
Item Response Probability	Probability of endorsing an item given an assigned class	0 to 1	Class-level	Interpreting class characteristics
Threshold	Log-odds of item response probability	−∞ to +∞	Class-level	Statistical testing (e.g., invariance)

Classes 1 (high utilizers) and 2 (occasional utilizers) were not statistically significantly different from each other and, as expected, none of the thresholds were statistically significantly different from each other with those classes. Class 3 (never utilizers) was statistically significantly different between the states (p=0.015). There were three thresholds that were statistically significantly different between Oregon and California (NPTBL Never or Once category, p=0.04; NPT3M Never or Once, p=0.003; NPT3M A Few Times, p=0.018). This suggests that there is some degree of differential item functioning for never utilizers at baseline and 3-months between the states, i.e., those in Oregon and California in the never utilizer class have different probabilities of giving the same response at baseline and 3-months. This aligns with the implementation of the OBNP policy that would likely have influenced the proportion of individuals utilizing NPT services shortly after their new episode of back/neck pain.

Table 4.6. Measurement Invariance Testing for Multiple Group RMLCA

	Wald Value	p-value
Class 1: Occasional v. Occasional	8.141	0.6151
NPTBL		
Never or Once	0.176	0.6749
A few times	0.55	0.4582
NPT3M		
Never or Once	0.074	0.7851
A few times	0.783	0.3763
NPT6M		
Never or Once	0.301	0.5835
A few times	0.06	0.8062
NPT9M		
Never or Once	0.871	0.3506
A few times	2.508	0.1133
NPT12M		
Never or Once	0.044	0.8339
A few times	1.134	0.2868
Class 2: High v. High	15.839	0.1043
NPTBL		
Never or Once	1.174	0.2785
A few times	0.022	0.8831

NPT3M		
Never or Once	3.06	0.0803
A few times	0.364	0.5464
NPT6M		
Never or Once	0.014	0.9053
A few times	0.654	0.4187
NPT9M		
Never or Once	0.565	0.4521
A few times	0.05	0.8223
NPT12M		
Never or Once	3.638	0.0565
A few times	1.513	0.2187
Class 3: Never v. Never	21.968	0.0153
NPTBL		
Never or Once	4.218	**0.04**
A few times	1.882	0.1701
NPT3M		
Never or Once	8.895	**0.0029**
A few times	5.589	**0.0181**
NPT6M		
Never or Once	1.164	0.2806
A few times	0.761	0.3829
NPT9M		
Never or Once	0.071	0.7892
A few times	616	0.4326
NPT12M		
Never or Once	0.004	0.9482
A few times	0.907	0.3408

4.4.3 Final Unadjusted Model

The final model item response probabilities are presented in Figures 4.1, 4.2, and 4.3 and Table 4.7 with the highest item response probabilities at each timepoint in each class highlighted to help illustrate class patterns. Because measurement invariance testing showed that only three thresholds in the never utilizer class were statistically significantly different between Oregon and California, all other parameters are held constant across the states. Mplus requires that if one parameter is freed within a timepoint, then all parameters in that timepoint must vary, so all thresholds in NPTBL and NPT3M in the never utilizer class are freely varying.

Class 1, high utilizers, is characterized by frequent utilization at the majority of timepoints relative to the observed distributions in both states and the highest frequency of weekly or more utilization at 3-months (58.6%), 6-months (70.1%), and 9-months (56.9%). Class 2, occasional utilizers, is characterized by individuals who reported NPT utilization of “a few times” at the majority of timepoints, with the highest frequencies at 3-months (54.4%), 6-months (71.2%), and 9-months (54.2%). Finally, class 3, never utilizers, is characterized by never or only once NPT utilization at all timepoints. Freely varying parameters are bolded in Table 4.7.

California and Oregon had similar prevalences in each class, though Oregon had a higher prevalence of high utilizers (p=0.09). Among high utilizers, Oregon’s prevalence was 61.2% and California’s was 38.8%. Among occasional utilizers, Oregon’s prevalence was 47.2% and California’s was 52.8%. Finally, among never utilizers, Oregon’s prevalence was 49.8% and California’s was 50.2%.

Table 4.7. Unadjusted Item Response Probabilities for the Multiple Group Model

	California			**Oregon**		
	High utilizers	**Occ. utilizers**	**Never utilizers**	**High utilizers**	**Occ. utilizers**	**Never utilizer**
NPTBL						
Never + Once	0.522	0.453	**0.896***	0.522	0.453	**0.831**
A Few Times	0.101	0.353	**0.041**	0.101	0.353	**0.067**
Weekly+	0.377	0.194	**0.063**	0.377	0.194	**0.101**
NPT3M						
Never + Once	0.247	0.221	**0.878**	0.247	0.221	**0.708**
A Few Times	0.167	0.544	**0.087**	0.167	0.544	**0.167**
Weekly+	0.586	0.235	**0.035**	0.586	0.235	**0.125**
NPT6M						
Never + Once	0.196	0.237	0.903	0.196	0.237	0.903
A Few Times	0.103	0.712	0.047	0.103	0.712	0.047

Weekly+	0.701	0.051	0.050	0.701	0.051	0.050
NPT9M						
Never + Once	0.200	0.325	0.953	0.200	0.325	0.953
A Few Times	0.231	0.542	0.036	0.231	0.542	0.036
Weekly+	0.569	0.133	0.012	0.569	0.133	0.012
NPT12M						
Never + Once	0.403	0.426	0.887	0.403	0.426	0.887
A Few Times	0.194	0.408	0.064	0.194	0.408	0.064
Weekly+	0.403	0.167	0.048	0.403	0.167	0.048

*Bolded items are freely estimated parameters.

Figure 4.1 Unadjusted Item Response Probabilities for the Multiple Group Model: High Utilizers

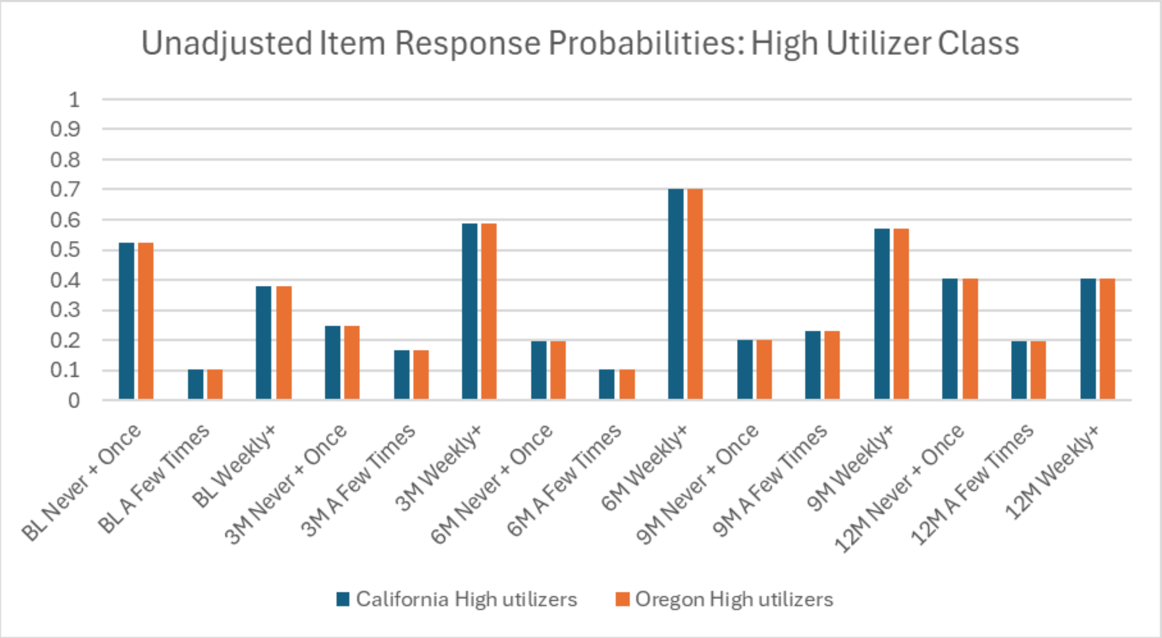


Figure 4.2 Unadjusted Item Response Probabilities for the Multiple Group Model: Occasional Utilizers

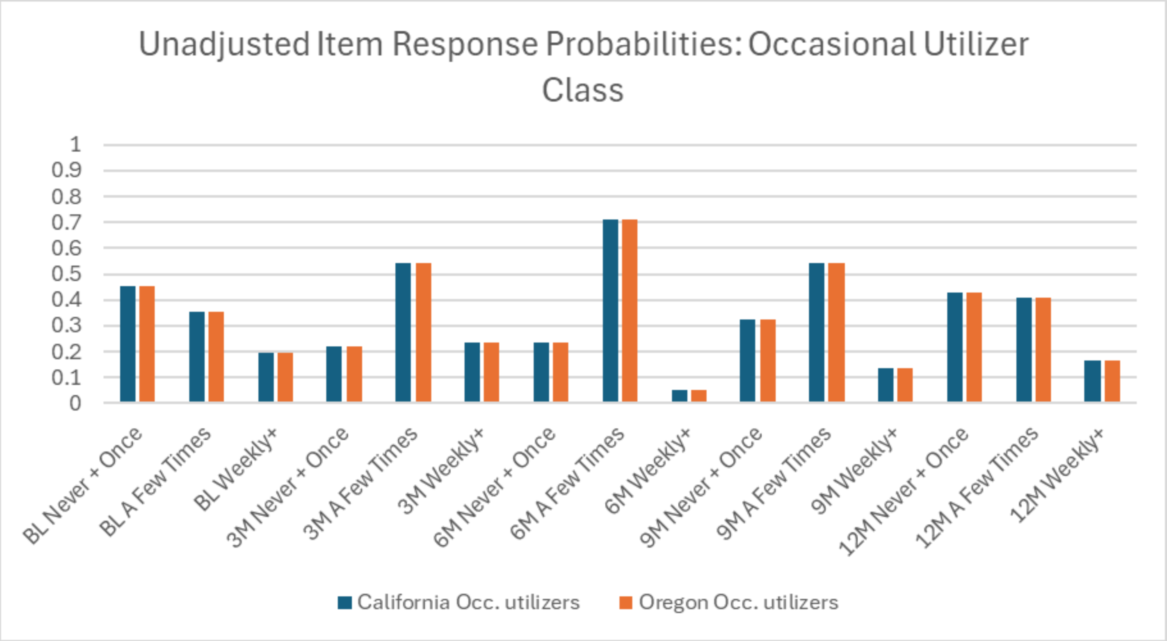
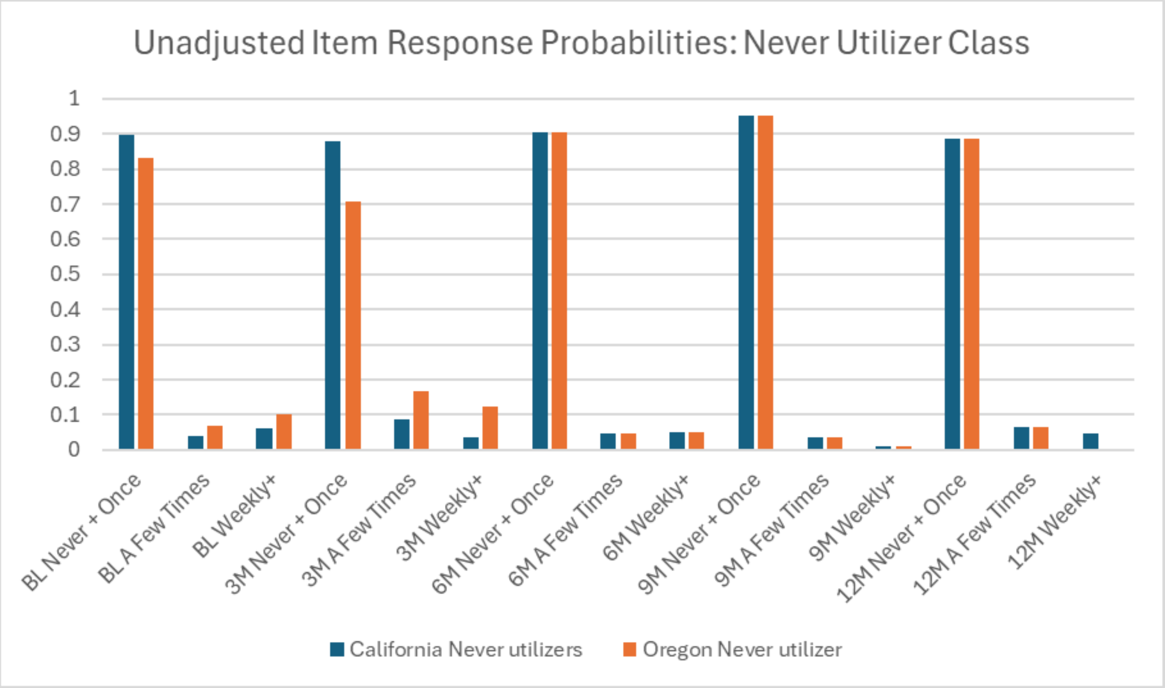


Figure 4.3 Unadjusted Item Response Probabilities for the Multiple Group Model: Never Utilizers



4.4.4 Aim 1 Summary

Results from the multiple-group repeated measures latent class analysis (MG RMLCA) indicated that a 3-class solution—comprising high, occasional, and never utilizers of nonpharmacologic therapy (NPT)—was the best fit for the data, with strong measurement invariance across Oregon and California. There were slight differences at the baseline and 3-month time-points in the never utilizer class suggesting that individuals in Oregon had slightly higher utilization of NPT utilization than those in California in the never utilizer class. This higher utilization at baseline and 3-months among the never utilizer class may suggest a policy effect where the OBNP policy encouraged higher NPT engagement than in California where a similar policy was not in place The final unadjusted model results are presented in Table 4.7 showing the probabilities for each class by state with only the baseline and 3-month timepoints varying in the never utilizer class. All other class probabilities are the same across Oregon and California.

4.5 Aim 2 Results

Aim 2: Examine the effects of social risks, socio-demographic characteristics, and clinical characteristics on patterns of self-reported use of nonpharmacological therapy (NPT) over 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

4.5.1 Adjusted Latent Class Results

Results from the MG RMLCA suggested that a 3-class solution was the best fit for the data and that measurement invariance held across California and Oregon. These results have been described in detail in the previous section. Because the latent class probabilities are estimated simultaneously with the regression model, certain model fit criteria and class probabilities can change when covariates are added. The absolute model fit, measured by entropy, improved when all covariates were included, going from 0.634 in the unadjusted model to 0.706 in the adjusted model.

Additionally, the average latent class probabilities for most likely latent class membership by latent class was also improved with the inclusion of covariates. This indicates that the probability that someone is in a certain class is correctly classified into that class increased with covariates included in the model. Table 4.8 shows the classification probabilities for most likely latent class based on the unadjusted model and Table 4.9 shows the same for the adjusted model. The probabilities on the diagonal should be >0.8 to have a high degree of confidence in classification.[175,176] For Class 1 (high utilizers) in the unadjusted model, the classification probability is 0.834, 0.767 for Class 2 (occasional utilizers), and 0.877 for Class 3 (never utilizers). Because Class 2 is below the 0.8 threshold, this indicates that there is some imprecision in classification and individuals could belong to another class. In this case, the second most likely class they could belong to is Class 1 (probability=0.136). In the adjusted model, the classification probabilities improve. The probability for Class 1 is 0.862, 0.799 for Class 2, and 0.892 for Class 3. The classification probability increased for Class 2 to near the 0.8 threshold.

Table 4.8. The Average Latent Class Posterior Probabilities for Most Likely Latent Class Membership by Latent Class – Unadjusted Model

	Most Likely Latent Class Membership		
Avg. Latent Class Prob.	**Class 1**	**Class 2**	**Class 3**
Class 1	**0.834**	0.089	0.077
Class 2	0.136	**0.767**	0.098

Class 3	0.068	0.054	**0.877**

Table 4.9. The Average Latent Class Posterior Probabilities for Most Likely Latent Class Membership by Latent Class – Adjusted Model

	Most Likely Latent Class Membership		
Avg. Latent Class Prob.	**Class 1**	**Class 2**	**Class 3**
Class 1	**0.868**	0.061	0.071
Class 2	0.116	**0.804**	0.080
Class 3	0.065	0.040	**0.895**

Measurement invariance held across states for all but two thresholds. The latent classes in the 3-class solution were the same across California and Oregon (adjusted item response probabilities presented in Table 4.10 and Figures 4.4, 4.5, 4.6), with only the baseline and 3-month indicators varying in Class 3. Class 3 composition varies slightly between Oregon and California as evidenced in the freely estimated item response probabilities for the baseline and 3-month timepoints. Oregon participants are somewhat more likely to report higher utilization at 3 months (Weekly or More item response probability=0.147; A Few Times item response probability=0.136) compared to California (Weekly or More item response probability=0.032; A Few Times item response probability=0.079). However, Oregonians in Class 3 were still more likely to report never or only once using an NPT service during the prior three months (item response probability=0.717) compared to the observed distribution (0.477).

Table 4.10. Adjusted California Item Response Probabilities

	California			Oregon		
	High utilizers	**Occ. utilizers**	**Never utilizers**	**High utilizers**	**Occ. utilizers**	**Never utilizer**
NPTBL						
Never + Once	0.490	0.463	0.894	0.490	0.463	0.853
A Few Times	0.114	0.369	0.041	0.114	0.369	0.061
Weekly+	0.396	0.168	0.065	0.396	0.168	0.086
NPT3M						
Never + Once	0.257	0.123	0.890	0.257	0.123	0.717
A Few Times	0.175	0.651	0.079	0.175	0.651	0.136
Weekly+	0.568	0.226	0.032	0.568	0.226	0.147
NPT6M						
Never + Once	0.213	0.246	0.900	0.213	0.246	0.900
A Few Times	0.166	0.683	0.046	0.166	0.683	0.046
Weekly+	0.620	0.072	0.054	0.620	0.072	0.054
NPT9M						
Never + Once	0.177	0.425	0.945	0.177	0.425	0.945
A Few Times	0.238	0.519	0.041	0.238	0.519	0.041
Weekly+	0.585	0.057	0.014	0.585	0.057	0.014
NPT12M						
Never + Once	0.405	0.515	0.883	0.405	0.515	0.883
A Few Times	0.226	0.351	0.064	0.226	0.351	0.064
Weekly+	0.369	0.134	0.053	0.369	0.134	0.053

Figure 4.4 Adjusted Item Response Probabilities for the Multiple Group Model : High Utilizers

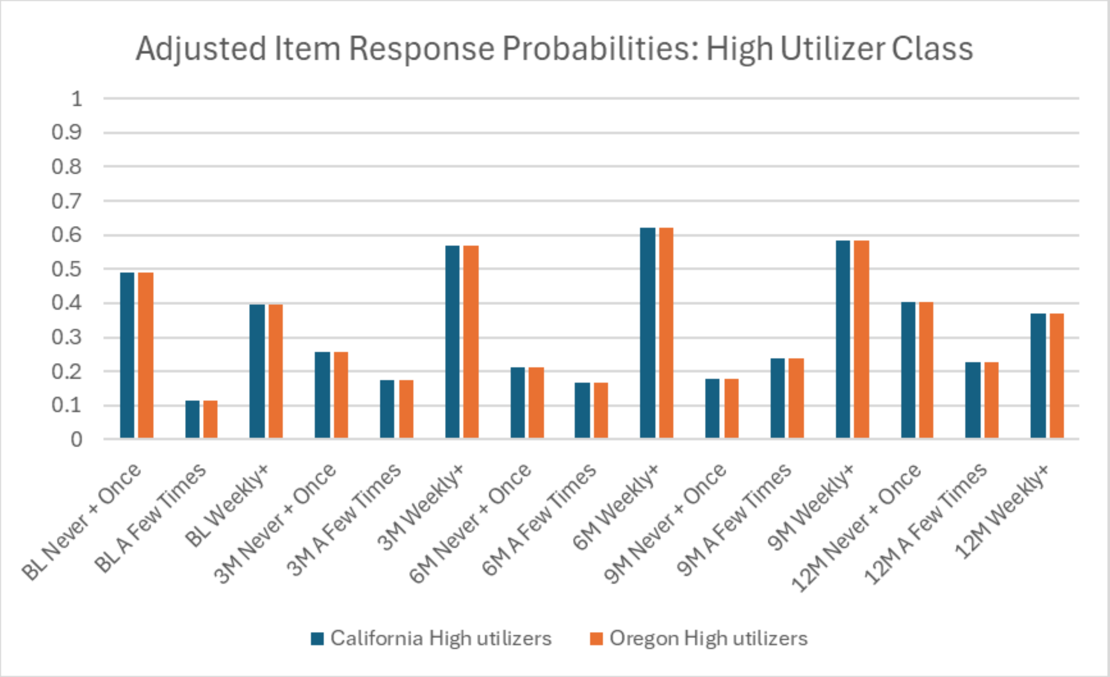


Figure 4.5 Adjusted Item Response Probabilities for the Multiple Group Model : Occasional Utilizers

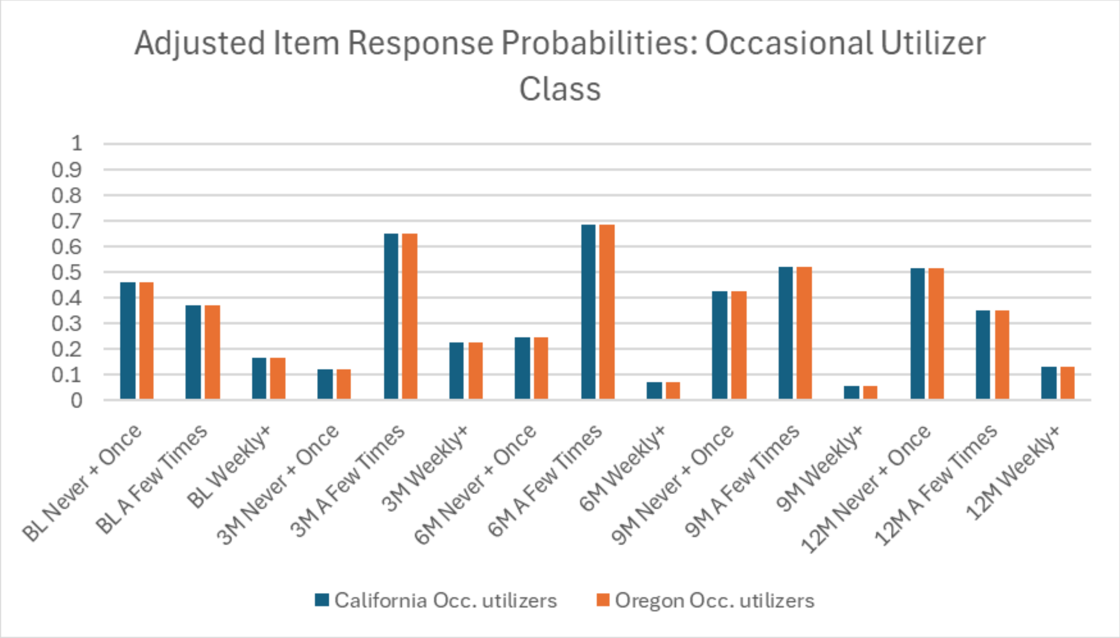
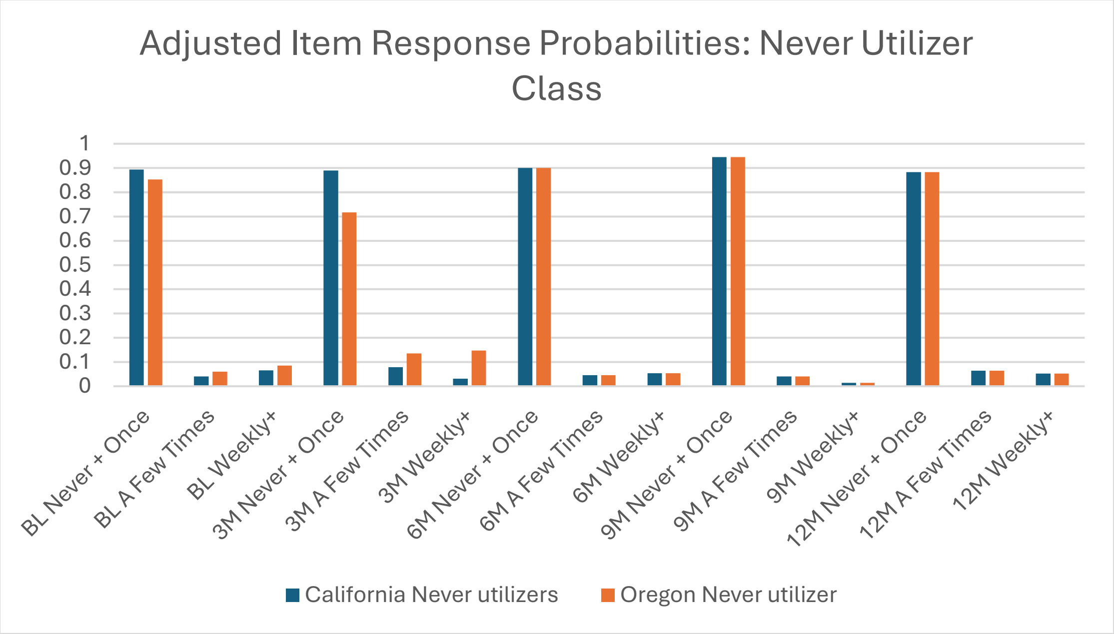


Figure 4.6 Adjusted Item Response Probabilities for the Multiple Group Model : Never Utilizers



Adjusted class prevalences are similar to the unadjusted prevalences. Oregon participants represent 63.8% and California participants 36.2% of Class 1 (“high utilizers”) which is characterized by a higher probability (> 0.5) of reporting use of NPT services weekly or more at 3-, 6-, and 9-months, with higher than observed rates of utilization at baseline and 12-months. Class 2 (“occasional utilizers) is comprised of 47.1% Oregon participants and 52.9% California participants and is characterized by a higher probability of reporting infrequent utilization (i.e., those reporting “a few times” in the prior three months) during the 3-, 6-, and 9-month periods. Finally, Class 3 (“never utilizers”) is comprised of 54.5% of Oregon participants and 45.5% of California participants and is characterized by reported patterns of very low (i.e., “once”) or never NPT utilization at all timepoints.

4.5.2 Logistic Regression Results

Table 4.11 shows the adjusted odds ratios (ORs) and 95% confidence intervals (CIs) for each of the predictors regressed on the three NPT utilization latent classes, using the "never utilizer" class as the reference group, across California and Oregon. Neither food insecurity nor housing insecurity were associated with NPT utilization class membership in either state. Medical financial insecurity was associated with higher odds of being a high utilizer than a never utilizer in Oregon (OR=2.16, 95% CI=1.214-3.823). Social support for pain management was associated with higher odds of being in both the high utilizer and occasional utilizer class compared to the never utilizers in Oregon (high utilizer OR=2.97, 95% CI=1.815-4.854; occasional utilizer OR=2.64, 95% CI=1.095-6.341).

FPL had opposite effects across states among the high utilizer class. Individuals in California who were 0.01%-99.99% of the FPL were less likely to be a high utilizer versus a never utilizer compared to those who were at least 150% of the FPL ($OR_{0.01\%-99.99\%}$=0.33, 95% CI=0.128-0.852). Individuals in Oregon who were 100%-149.9% of the FPL were more likely to be a high utilizer versus a never utilizer compared to those who were at least 150% of the FPL ($OR_{100\%-149.9\%}$=2.77, 95% CI=1.151-6.683). In both states, having a lower FPL was associated with lower odds of being an occasional utilizer than a never utilizer, though none of these ORs were significant.

Other statistically significant predictors of NPT utilization class membership included education, STarT Back Score, type of qualifying pain diagnosis, and the Charlson Comorbidity Index. Less than a high school education was associated with lower odds of being a high utilizer than a never utilizer compared to having at least some college education in both states (CA OR_{LessHS}=0.45, 95% CI=0.215-0.926; OR OR_{LessHS}=0.30, 95% CI=0.130-0.685) and associated with being an occasional utilizer versus a never utilizer in Oregon (OR_{LessHS}=0.11, 95% CI=0.015-0.825). Having a high school degree was associated with lower odds of being a high utilizer versus a never utilizer compared to having at least some college education in California (OR_{HS}=0.39, 95% CI=0.184-0.838) and with lower odds of being an occasional utilizer versus a never utilizer in Oregon (OR_{HS}=0.25, 95% CI=0.067-0.957).

Having low risk on the STarT Back Score was associated with lower odds of being a high utilizer versus a never utilizer compared to having a high-risk score in California ($OR_{LowRisk}$=0.11, 95% CI=0.020-0.648). Having both back and neck pain was associated with greater odds of being an occasional utilizer versus a never utilizer compared to having only back pain in California (OR_{Both}=4.05, 95% CI=1.131-14.517). Finally, having a higher Charlson Comorbidity Index score was associated with lower odds of being an occasional utilizer versus a never utilizer in California (OR_{CCI}=0.76, 95% CI=0.594-0.963).

Table 4.11. Adjusted Odds Ratios for Predictors of NPT Utilization Latent Classes

	California					Oregon				
	High Utilizer		Occasional Utilizer		Never Utilizer	High Utilizer		Occasional Utilizer		Never Utilizer
Model	**OR**	**95% CI**	**OR**	**95% CI**		**OR**	**95% CI**	**OR**	**95% CI**	
FPL Percentage, social risk, social support, covariates					Referent Class					Referent Class
Food Insecurity	1.162	0.653-2.068	0.923	0.372-2.287		1.198	0.664-2.164	1.550	0.538-4.471	
Housing Insecurity	0.881	0.464-1.675	1.184	0.496-2.825		0.994	0.541-1.827	0.589	0.198-1.747	
Medical Financial Insecurity	1.087	0.522-2.264	1.561	0.647-3.767		**2.155**	**1.214-3.823**	3.092	0.939-10.183	
Social Support	1.704	0.972-2.988	1.594	0.695-3.652		**2.968**	**1.815-4.854**	**2.635**	**1.095-6.341**	
FPL										
0%	0.436	0.151-1.256	0.948	0.224-4.009		2.065	0.875-4.876	0.256	0.058-1.122	
0.01%-99.99%	**0.330**	**0.128-0.852**	0.377	0.114-1.25		1.122	0.49-2.569	0.559	0.201-1.554	
100%-149.9%	0.371	0.125-1.103	0.465	0.067-3.212		**2.773**	**1.151-6.683**	0.662	0.203-2.155	
>150%	Referent					Referent				
Age	0.992	0.967-1.017	0.975	0.945-1.006		1.005	0.985-1.026	1.017	0.977-1.059	
Female	1.722	0.906-3.273	3.633	0.988-13.353		1.525	0.88-2.643	0.696	0.259-1.871	
Race/Ethnicity										
Non-Hispanic white	Referent					Referent				
Non-Hispanic BIPOC	0.365	0.12-1.113	0.74	0.175-3.129		0.726	0.340-1.553	0.740	0.084-6.497	
Hispanic	1.053	0.87-1.273	1.127	0.855-1.486		0.842	0.671-1.056	1.187	0.821-1.716	
Education										
Less than high school	**0.446**	**0.215-0.926**	0.386	0.117-1.276		**0.299**	**0.130-0.685**	**0.111**	**0.015-0.825**	
High school	**0.392**	**0.184-0.838**	0.63	0.239-1.659		0.783	0.449-1.367	**0.253**	**0.067-0.957**	
College or more	Referent					Referent				
Rural	1.552	0.799-3.017	0.266	0.024-2.907		0.735	0.418-1.292	0.428	0.117-1.564	
Number of pain conditions	0.959	0.746-1.234	0.922	0.709-1.199		**1.265**	**1.043-1.535**	1.222	0.793-1.882	
STarT Back Score										
Low risk	**0.114**	**0.020-0.648**	2.075	0.524-8.212		0.580	0.251-1.339	1.248	0.318-4.906	

Medium risk	0.591	0.249-1.405	1.083	0.338-3.474		0.624	0.279-1.394	1.748	0.536-5.698	
High risk	Referent					Referent				
Back and Neck Pain										
Back pain	Referent					Referent				
Neck pain	1.211	0.511-2.868	0.27	0.022-3.381		1.399	0.698-2.805	1.438	0.288-7.184	
Both	1.314	0.616-2.800	**4.051**	**1.131-14.517**		1.612	0.889-2.922	1.099	0.406-2.974	
Any substance use condition	2.718	0.929-7.950	1.72	0.209-14.144		0.854	0.402-1.816	1.871	0.395-8.862	
Any mental health condition	1.032	0.556-1.916	1.095	0.406-2.953		0.723	0.441-1.185	1.269	0.452-3.562	
Charlson comorbidity index	0.940	0.771-1.148	**0.756**	**0.594-0.963**		1.000	0.861-1.162	0.716	0.398-1.288	

4.5.3 Aim 2 Summary

The RMLCA 3-class solution model fit and classification accuracy improved after adding covariates, with entropy increasing from 0.634 to 0.706. Classification probabilities also improved, particularly for Class 2, indicating greater confidence in class assignment after adjustment.

Adjusted class prevalence estimates showed that Oregon participants made up a higher proportion of high utilizers (63.8%) compared to California (36.2%), reflecting higher NPT engagement, possibly due to the Oregon Back and Neck Pain (OBNP) policy. While both states shared similar class structures, Oregon participants in the low/never use class reported modestly higher use at baseline and 3-months than California participants, suggesting that Oregon's policy increased early engagement with NPT.

In adjusted regression models, social support and medical financial insecurity were significant predictors of NPT utilization class membership in Oregon. Participants with these characteristics were more likely to be high or occasional utilizers than never utilizers. Financial status (FPL) was a significant and divergent predictor of class membership by state: in Oregon, mid-level FPL (100–149%) was associated with being in the high utilizer class, while in California, the lowest FPL group (<100%) was associated with a lower likelihood of being in the high utilizer class.

Educational attainment, STarT Back risk scores, pain diagnosis type, and comorbidity burden also influenced class membership. Notably, lower education was consistently associated with lower odds of membership in the high utilization class, emphasizing persistent disparities even in policy-supportive environments.

4.6 Aim 3 Results

Aim 3: Examine the effects of social risks, socio-demographic characteristics, and clinical characteristics on change in pain-related outcomes between baseline and 6-months and 6-months to 12-months across states with and without the Oregon Back and Neck Pain policy (Oregon v. California).

4.6.1 Aim 3 Overview

The Aim 3 analysis included a multiple group, piecewise latent growth model. In addition, linear regression was used to examine predictors of change in BPI score simultaneously in Oregon and California with the same primary predictors and covariates used in Aim 2. The specific outcomes were the change (slope) in BPI score between baseline and 6-months and the change (slope) in BPI score between 6-months and 12-months, all as latent variables as indicated in Figure 3.5 These two 6-month time periods during the 12-month follow-up were chosen to reflect when newly diagnosed participants would have first been exposed to NPT services for their pain and when they were most likely to use the majority of these services. The second time period from 6-months to 12-months reflects the time when fewer NPT services were likely utilized and, thus, more likely reflects sustained maintenance effects or attenuated effects of treatment on pain for those for whom NPT services received. The result of the 6-month to 12-month BPI score is dependent on where the participant ended up after their first six months in the study. First, model fit and overall change in slope at each time segment for Oregon and California are presented and then Table 4.13 shows the results of the multiple group piecewise latent growth model results at the two timepoints. The intercepts were not the primary outcome of interest and thus are not reported, but is a latent variable modeled in the piecewise LGM along with the two latent slope variables.

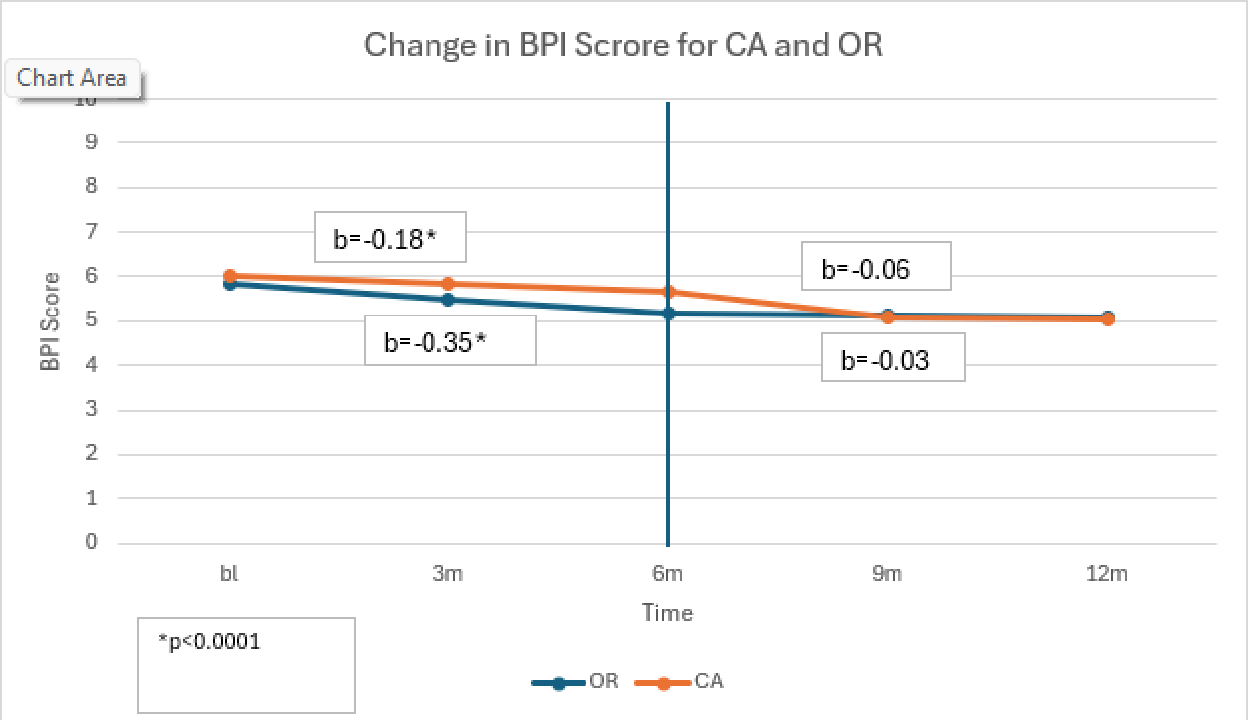
4.6.2 Latent Growth Model Fit Indices and Overall Slopes

The fit indices of the model suggest the model fits the data well. The chi-square (p=0.967), probability RMSEA <0.05 (100%), CFI (1.0), and the SRMR (0.012) all indicate the model is a good fit for the data (Table 4.12). Figure 4.7 shows the overall change in BPI score between baseline and 6-months and 6-months to 12-months for each state. Participants in California had a slightly higher BPI score than participants in Oregon at baseline. In Oregon, the mean score of the BPI at baseline was 5.85 (SE=0.120) and the mean score of the BPI at baseline in California was 6.02 (SE=0.095). Participants in Oregon had a greater reduction in BPI score from baseline to 6-months (slope=-0.35, SE=0.038) than participants in California (slope=-0.18, SE=0.040) and both were statistically significantly different from zero (p<0.0001). There were similar modest rates of reduction in the BPI score from 6-months to 12-months for both states and neither were statistically significant (OR slope=-0.03, SE=0.037; CA slope=-0.06, SE=0.037).

Table 4.12. Piecewise Latent Growth Model Fit Indices

Fit Indices	Value
Chi-square p-value	0.97
Probability RMSEA <0.05	100%
CFI	1.0
SRMR	0.01

Figure 4.7. Overall Changes in BPI Score for Oregon and California from Baseline to 6-months and 6-months to 12-months



4.6.3 Piecewise Linear Regression Results

Food insecurity, housing insecurity, and medical financial insecurity were not significant predictors of change in BPI score in either interval. Social support for pain management was a statistically significant predictor of the change in BPI score from baseline to 6-months (β = -0.23, SE=0.078, *p*=0.003) and maintained from 6-months to 12-months (β=0.04, p=0.5) in Oregon.

Race/ethnicity was a statistically significant predictor of change in BPI score in both intervals in California. Non-Hispanic Black or other race had a reduction in BPI score from 6-months to 12-months *(*β= -0.21, SE=0.104, p=0.05) compared to Non-Hispanic white participants. Hispanic participants had an increase in BPI score from baseline to 6-months

(β=0.07, SE=0.027, p=0.008) and a reduction from 6-months to 12-months (β=-0.05, SE=0.026, p=0.05) compared to Non-Hispanic white participants. High school education was a statistically significant predictor of change in BPI score from baseline to 6-months in Oregon. Those in Oregon with a high school education had an increase in BPI score between baseline and 6-months (β=0.18, SE=0.088, p=0.04) compared to those with at least some college.

The STarT Back Score was a statistically significant predictor of change in BPI from baseline to 6-months in both Oregon and California. Those in California with low risk (β=0.74, SE=0.146, p=<0.0001) medium risk (β=0.39, SE=0.129, p=0.002) had an increase in BPI score from baseline to 6-months compared to those with high risk. Those in Oregon with medium risk had an increase in BPI score from baseline to 6-months compared to those with high risk (β=0.31, SE=0.119, p=0.01). Having both back and neck pain was associated with an increase in BPI score (β=0.20, SE=0.091, p=0.03) in Oregon between baseline and 6-months compared to having back pain only. In California, having at least one substance use condition was associated with an increase in BPI score between baseline and 6-months compared to individuals without a substance use condition (β=0.26, SE=0.131, p=0.05). In Oregon, those with depression or anxiety had a decrease in BPI score from 6-months to 12-months compared to individuals without depression or anxiety (β=-0.16, SE=0.077, p=0.04).

Table 4.13. Results of Multiple Group Piecewise Latent Growth Modeling in Oregon and California

	California				Oregon			
	β (SE) BL-6M	p-value	β (SE) 6M-12M	p-value	β (SE) BL-6M	p-value	β (SE) 6M-12M	p-value
Food insecurity	0.153 (0.087)	0.08	0.064 (0.083)	0.439	0.06 (0.089)	0.5	0.118 (0.085)	0.167
Housing insecurity	-0.007 (0.09)	0.935	-0.081 (0.085)	0.341	0.052 (0.09)	0.563	0.01 (0.087)	0.907
Medical Financial Insecurity	0.076 (0.1)	0.448	-0.104 (0.094)	0.272	-0.086 (0.092)	0.35	0.156 (0.091)	0.085
Any social support for pain	0.06 (0.081)	0.457	-0.083 (0.076)	0.28	**-0.23 (0.078)**	**0.003**	0.044 (0.075)	0.554
Federal Poverty Level (FPL)								
0% FPL	0.019 (0.153)	0.9	0.125 (0.141)	0.376	0.004 (0.127)	0.974	0.044 (0.123)	0.719
0.01-99.99% FPL	0.049 (0.142)	0.732	0.251 (0.13)	0.053	0.052 (0.12)	0.669	0.032 (0.117)	0.785
100-149.9% FPL	0.118 (0.167)	0.479	0.006 (0.154)	0.968	0.001 (0.131)	0.995	-0.029 (0.128)	0.818
150-200+%								
Age (centered)	0.001 (0.003)	0.773	-0.004 (0.003)	0.229	-0.002 (0.003)	0.598	-0.003 (0.003)	0.419
Sex								
Female	0.099 (0.084)	0.239	-0.042 (0.081)	0.601	0.031 (0.083)	0.71	-0.089 (0.08)	0.263
Male								
Race/Ethnicity								
Non-Hispanic Black or other	0.048 (0.109)	0.659	**-0.207 (0.104)**	**0.047**	0.048 (0.138)	0.728	-0.018 (0.136)	0.896
Hispanic	**0.072 (0.027)**	**0.008**	**-0.051 (0.026)**	**0.045**	-0.006 (0.035)	0.871	-0.02 (0.035)	0.563
Non-Hispanic white								
Education								
Less than high school	-0.012 (0.116)	0.915	-0.006 (0.114)	0.959	0.153 (0.114)	0.181	0.059 (0.111)	0.598
High school	0.073 (0.09)	0.422	0.024 (0.086)	0.78	**0.179 (0.088)**	**0.043**	-0.1 (0.086)	0.247
Some college or more								
Rurality								
Rural	-0.091 (0.099)	0.358	-0.055 (0.093)	0.55	-0.037 (0.094)	0.694	0.117 (0.09)	0.193
Urban								
Number of painful conditions	-0.004 (0.033)	0.907	-0.03 (0.031)	0.329	-0.001 (0.032)	0.983	-0.02 (0.031)	0.51
STaRT Back Score								

Low risk	**0.741 (0.146)**	**<0.0001**	-0.237 (0.138)	0.085	0.265 (0.144)	0.066	-0.117 (0.138)	0.397
Medium risk	**0.39 (0.129)**	**0.002**	-0.158 (0.119)	0.184	**0.306 (0.119)**	**0.01**	-0.09 (0.113)	0.426
High risk								
Type of qualifying pain								
Neck pain	-0.05 (0.148)	0.737	-0.011 (0.145)	0.938	0.167 (0.117)	0.155	-0.096 (0.113)	0.397
Neck and back pain	-0.02 (0.091)	0.827	-0.04 (0.086)	0.638	**0.202 (0.091)**	**0.026**	0.007 (0.087)	0.937
Back pain								
Any substance use condition	**0.258 (0.131)**	**0.049**	0.054 (0.126)	0.67	0.068 (0.112)	0.544	0.027 (0.108)	0.803
Any depression or anxiety	-0.097 (0.083)	0.242	0.065 (0.079)	0.412	0.037 (0.08)	0.644	**-0.163 (0.077)**	**0.035**
Charlson comorbidity index	0.024 (0.028)	0.387	0.018 (0.026)	0.486	-0.022 (0.027)	0.402	0.019 (0.025)	0.459

4.6.4 Aim 3 Summary

The latent growth model fit indices indicated excellent fit (χ^2 p=0.967; RMSEA=0; CFI=1.0; SRMR=0.012). At baseline, California participants reported slightly higher pain scores (BPI=6.02) than Oregon participants (BPI=5.85). Oregon participants experienced greater reductions in pain from baseline to 6 months (slope=–0.35) than Californians (slope=–0.18), with similar reductions from 6 to 12 months in both states. Social support for pain management significantly predicted pain reduction in Oregon from baseline to 6 months (β=–0.23, p=0.003). In California, race/ethnicity predicted relative pain change: Hispanic participants had modestly increased pain from baseline to 6 months (β=0.07) relative to white participants while Non-Hispanic Black or other race participants had pain reductions from 6–12 months (β=–0.21). In Oregon, high school education was associated with increased pain over the first 6 months. STarT Back scores significantly predicted pain increases from baseline to 6 months in both states for low- and medium-risk groups. Other predictors included comorbid pain conditions, substance use, and mental health diagnoses.

Chapter 5: Conclusion

5.0 Discussion Overview

This study advances our understanding of how Medicaid policy influences the use of nonpharmacologic therapies (NPT) for back and neck pain by identifying distinct patterns of utilization and exploring their predictors. Using repeated measures latent class analysis across Medicaid populations in Oregon and California, the research identified three distinct patterns of NPT utilization over 12 months —high utilizers, occasional utilizers, and low/never utilizers—demonstrating empirical support for the existence of subgroups of NPT engagement that have the potential to inform Medicaid policies and clinical initiatives designed to increase access to NPT services. This structure was consistent across states, providing a stable foundation for further analysis of predictors and outcomes.

Importantly, this work extends prior literature by linking the existence of these latent subgroups to a specific policy context: Oregon's Back and Neck Pain (OBNP) policy. While both states included individuals initiating care for a new episode of back and neck pain and offered some NPT coverage, Oregon's comprehensive policy and coordinated care organization (CCO) model led to modestly higher NPT utilization even among the "never" class, suggesting that state-level policy may influence engagement even among those less likely to seek care. This underscores that policy interventions can alter the broader care landscape, not only for those who fully engage but also for those on the margins of use.

One of the study's most novel contributions is its examination of how social support and socioeconomic context intersect with policy to influence care use and outcomes. In Oregon, individuals with social support for pain management were more likely to fall into the high or occasional NPT user classes and also reported modest improvements in pain scores over time relative to individuals without social support for pain management. These relationships were not observed in California, providing suggestive evidence that the OBNP policy, particularly its integration of community health workers and emphasis on addressing social needs, may have enhanced feelings of support and facilitated care engagement. These findings highlight the importance of structural supports in enabling patient-centered, equitable care.

Additionally, the study identified persistent disparities in NPT utilization by education level and variation in pain severity (i.e., BPI score) by race and ethnicity, particularly in California. These findings suggest that even with access to NPT, marginalized groups may face additional barriers to effective engagement. Oregon's more integrated and equity-focused policy model may mitigate some of these disparities, although more targeted interventions remain necessary to increase early engagement with NPT services.

Oregon and California had modest reductions in their pain severity scores between baseline and 6-months with the reductions persisting up to 12-months. Oregon had slightly greater reduction than California from baseline to 6-months which may be due to the expanded access of NPT services under the OBNP; however, modest results were not unexpected for two primary reasons. First, while California did offer some coverage for services such as physical therapy and acupuncture, they did not have a comprehensive Medicaid reimbursement policy for NPT services similar to OBNP and California residents found access to NPT services limited because of the stringent qualifications.[177] Second, the majority of participants in both states did not report using any NPT service for pain management and among those that did, it is possible they did not receive therapeutic dose.

Finally, the association between lower STarT Back scores and relative increases in pain severity highlights limitations in using existing risk stratification tools for chronic pain populations without allowing providers to override the risk stratification rules. The STaRT Back Tool is intended to allow providers to apply their clinical judgement about a person's risk of developing persistent disabling symptoms even when the tool designates someone as low risk.[120] When used as risk-stratification tool to determine care pathways, providers should be given the freedom to deviate from the STaRT Back score when clinically appropriate.

Together, these findings suggest that Medicaid policies aiming to expand access to nonpharmacologic care for pain management should address not only coverage but also the systems, supports, and social environments in which care is delivered. By identifying meaningful subgroups and understanding how structural factors shape engagement, states can design more targeted, equitable, and effective interventions to improve outcomes for people with chronic pain.

5.1 Latent Subgroups

The class enumeration process using data from California, Oregon, and the combined sample showed that the 3-class solution was the best fitting model. This offers good evidence that the 3-class solution in the final, multiple group model fit the data best given the concordance between the three samples.[146] Measurement invariance testing provided confidence that the latent classes have the same meaning and interpretation across the states. There were differences in the baseline and 3-month timepoints among the never utilizer class in that Oregon participants had a higher probability of reporting higher rates of NPT utilization than California, suggesting that the OBNP policy may have nudged early NPT engagement compared to California. While both samples were entering new episodes of care for back/neck pain and some coverage was available for NPT services in California, the comprehensive coverage of the OBNP policy along with the structure of the CCO care model in Oregon resulted in modestly greater increases in reported use.

Understanding latent subgroups of NPT utilization over time is a foundational step in health services and policy research. Before examining predictors or outcomes, latent class analysis (LCA) allows researchers to uncover naturally occurring patterns in how individuals engage with the healthcare system especially in contexts where utilization is highly variable and influenced by both individual and structural factors.

In this study, identifying subgroups of NPT use ranging from high utilizers to occasional and low/never users provides a critical empirical basis for several reasons. First, it can reveal real-world heterogeneity. NPT services are often delivered in diverse settings, with varying frequency and patient engagement. By identifying distinct utilization subgroups, we can characterize the real-world complexity of how patients actually use these services over time, beyond what average utilization statistics can show. This is especially important for Medicaid populations, where access, preferences, and barriers differ significantly.

Second, these subgroups can inform policies targeting resource allocation. Policymakers need to understand who is using services and how often to design policies that promote equitable and efficient care. For example, a low-utilizer group may signal unmet need, access barriers, issues with knowledge of available services, or simply lack of interest. Mapping these subgroups is essential for tailoring interventions, payment reforms, and benefit design.

Finally, these subgroups lay the groundwork for more advanced modeling. Before examining predictors or outcomes, class enumeration defines the dependent structure that will guide subsequent modeling. Knowing that three distinct patterns exist rather than assuming uniform use improves the conceptual and statistical validity of regression analyses that follow. It ensures that policy effects or patient characteristics are evaluated in relation to meaningful behavioral phenotypes rather than arbitrary groupings.

5.2 Predictors of Latent Subgroups and Pain Severity

This study offers important insights into how Medicaid policy design can shape utilization patterns of NPT and influence pain outcomes. Despite similar latent class structures in Oregon and California, these findings offer suggestive evidence that Oregon's Back and Neck Pain policy may have had a broader impact on engagement with NPT, particularly through its relationship with social support for pain management, and early reductions in pain scores. These results point to the potential of state-level policy interventions to do more than expand coverage; they can also shift care norms, social contexts, and therapeutic engagement.

Results in Oregon suggest that the OBNP had a positive effect of increasing access to and utilization of services for individuals with low financial resources. This may be due to two different policy mechanisms. In Oregon as part of the OBNP, community health workers (CHWs) were responsible for helping to connect individuals to services to help address their social needs prior to or at the same time as referral to NPT services. This plausibly could account for the increased likelihood of higher utilization for those who reported having medical financial insecurity or lower FPL if they were referred to services that provided financial assistance. In randomized trials, CHW-led interventions for individuals with chronic pain in low resource settings have shown clinical and functional improvements among people who worked directly with the CHW for their pain management and navigation of the healthcare system.[178] CHW's also reported that their primary roles in safety net hospitals are often focused on addressing social determinants of health, but they also feel that they play a vital role in directly improving access to NPT services.[179]

Additionally, because medical financial insecurity was associated with higher odds of being a high utilizer of NPT services, the fact that the OBNP allowed for NPT services to be covered by Medicaid may account for this association. Individuals with lower socioeconomic status are more likely to report not utilization treatments for pain[44] and more likely to report having severe pain, so increasing access to this population is critical to improving their ability to manage pain.[180]

Moreover, the association between social support and improvements in pain scores in Oregon during the first six months aligns with the timing of when most NPT services were likely delivered. This temporal pattern reinforces the possibility that availability of NPT services, especially when socially-supported and policy-enabled, can lead to measurable improvements in pain outcomes. The absence of a similar effect in California suggests that coverage alone may not be enough to generate meaningful or equitable outcomes without a supportive policy and care delivery infrastructure.

Participants were asked on the baseline assessment whether they sought support from others in their life to manage their pain. In the case of participants from Oregon, it is possible that during their recent qualifying clinic visit in which back or neck pain was diagnosed, that they began the referral or, in some cases, treatment with NPT services. As mentioned earlier, a central tenet of the CCO model is the engagement of CHWs and the prioritization of social risks for the Medicaid population. So, it is also possible that the structure of the CCOs and the embedded OBNP policy increased feelings of social support which increased utilization of NPT services and reduced pain outcomes over time. This aligns with literature on the role of the CHW in primary care safety net settings where CHWs report providing support in addressing social determinants of health, assisting in navigating the healthcare system, and in providing direct access to community-based NPT service.[179] Social support is a core tenet of the Multi-level Influences on Quality of Care[62,63] which influences the quality of care and outcomes.

Persistent disparities in NPT utilization by education level in both states highlight the need for targeted efforts to improve access and engagement among populations with lower educational attainment. This could include culturally and linguistically appropriate outreach, navigation services, transportation supports, and strategies to improve health literacy around nonpharmacologic treatment options. Engagement with NPT services has been shown to be influenced by patient familiarity with or knowledge about specific treatment options.[181] In one review, the authors identified that patients are generally interested in NPT services, but without knowledge about the services then they are less likely to engage.[181] Without such supports, individuals with lower education may remain underserved even in contexts with generous coverage.[182]

The differential effects of race and ethnicity on pain trajectories in California, but not Oregon, raise additional concerns about structural inequities in pain care. The delayed improvements in pain among BIPOC individuals and the early worsening among Hispanic individuals may reflect systemic barriers to timely or culturally responsive care.[66,101] Delayed improvements may also be due to the time needed to build trust with providers to become engaged in treatment, particularly for individuals with chronic pain[183] The absence of these associations in Oregon suggests that integrated care models and policy-driven NPT access may help mitigate some racial disparities, although it is also possible that the lack of association between race and NPT utilization is due to the low sample size in Oregon.

Finally, the finding that individuals classified as low or medium risk on the STaRT Back tool had greater increases in pain than those at high-risk challenges existing assumptions about stratified care. It may be that high-risk individuals received more attention and resources due to their risk, while others were under-treated. However, it’s more likely that the tool was not appropriate for use in our sample without allowing providers to override the STaRT Back score stratification. The STarT Back tool was validated in a study that allowed for providers to apply their clinical judgement about the risk individuals had on developing persistent disabling pain regardless of what the tool indicated. This resulted in people being stratified manually as medium or high risk when the tool scored them as low risk.[37,120] The findings of this study suggest this is an appropriate and necessary approach if the STaRT Back tool is to be used to determine treatment pathways under Medicaid policies.

In clinical settings, knowing which patients fall into distinct utilization profiles can help tailor care plans. For example, a patient likely to fall into the “occasional user” class may benefit from additional outreach or motivational support, while a “high utilizer” may require coordinated care planning to ensure all services being utilized are appropriate. From a value-based care perspective, these subgroups can inform performance measurement, risk adjustment, and care management strategies.

Policies like Oregon’s Back and Neck Pain policy operate in complex, real-world systems. Latent class analysis helps to characterize variation in service uptake that could otherwise confound or mask policy effects. Understanding utilization patterns and their predictors is essential for interpreting heterogeneity in policy impact and informing adaptive implementation strategies.

5.3 Limitations

Limitations of this study include that the item response probabilities for the high and occasional utilizers are just over 0.50 and only over 0.50 at 3-months, 6-months, and 9-months for the high utilizers before dropping lower. This means that even though they have a higher probability than not of reporting weekly or occasional use of an NPT service, that the probability of being in a high or occasional utilizer class is not very strong. These labels were chosen to describe the patterns broadly, but may not be the best descriptors. The lower probabilities could be due to either the survey construction or due to low reported use of any NPT service.

The timing of the study relative to implementation of the OBNP policy is another limitation. The OBNP policy was initiated two years prior and was deemed fully implemented 6-months prior to study enrollment. The effects of policy implementation on CCOs, clinics, CHWs, and patients could have influenced patterns of and exposure to NPT utilization before enrollment if use had begun prior to study enrollment. However, the study attempted to control for this by requiring that all participants have a new episode of care defined by a new diagnosis of back/neck pain near the time of enrollment to try to prevent enrolling individuals who may have already had back/neck pain and been receiving NPT treatment in the year prior.

Another main limitation of the current study includes the construction of indicators of the NPT utilization latent class model, which does not allow for the specific type of NPT service or multiple NPT services to be accounted for when characterizing patterns of use. To do so would have required multiple complex models and would have complicated interpretation of patterns. Additionally, the item response options were collapsed such that those who reported never utilizing and utilizing a service once were included in the same category. This does not allow for a true characterization of a “never” utilization group because there are some who reported using a service one time; however, the majority of participants reported never using a service, so it is reasonable to interpret this class in this way.

Additionally, the NPT baseline measure used in this study is not a true measure of exposure to NPT services or pain levels before the qualifying back or neck pain diagnosis. Rather, it was a measure of exposure and pain within a month of their new episode of care. The study collected some data on NPT utilization up to 6 months prior to the new episode of care; however, this question did not include other information about frequency of use and whether the service was used for back/neck pain, a requirement for the NPT utilization model in the current study.

The analysis and interpretation of results was also limited in the conclusions that can be drawn from the social support for pain management measure. This was a single measure that was not psychometrically validated to measure social support and did not give explicit guidance to participants about what is meant by “social support for pain management”. I have contextualized the findings in this dissertation within the Oregon Back and Neck Pain policy, wraparound services that CCOs provided to individuals with pain (e.g., in-house pain services, free NPT services), and the CCO 2.0 emphasis on helping to address social needs. This contextualization is based on qualitative findings from the main study and discussions with the parent study PI; however, it is not possible to know whether these are the elements participants were considering when they answered this question in Oregon since this dissertation did not include qualitative data.

Finally, policy mechanisms that may have contributed to the findings were not measured during the study. These include the role CHWs played in helping individuals navigate social needs in the community, other programs at CCOs that aided in addressing social risks, and the variability of how NPT services or the referral processes were embedded within each CCO clinic. This would allow more nuanced understanding of how the Oregon CCO model and the OBNP policy allowed for higher utilization among those with lower socioeconomic resources and to it would help explain the social support findings.

5.4 Future Directions

Future research should examine mechanisms through which social support, provided by structural policy mechanism or at the individual level provided by caregivers and family, modifies the effect of policy interventions on pain outcomes, including qualitative studies of patient and provider perspectives. Comparative evaluations of different state Medicaid policies, particularly those embedding NPT into value-based care, can help identify best practices. Research should also explore interventions, such as delivering services in medically underserved areas, developing strategies to increase knowledge about NPT services, or testing ways to enhance provider-patient trust, to reduce education- and race-based disparities in NPT access. Longitudinal studies beyond 12 months may reveal longer-term effects of NPT engagement. Finally, exploring the role of care team integration, referral networks, and provider attitudes within policy environments may help refine strategies for effective implementation of NPT policy reforms.

5.5 Conclusions

These findings suggest that Medicaid policies aiming to expand access to NPT services should go beyond coverage alone. Integrating NPT services into delivery systems via care coordination, community outreach, and payment models may enhance both utilization and patient outcomes. Policies should also address social determinants of care engagement by fostering environments where NPT is supported by providers, peers, and families. Embedding these therapies into value-based payment arrangements and leveraging Medicaid managed care entities may be key pathways for broader impact.

Clinically, these results underscore the potential importance of screening for and facilitating social support for pain management as part of routine care. Providers should be trained to discuss nonpharmacologic options, refer to NPT providers within Medicaid networks, and encourage shared decision-making that reflects patients' social context. Risk stratification tools like STaRT Back may require revisiting to ensure they effectively guide care pathways in diverse populations. Integrating community health workers or peer support roles into chronic pain care teams may also enhance outcomes, especially for those at lower educational or socioeconomic levels.

6.0 Supplement 1

The analysis presented in Table S.1 was completed to understand what the distribution of payment type was overall and across states for the highest frequency of utilization (i.e., the variable that defines the latent class indicator at each time point) to ensure that payment type was not biasing how the classes were defined. This addressed concerns that a large proportion of participants may have self-paid for services and thus may make drawing conclusions about policy effectiveness difficult.

Table S.1 shows the distribution of payment type for the highest frequency of utilization at each timepoint among those with any NPT service use. At all timepoints for both Oregon and California, the majority of participants reported that insurance paid for their service use in full or in part. At all five timepoints, California participants reported using services for free the same or slightly more than those in Oregon. At 12-months, the proportion of Oregon participants who reported that they self-paid for a service increased to 23%; at all other timepoints, the proportion in Oregon ranged from 11.5%-17% and the proportion in California ranged from 15%-20%.

At nearly all timepoints in both states, the proportion of participants who said that insurance covered at least part of their service was >70%. Additionally, the results show that at all timepoints, except 12-months, Oregon participants reported insurance covering their services at a higher rate than in California, something that makes sense given the coverage of the OBNP policy.

Table S.1. Payment Type Among Those with Any NPT Service Use for Back Pain by State

	CA N (%)	OR N (%)	Total N (%)
Baseline			

Insurance Paid in Full or Part	189 (71.1)	246 (78.6)	435 (75.1)
Free	25 (9.4)	20 (6.4)	45 (7.8)
Self-pay	52 (19.6)	47 (15.0)	99 (17.1)
3-Months			
Insurance Paid in Full or Part	169 (72.8)	286 (82.0)	455 (78.3)
Free	28 (12.1)	23 (6.6)	51 (8.8)
Self-pay	35 (15.1)	40 (11.5)	75 (12.9)
6-Months			
Insurance Paid in Full or Part	181 (75.4)	200 (76.1)	381 (75.8)
Free	23 (9.6)	18 (6.8)	41 (8.2)
Self-pay	36 (15.0)	45 (17.1)	81 (16.1)
9-Months			
Insurance Paid in Full or Part	131 (66.2)	177 (70.2)	308 (68.4)
Free	32 (16.2)	37 (14.7)	69 (15.3)
Self-pay	35 (17.7)	38 (15.1)	73 (16.2)
12-Months			
Insurance Paid in Full or Part	120 (70.6)	130 (63.4)	250 (66.7)
Free	23 (13.5)	28 (13.7)	51 (13.6)
Self-pay	27 (15.88)	47 (22.9)	74 (19.7)

Table S.2 shows the number of NPT services reported at each timepoint overall and by state. This analysis is supplementary and descriptive data to help readers have a better understanding of all NPT data available versus what was used in construction of the latent class indicators which does not take into account multiple service use, but only the highest frequency of service use regardless of how many (or which) services were reported. At nearly all timepoints, the majority of participants did not report using any NPT service, except for Oregon participants at 3-months (43.3%). This aligns with the OBNP policy implementation where the sample with a new episode of neck/back pain would have been offered services/referrals to services early in the course of their episode of care for back/neck pain. Among participants who used any service, the majority in both states used only one. Oregon participants were more likely to report using three or more services compared to California which also may reflect the ability of Oregon participants to have access to a broader range of covered NPT services under the OBNP policy. This was not a central question of the dissertation, but rather is provided as descriptive data on the frequency of number of NPT service types used to better inform the reader of the extant data available on NPT service use.

Table S.2. Number of NPT Service Types[1] Used at Each Timepoint by State

	CA N (%)	OR N (%)	Total N (%)
Baseline			
0	508 (63.2)	507 (57.4)	1015 (60.1)
1	125 (15.6)	163 (18.4)	288 (17.1)
2	83 (10.3)	106 (12.0)	189 (11.2)
3	54 (6.7)	67 (7.6)	121 (7.2)
4	22 (2.7)	24 (2.7)	46 (2.7)
5	8 (1.0)	12 (1.4)	20 (1.2)
6	4 (0.5)	4 (0.5)	8 (0.5)
7	-	1 (0.1)	1 (0.1)
3-Months			
0	348 (56.0)	299 (43.3)	647 (49.3)
1	117 (18.8)	157 (22.7)	274 (20.9)
2	81 (13.0)	118 (17.1)	199 (15.2)
3	45 (7.3)	63 (9.1)	108 (8.2)
4	24 (3.9)	41 (5.9)	65 (5.0)
5	4 (0.6)	9 (1.3)	13 (1.0)
6	2 (0.3)	2 (0.3)	4 (0.3)
7	-	2 (0.3)	2 (0.2)
6-Months			
0	336 (52.3)	373 (54.1)	709 (53.3)
1	132 (20.6)	129 (18.7)	261 (19.6)
2	100 (15.6)	89 (12.9)	189 (14.2)
3	48 (7.5)	69 (10.0)	117 (8.8)
4	21 (3.3)	18 (2.6)	39 (2.9)
5	4 (0.6)	9 (1.3)	13 (1.0)
6	-	2 (0.3)	2 (0.2)
7	1 (0.2)	-	1 (0.1)
9-Months			
0	362 (58.3)	386 (56.6)	748 (57.4)
1	117 (18.8)	131 (19.2)	248 (19.0)

2	86 (13.9)	83 (12.2)	169 (13.0)
3	33 (5.3)	53 (7.8)	86 (6.6)
4	12 (1.9)	17 (2.5)	29 (2.2)
5	9 (1.5)	7 (1.0)	16 (1.2)
6	2 (0.3)	3 (0.4)	5 (0.4)
7	-	2 (0.3)	2 (0.2)
12-Months			
0	366 (61.4)	421 (63.2)	787 (62.4)
1	97 (16.3)	101 (15.2)	198 (15.7)
2	95 (15.9)	81 (12.2)	176 (14.0)
3	25 (4.2)	37 (5.6)	62 (4.9)
4	7 (1.2)	20 (3.0)	27 (2.1)
5	3 (0.5)	4 (0.6)	7 (0.6)
6	3 (0.5)	2 (0.3)	5 (0.4)
7	-	-	-

1. NPT service types includes acupuncture, chiropractic therapy, cognitive behavioral therapy, other psychotherapy, yoga, massage, and physical or occupational therapy.

7.0 References

1. Dahlhamer J, Lucas J, Zelaya, C, et al. Prevalence of Chronic Pain and High-Impact Chronic Pain Among Adults — United States, 2016. *MMWR Morb Mortal Wkly Rep*. 2018;67(36):1001-1006. doi:10.15585/mmwr.mm6736a2

2. Schappert SM, Burt CW. National Center for Health Statistics. :73.

3. Skelly AC, Chou R, Dettori JR, et al. *Noninvasive Nonpharmacological Treatment for Chronic Pain: A Systematic Review Update*. Agency for Healthcare Research and Quality (AHRQ); 2020. doi:10.23970/AHRQEPCCER227

4. *Relieving Pain in America: A Blueprint for Transforming Prevention, Care, Education, and Research*. National Academies Press; 2011:13172. doi:10.17226/13172

5. Treede RD, Rief W, Barke A, et al. A classification of chronic pain for ICD-11. *Pain*. 2015;156(6):1003-1007. doi:10.1097/j.pain.0000000000000160

6. Noninvasive, Nonpharmacological Treatment for Chronic Pain. Published online 2017:28.

7. Ballantyne JC, Shin NS. Efficacy of Opioids for Chronic Pain: A Review of the Evidence. *Clin J Pain*. 2008;24(6):469-478. doi:10.1097/AJP.0b013e31816b2f26

8. Eriksen J, Sjogren P, Bruera E, Ekholm O, Rasmussen NK. Critical issues on opioids in chronic non-cancer pain: An epidemiological study. *Pain*. Published online June 8, 2006:254-255. doi:10.1016/S1073-5437(08)70984-7

9. Hartvigsen J, Hancock MJ, Kongsted A, et al. What low back pain is and why we need to pay attention. *The Lancet*. 2018;391(10137):2356-2367. doi:10.1016/S0140-6736(18)30480-X

10. Kuehn BM. Opioid Prescriptions Soar. *JAMA*. 2007;297(3):249. doi:10.1001/jama.297.3.249

11. Murthy VH. U.S. Surgeon General's Letter to Prescribers Regarding Opioid Epidemic. Published online August 2016:1.

12. Sullivan MD, Edlund MJ, Fan MY, DeVries A, Braden JB, Martin BC. Trends in use of opioids for non-cancer pain conditions 2000–2005 in Commercial and Medicaid insurance plans: The TROUP study. *Pain*. 2008;138(2):440-449. doi:10.1016/j.pain.2008.04.027

13. Boudreau D, Von Korff M, Rutter CM, et al. Trends in long-term opioid therapy for chronic non-cancer pain. *Pharmacoepidemiol Drug Saf*. 2009;18(12):1166-1175. doi:10.1002/pds.1833

14. Lerman SF, Rudich Z, Brill S, Shalev H, Shahar G. Longitudinal Associations Between Depression, Anxiety, Pain, and Pain-Related Disability in Chronic Pain Patients. *Psychosom Med*. 2015;77(3):333-341. doi:10.1097/PSY.0000000000000158

15. Foster NE, Anema JR, Cherkin D, et al. Prevention and treatment of low back pain: evidence, challenges, and promising directions. *The Lancet*. 2018;391(10137):2368-2383. doi:10.1016/S0140-6736(18)30489-6

16. Wallace B, Varcoe C, Holmes C, et al. Towards health equity for people experiencing chronic pain and social marginalization. *Int J Equity Health*. 2021;20(1):53. doi:10.1186/s12939-021-01394-6

17. Braveman P, Gruskin S. Defining equity in health. *J Epidemiol Community Health*. 2003;57(4):254-258. doi:10.1136/jech.57.4.254

18. Oregon Health Authority. Guideline Note 56. Accessed November 1, 2021. https://www.oregon.gov/oha/HPA/DSI-HERC/Pages/Searchable-List.aspx?wp7687=se:%22NON-INTERVENTIONAL+TREATMENTS%22

19. Oregon Health Authority. Guideline Note 60. Accessed November 1, 2021. www.oregon.gov/oha/HPA/DSI-HERC/ Pages/Searchable-List.aspx?wp7687=se:%22OPIOIDS+FOR+ CONDITIONS+OF+THE+BACK+AND+SPINE%22

20. Busse JW, Wang L, Kamaleldin M, et al. Opioids for Chronic Noncancer Pain: A Systematic Review and Meta-analysis. *JAMA*. 2018;320(23):2448. doi:10.1001/jama.2018.18472

21. Chou R, Hartung D, Turner J, et al. *Opioid Treatments for Chronic Pain*. Agency for Healthcare Research and Quality (AHRQ); 2020. doi:10.23970/AHRQEPCCER229

22. Olsen Y, Daumit GL, Ford DE. Opioid Prescriptions by U.S. Primary Care Physicians From 1992 to 2001. *J Pain*. 2006;7(4):225-235. doi:10.1016/j.jpain.2005.11.006

23. Bendtsen P, Hensing G, Ebeling C, Schedin A. What are the qualities of dilemmas experienced when prescribing opioids in general practice? *Pain*. 1999;82(1):89-96. doi:10.1016/S0304-3959(99)00036-6

24. Brennan F, Carr DB, Cousins M. Pain Management: A Fundamental Human Right. *Anesth Analg*. 2007;105(1):205-221. doi:10.1213/01.ane.0000268145.52345.55

25. Von Korff M, Kolodny A, Deyo RA, Chou R. Long-Term Opioid Therapy Reconsidered. *Ann Intern Med*. 2011;155(5):325. doi:10.7326/0003-4819-155-5-201109060-00011

26. Tick H, Nielsen A, Pelletier KR, et al. Evidence-Based Nonpharmacologic Strategies for Comprehensive Pain Care. *EXPLORE*. 2018;14(3):177-211. doi:10.1016/j.explore.2018.02.001

27. McDonagh MS, Selph SS, Buckley DI, et al. *Nonopioid Pharmacologic Treatments for Chronic Pain*. Agency for Healthcare Research and Quality (AHRQ); 2020. doi:10.23970/AHRQEPCCER228

28. Forum on Neuroscience and Nervous System Disorders, Global Forum on Innovation in Health Professional Education, Board on Health Sciences Policy, Board on Global Health, Health and Medicine Division, National Academies of Sciences, Engineering, and Medicine. *The Role of Nonpharmacological Approaches to Pain Management: Proceedings of a Workshop*. (Bain L, Norris SMP, Stroud C, eds.). National Academies Press; 2019:25406. doi:10.17226/25406

29. National Pain Strategy: A Comprehensive Population Health-Level Strategy for Pain.

30. Gatchel RJ, Peng YB, Peters ML, Fuchs PN, Turk DC. The biopsychosocial approach to chronic pain: Scientific advances and future directions. *Psychol Bull*. 2007;133(4):581-624. doi:10.1037/0033-2909.133.4.581

31. Gatchel RJ. Comorbidity of Chronic Pain and Mental Health Disorders: The Biopsychosocial Perspective. *Am Psychol*. 2004;59(8):795-805. doi:10.1037/0003-066X.59.8.795

32. Turner JA, Aaron LA. Pain-Related Catastrophizing: What Is It?: *Clin J Pain*. 2001;17(1):65-71. doi:10.1097/00002508-200103000-00009

33. Fifi AC, Holton KF. Food in Chronic Pain: Friend or Foe? *Nutrients*. 2020;12(8):2473. doi:10.3390/nu12082473

34. Dorr H, Townley C. Chronic Pain Management Therapies in Medicaid: :11.

35. Heyward J, Jones CM, Compton WM, et al. Coverage of Nonpharmacologic Treatments for Low Back Pain Among US Public and Private Insurers. *JAMA Netw Open*. 2018;1(6):e183044. doi:10.1001/jamanetworkopen.2018.3044

36. Eaves ER, Hsu CW, DeBar LL, et al. Whole Systems Within Whole Systems: The Oregon Health Plan's Expansion of Services for Back and Neck Pain. *J Altern Complement Med*. 2019;25(S1):S61-S68. doi:10.1089/acm.2018.0431

37. Hill JC, Whitehurst DG, Lewis M, et al. Comparison of stratified primary care management for low back pain with current best practice (STarT Back): a randomised controlled trial. *The Lancet*. 2011;378(9802):1560-1571. doi:10.1016/S0140-6736(11)60937-9

38. Oregon HERC votes to table OHP expansion for chronic pain, change opioid tapering requirements. Published online May 16, 2019. https://stateofreform.com/news/oregon/2019/05/oregon-herc-votes-to-table-ohp-expansion-for-chronic-pain-change-opioid-tapering-requirement/

39. HERC removes OHP opioid tapering requirment for neck and back pain. Published online May 16, 2019. https://www.oregon.gov/oha/ERD/Pages/HERCRemovesOHPOpioidTaperingRequirementNeckBackPain.aspx

40. DeBar L. Personal conversation. Published online January 24, 2021.

41. Campbell CM, Edwards RR. Ethnic differences in pain and pain management. *Pain Manag*. 2012;2(3):219-230. doi:10.2217/pmt.12.7

42. Campbell LC, Robinson K, Meghani SH, Vallerand A, Schatman M, Sonty N. Challenges and Opportunities in Pain Management Disparities Research: Implications for Clinical Practice, Advocacy, and Policy. *J Pain*. 2012;13(7):611-619. doi:10.1016/j.jpain.2012.02.004

43. Green CR, Anderson KO, Baker TA, et al. The Unequal Burden of Pain: Confronting Racial and Ethnic Disparities in Pain. *Pain Med*. 2003;4(3):277-294. doi:10.1046/j.1526-4637.2003.03034.x

44. Meghani SH, Cho E. Self-Reported Pain and Utilization of Pain Treatment Between Minorities and Nonminorities in the United States. *Public Health Nurs*. 2009;46(4). doi:https://doi.org/10.1111/j.1525-1446.2009.00785.x

45. Portenoy RK, Ugarte C, Fuller I, Haas G. Population-based survey of pain in the united states: Differences among white, african american, and hispanic subjects. *J Pain*. 2004;5(6):317-328. doi:10.1016/j.jpain.2004.05.005

46. Reyes-Gibby CC, Aday LA, Todd KH, Cleeland CS, Anderson KO. Pain in Aging Community-Dwelling Adults in the United States: Non-Hispanic Whites, Non-Hispanic Blacks, and Hispanics. *J Pain*. 2007;8(1):75-84. doi:10.1016/j.jpain.2006.06.002

47. Green CR, Baker TA, Sato Y, Washington TL, Smith EM. Race and chronic pain: a comparative study of young black and white Americans presenting for management. *J Pain*. 2003;4(4):176-183. doi:10.1016/S1526-5900(02)65013-8

48. Green CR, Baker TA, Smith EM, Sato Y. The effect of race in older adults presenting for chronic pain management: A comparative study of black and white Americans. *J Pain*. 2003;4(2):82-90. doi:10.1054/jpai.2003.8

49. The Common Wealth Fund. Why not the best? Results from the national scorecard on U.S. health system performance in 2008. Accessed December 29, 2021. https://www.commonwealthfund.org/publications/scorecard/2011/oct/why-not-best-results-national-scorecard-us-health-system

50. Choo EK, Charlesworth CJ, Gu Y, Livingston CJ, McConnell KJ. Increased Use of Complementary and Alternative Therapies for Back Pain Following Statewide Medicaid Coverage Changes in Oregon. *J Gen Intern Med*. 2021;36(3):676-682. doi:10.1007/s11606-020-06352-6

51. Braveman P, Gottlieb L. The Social Determinants of Health: It's Time to Consider the Causes of the Causes. *Public Health Rep*. 2014;129(1_suppl2):19-31. doi:10.1177/00333549141291S206

52. Wilkinson R, Weltgesundheitsorganisation, eds. *The Solid Facts: Social Determinants of Health*. 2nd ed. WHO Regional Office for Europe; 2003.

53. Dawes DE. *The Political Determinants of Health*. Johns Hopkins University Press; 2020.

54. Alderwick H, Gottlieb LM. Meanings and Misunderstandings: A Social Determinants of Health Lexicon for Health Care Systems. *Milbank Q*. 2019;97(2):407-419. doi:10.1111/1468-0009.12390

55. Artiga S, Hinton E. Beyond Health Care: The Role of Social Determinants in Promoting Health and Health Equity. :13.

56. Brennan F. The US Congressional "Decade on Pain Control and Research" 2001–2011: A Review. *J Pain Palliat Care Pharmacother*. 2015;29(3):212-227. doi:10.3109/15360288.2015.1047553

57. Krieger N. Epidemiology and the web of causation: Has anyone seen the spider? *Soc Sci Med*. 1994;39(7):887-903. doi:10.1016/0277-9536(94)90202-X

58. Krieger N. The Ostrich, the Albatross, and Public Health: An Ecosocial Perspective—Or Why an Explicit Focus on Health Consequences of Discrimination and Deprivation Is Vital for Good Science and Public Health Practice. *Public Health Rep*. 2001;116:5.

59. Krieger N. Theories for social epidemiology in the 21st century: an ecosocial perspective. *Int J Epidemiol*. 2001;30(4):668-677. doi:10.1093/ije/30.4.668

60. Krieger N. Proximal, Distal, and the Politics of Causation: What's Level Got to Do With It? *Am J Public Health*. 2008;98(2):221-230. doi:10.2105/AJPH.2007.111278

61. Krieger N. *Ecosocial Theory, Embodied Truths, and the People's Health*. Oxford University Press; 2021.

62. Clauser SB, Taplin SH, Foster MK, Fagan P, Kaluzny AD. Multilevel Intervention Research: Lessons Learned and Pathways Forward. *JNCI Monogr*. 2012;2012(44):127-133. doi:10.1093/jncimonographs/lgs019

63. Taplin SH, Anhang Price R, Edwards HM, et al. Introduction: Understanding and Influencing Multilevel Factors Across the Cancer Care Continuum. *JNCI Monogr*. 2012;2012(44):2-10. doi:10.1093/jncimonographs/lgs008

64. Aday LA, Andersen R. A Framework for the Study of Access to Medical Care. *Health Serv Res*. Published online 1974:13.

65. 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).

66. Meghani SH, Polomano RC, Tait RC, Vallerand AH, Anderson KO, Gallagher RM. Advancing a National Agenda to Eliminate Disparities in Pain Care: Directions for Health Policy, Education, Practice, and Research. *Pain Med*. 2012;13(1):5-28. doi:10.1111/j.1526-4637.2011.01289.x

67. Hoffman KM, Trawalter S, Axt JR, Oliver MN. Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites. *Proc Natl Acad Sci*. 2016;113(16):4296-4301. doi:10.1073/pnas.1516047113

68. Kingdon J. *Agendas, Alternatives, and Public Policies*. Harper Collins; 1984.

69. The US Burden of Disease Collaborators, Mokdad AH, Ballestros K, et al. The State of US Health, 1990-2016: Burden of Diseases, Injuries, and Risk Factors Among US States. *JAMA*. 2018;319(14):1444. doi:10.1001/jama.2018.0158

70. Zajacova A, Grol-Prokopczyk H, Zimmer Z. Pain Trends Among American Adults, 2002–2018: Patterns, Disparities, and Correlates. *Demography*. 2021;58(2):711-738. doi:10.1215/00703370-8977691

71. Melzack R, Wall PD. Pain Mechanisms: A New Theory. *Science*. 1965;150(3699).

72. Melzack R. Pain and the Neuromatrix in the Brain. *J Dent Educ*. 2001;65(12):1378-1382. doi:10.1002/j.0022-0337.2001.65.12.tb03497.x

73. Waddell G. A New Clinical Model for the Treatment of Low-Back Pain. 1987;12(7):632-644.

74. Bair MJ, Robinson RL, Katon W, Kroenke K. Depression and Pain Comorbidity: A Literature Review. *Arch Intern Med*. 2003;163(20):2433. doi:10.1001/archinte.163.20.2433

75. Angst F, Benz T, Lehmann S, et al. Extended overview of the longitudinal pain-depression association: A comparison of six cohorts treated for specific chronic pain conditions. *J Affect Disord*. 2020;273:508-516. doi:10.1016/j.jad.2020.05.044

76. Kroenke K, Wu J, Bair MJ, Krebs EE, Damush TM, Tu W. Reciprocal Relationship Between Pain and Depression: A 12-Month Longitudinal Analysis in Primary Care. *J Pain*. 2011;12(9):964-973. doi:10.1016/j.jpain.2011.03.003

77. Kroenke K, Bair MJ, Damush TM, et al. Optimized Antidepressant Therapy and Pain Self-management in Primary Care Patients With Depression and Musculoskeletal Pain: A Randomized Controlled Trial. *JAMA*. 2009;301(20):2099. doi:10.1001/jama.2009.723

78. Bushnell MC, Case LK, Ceko M, et al. Effect of environment on the long-term consequences of chronic pain. *Pain*. 2015;156(Supplement 1):S42-S49. doi:10.1097/01.j.pain.0000460347.77341.bd

79. Davis LL, Kroenke K, Monahan P, Kean J, Stump TE. The SPADE Symptom Cluster in Primary Care Patients With Chronic Pain. *Clin J Pain*. 2016;32(5):388-393. doi:10.1097/AJP.0000000000000286

80. Sullivan MJL, Thorn B, Haythornthwaite JA, et al. Theoretical Perspectives on the Relation Between Catastrophizing and Pain: *Clin J Pain*. 2001;17(1):52-64. doi:10.1097/00002508-200103000-00008

81. Picavet HSJ. Pain Catastrophizing and Kinesiophobia: Predictors of Chronic Low Back Pain. *Am J Epidemiol*. 2002;156(11):1028-1034. doi:10.1093/aje/kwf136

82. Covic T. A biopsychosocial model of pain and depression in rheumatoid arthritis: a 12-month longitudinal study. *Rheumatology*. 2003;42(11):1287-1294. doi:10.1093/rheumatology/keg369

83. Sullivan MJL, Bishop SR, Pivik J. The Pain Catastrophizing Scale: Development and Validation. :9.

84. Osman A, Barrios FX, Kopper BA, Hauptmann W, Jones J, O'Neill E. Factor Structure, Reliability, and Validity of the Pain Catastrophizing Scale. :17.

85. Osman A, Barrios FX, Gutierrez PM, Kopper A, Merrifield T, Grittmann L. The Pain Catastrophizing Scale: Further Psychometric Evaluation with Adult Samples. *J Behav Med*. Published online 2000:15.

86. Sullivan MJL, D'Eon JL. Relation Between Catastrophizing and Depression in Chronic Pain Patients. :4.

87. Turner JA, Jensen MP, Romano JM. Do beliefs, coping, and catastrophizing independently predict functioning in patients with chronic pain? *Pain*. 2000;85(1):115-125. doi:10.1016/S0304-3959(99)00259-6

88. Mills SEE, Nicolson KP, Smith BH. Chronic pain: a review of its epidemiology and associated factors in population-based studies. *Br J Anaesth*. 2019;123(2):e273-e283. doi:10.1016/j.bja.2019.03.023

89. Brennan PL, Schutte KK, Moos RH. Pain and use of alcohol to manage pain: prevalence and 3-year outcomes among older problem and non-problem drinkers. *Soc Study Addict*. 2004;100:777-786. doi:0.1111/j.1360-0443.2005.01074.x

90. Brain K, Burrows TL, Rollo ME, et al. A systematic review and meta-analysis of nutrition interventions for chronic noncancer pain. *J Hum Nutr Diet*. 2019;32:198-225. doi:https://doi.org/10.1111/jhn.12601

91. Elliott AM, Smith BH, Hannaford PC, Smith WC, Chambers WA. The course of chronic pain in the community: results of a 4-year follow-up study. *Pain*. 2002;99(1):299-307. doi:10.1016/S0304-3959(02)00138-0

92. Dominick CH, Blyth FM, Nicholas MK. Unpacking the burden: Understanding the relationships between chronic pain and comorbidity in the general population. *Pain*. 2012;153(2):293-304. doi:10.1016/j.pain.2011.09.018

93. Macfarlane GJ, Barnish MS, Jones GT. Persons with chronic widespread pain experience excess mortality: longitudinal results from UK Biobank and meta-analysis. *Ann Rheum Dis*. 2017;76(11):1815-1822. doi:10.1136/annrheumdis-2017-211476

94. Stone AA, Broderick JE. Obesity and Pain Are Associated in the United States. *Obesity*. 2012;20(7):1491-1495. doi:10.1038/oby.2011.397

95. Hitt HC, McMillen RC, Thornton-Neaves T, Koch K, Cosby AG. Comorbidity of Obesity and Pain in a General Population: Results from the Southern Pain Prevalence Study. *J Pain*. 2007;8(5):430-436. doi:10.1016/j.jpain.2006.12.003

96. Zorina-Lichtenwalter K, Meloto CB, Khoury S, Diatchenko L. Genetic predictors of human chronic pain conditions. *Neuroscience*. 2016;338:36-62. doi:10.1016/j.neuroscience.2016.04.041

97. James S. Human pain and genetics: some basics. *Br J Pain*. 2013;7(4):171-178. doi:10.1177/2049463713506408

98. Men F, Fischer B, Urquia ML, Tarasuk V. Food insecurity, chronic pain, and use of prescription opioids. *SSM - Popul Health*. 2021;14:100768. doi:10.1016/j.ssmph.2021.100768

99. Hruschak V, Cochran G. Psychosocial and environmental factors in the prognosis of individuals with chronic pain and comorbid mental health. *Soc Work Health Care*. 2017;56(7):573-587. doi:10.1080/00981389.2017.1326074

100. Ridley M, Rao G, Schilbach F, Patel V. Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*. 2020;370(6522):eaay0214. doi:10.1126/science.aay0214

101. Maly A, Vallerand AH. Neighborhood, Socioeconomic, and Racial Influence on Chronic Pain. *Pain Manag Nurs*. 2018;19(1):14-22. doi:10.1016/j.pmn.2017.11.004

102. Newman AK, Van Dyke BP, Torres CA, et al. The relationship of sociodemographic and psychological variables with chronic pain variables in a low-income population. *Pain*. 2017;158(9):1687-1696. doi:10.1097/j.pain.0000000000000964

103. Rios R, Zautra AJ. Socioeconomic disparities in pain: The role of economic hardship and daily financial worry. *Health Psychol*. 2011;30(1):58-66. doi:10.1037/a0022025

104. Craig KD, Holmes C, Hudspith M, et al. Pain in persons who are marginalized by social conditions. *Pain*. 2020;161(2):261-265. doi:10.1097/j.pain.0000000000001719

105. Karran EL, Grant AR, Moseley GL. Low back pain and the social determinants of health: a systematic review and narrative synthesis. *Pain*. 2020;161(11):2476-2493. doi:10.1097/j.pain.0000000000001944

106. Adler NE, Ostrove JM. Socioeconomic Status and Health: What We Know and What We Don't. *Ann N Y Acad Sci*. 1999;896(1):3-15. doi:10.1111/j.1749-6632.1999.tb08101.x

107. Marmot M. Social determinants of health inequalities. *Public Health*. 2005;365:6.

108. Green CR, Hart-Johnson T. The Association Between Race and Neighborhood Socioeconomic Status in Younger Black and White Adults With Chronic Pain. *J Pain*. 2012;13(2):176-186. doi:10.1016/j.jpain.2011.10.008

109. Vallerand AH, Crawley J, Pieper B, Templin TN. The *Perceived Control over Pain* Construct and Functional Status: Perceived Control over Pain. *Pain Med*. Published online September 2015:n/a-n/a. doi:10.1111/pme.12924

110. Quinones S. *Dreamland: The True Tale of America's Opioid Epidemic*. Bloomsbury Publishing; 2019.

111. Van Zee A. The Promotion and Marketing of OxyContin: Commercial Triumph, Public Health Tragedy. *Am J Public Health*. 2009;99(2):221-227. doi:10.2105/AJPH.2007.131714

112. CDC Health Alert Network. Increase in Fatal Drug Overdoses Across the United States Driven by Synthetic Opioids Before and During the COVID-19 Pandemic. Published online December 17, 2020. https://emergency.cdc.gov/han/2020/han00438.asp

113. Dowell D, Haegerich TM, Chou R. CDC Guideline for Prescribing Opioids for Chronic Pain—United States, 2016. *JAMA*. 2016;315(15):1624. doi:10.1001/jama.2016.1464

114. NIH HEAL Initiative: Helping End Addiction Long-term. https://heal.nih.gov/

115. Parr AT. Caudal Epidural Injections in the Managementof Chronic Low Back Pain: A SystematicAppraisal of the Literature. *Pain Physician*. 2012;3;15(3;5):E158-E198. doi:10.36076/ppj.2012/15/E159

116. Duff JH, Tharakan SM, Davis-Castro CY, Cornell AS, Romero PD. Consumption of Prescription Opioids for Pain: A Comparison of Opioid Use in the United States and Other Countries. :48.

117. Braden JB, Young A, Sullivan MD, Walitt B, LaCroix AZ, Martin L. Predictors of Change in Pain and Physical Functioning Among Post-Menopausal Women With Recurrent Pain Conditions in the Women's Health Initiative Observational Cohort. *J Pain*. 2012;13(1):64-72. doi:10.1016/j.jpain.2011.10.007

118. Hina N, Fletcher D, Poindessous-Jazat F, Martinez V. Hyperalgesia induced by low-dose opioid treatment before orthopaedic surgery: An observational case–control study. *Eur J Anaesthesiol*. 2015;32(4):255-261. doi:10.1097/EJA.0000000000000197

119. Brinkhaus B. Acupuncture in Patients With Chronic Low Back Pain: A Randomized Controlled Trial. *Arch Intern Med*. 2006;166(4):450-457. doi:10.1001/.450

120. Hill JC, Dunn KM, Lewis M, et al. A primary care back pain screening tool: Identifying patient subgroups for initial treatment. *Arthritis Care Res*. 2008;59(5):632-641. doi:10.1002/art.23563

121. Berwick DM, Nolan TW, Whittington J. The Triple Aim: Care, Health, And Cost. *Health Aff (Millwood)*. 2008;27(3):759-769. doi:10.1377/hlthaff.27.3.759

122. Bodenheimer T. The Oregon Health Plan — Lessons for the Nation. *N Engl J Med*. Published online 1997:5.

123. Jacobs L, Marmor T, Oberlander J. The Oregon Health Plan and the Political Paradox of Rationing: What Advocates and Critics Have Claimed and What Oregon Did. *J Health Polit Policy Law*. 1999;24(1).

124. Mitchell JB, Haber SG, Khatutsky G, Donoghue S. Impact of the Oregon Health Plan on Access and Satisfaction of Adults with Low-income. *Health Serv Res*. 2002;37(1):19-39. doi:10.1111/1475-6773.00036

125. Bodenheimer T. The Oregon Health Plan — Lessons for the Nation Part 2. *N Engl J Med*. Published online 1997:4.

126. Perry PA, Hotze T. Oregon's Experiment with Prioritizing Public Health Care Services. *AMA J Ethics*. 2011;13(4):241-247. doi:10.1001/virtualmentor.2011.13.4.pfor1-1104

127. Finkelstein A, Taubman S, Wright B, et al. THE OREGON HEALTH INSURANCE EXPERIMENT: EVIDENCE FROM THE FIRST YEAR. Published online 2013:40.

128. Howard SW, Bernell SL, Yoon J, Luck J, Ranit CM. Oregon's Experiment in Health Care Delivery and Payment Reform: Coordinated Care Organizations Replacing Managed Care. *J Health Polit Policy Law*. 2015;40(1):245-255. doi:10.1215/03616878-2854919

129. McConnell KJ. Oregon's Medicaid Coordinated Care Organizations. *JAMA*. 2016;315(9):869. doi:10.1001/jama.2016.0206

130. McConnell KJ, Renfro S, Lindrooth RC, Cohen DJ, Wallace NT, Chernew ME. Oregon's Medicaid Reform And Transition To Global Budgets Were Associated With Reductions In Expenditures. *Health Aff (Millwood)*. 2017;36(3):451-459. doi:10.1377/hlthaff.2016.1298

131. McConnell KJ, Renfro S, Chan BKS, et al. Early Performance in Medicaid Accountable Care Organizations: A Comparison of Oregon and Colorado. *JAMA Intern Med*. 2017;177(4):538. doi:10.1001/jamainternmed.2016.9098

132. McConnell KJ, Charlesworth CJ, Meath THA, George RM, Kim H. Oregon's Emphasis On Equity Shows Signs Of Early Success For Black And American Indian Medicaid Enrollees. *Health Aff (Millwood)*. 2018;37(3):386-393. doi:10.1377/hlthaff.2017.1282

133. February 2022 Medicaid & CHIP Enrollment Data Highlights. https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/report-highlights/index.html

134. Kushner J, McConnell KJ. Addressing Social Determinants of Health through Medicaid: Lessons from Oregon. *J Health Polit Policy Law*. 2019;44(6):919-935. doi:10.1215/03616878-7785823

135. Center for Health Systems Effectiveness. Oregon leverages Medicaid to address social determinants of health and health equity. *Or Health Sci Univ*. Published online 2021.

136. Bronfenbrenner U. *The Ecology of Human Development*. Harvard University Press; 1979.

137. Andersen RM. Revisiting the Behavioral Model and Access to Medical Care: Does it Matter? *J Health Soc Behav*. 1995;36(1):1. doi:10.2307/2137284

138. Nersessian G, Mercurio C, Nenko A, Meyyazhagan N. *HMA Weekly Roundup: Trends in State Health Policy*. Health Management Associates; 2019.

139. Bindman A, Hulett D, Ostrer I, Kang T. *A Close Look at Medi-Cal Managed Care: Statewide Quality Trends from the Last Decade*. California Health Care Foundation; 2019.

140. Cooridnated Care: the Oregon Difference. Oregon Health Authority. Accessed February 2, 2025. https://www.oregon.gov/oha/hpa/pages/ccos-oregon.aspx

141. Crumley D, Houston R, Bank A. *Incorporating Community-Based Organizations in Medicaid Efforts to Address Health-Related Social Needs: Key State Considerations*. Center for Health Care Strategies; 2023.

142. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation. *J Chronic Dis*. 1987;40(5):373-383.

143. Mayhew M, DeBar LL, Deyo RA, et al. Development and Assessment of a Crosswalk Between ICD-9-CM and ICD-10-CM to Identify Patients with Common Pain Conditions. *J Pain*. 2019;20(12):1429-1445. doi:10.1016/j.jpain.2019.05.006

144. Krebs EE, Bair MJ, Damush TM, Tu W, Wu J, Kroenke K. Comparative Responsiveness of Pain Outcome Measures Among Primary Care Patients With Musculoskeletal Pain. *Med Care*. 2010;48(11):1007-1014. doi:10.1097/MLR.0b013e3181eaf835

145. Krebs EE, Lorenz KA, Bair MJ, et al. Development and Initial Validation of the PEG, a Three-item Scale Assessing Pain Intensity and Interference. *J Gen Intern Med*. 2009;24(6):733-738. doi:10.1007/s11606-009-0981-1

146. Masyn KE. Latent Class Analysis and Finite Mixture Modeling. In: *The Oxford Handbook of Quantitative Methods*. Vol 2. Oxford University Press; 2013:63.

147. Collins LM, Lanza ST. *Latent Class and Latent Transition Analysis: With Applications in the Social, Behavioral, and Health Sciences*. John Wiley & Sons; 2010.

148. Lacey RJ, Strauss VY, Rathod T, et al. Clustering of pain and its associations with health in people aged 50 years and older: cross-sectional results from the North Staffordshire Osteoarthritis Project. *BMJ Open*. 2015;5(11):e008389-e008389. doi:10.1136/bmjopen-2015-008389

149. Lanza ST, Cooper BR. Latent Class Analysis for Developmental Research. *Child Dev Perspect*. 2016;10(1):59-64. doi:10.1111/cdep.12163

150. Nagin DS, Odgers CL. Group-Based Trajectory Modeling in Clinical Research. *Annu Rev Clin Psychol*. 2010;6(1):109-138. doi:10.1146/annurev.clinpsy.121208.131413

151. Kongsted A, Nielsen AM. Latent Class Analysis in health research. *J Physiother*. 2017;63(1):55-58. doi:10.1016/j.jphys.2016.05.018

152. Schwartz G. Estimating the dimensions of a model. *Ann Stat*. 6:461-464.

153. Akaike H. Factor Analysis and AIC. *Psychometrika*. 1987;52(3):317-332.

154. Lo Y, Mendell NR, Rubin DB. Testing the number of components in a normal mixture. *Biometrika*. 2001;88(3):767-778.

155. Peel D, Mclachlan GJ. Robust mixture modelling using the t distribution. :10.

156. Nylund-Gibson K, Grimm RP, Masyn KE. Prediction from Latent Classes: A Demonstration of Different Approaches to Include Distal Outcomes in Mixture Models. *Struct Equ Model Multidiscip J*. 2019;26(6):967-985. doi:10.1080/10705511.2019.1590146

157. Cole DA, Maxwell SE. Multitrait-Multimethod Comparisons Across Populations: A Confirmatory Factor Analytic Approach. *Multivar Behav Res*. 1985;20(4):389-417. doi:10.1207/s15327906mbr2004_3

158. Vandenberg RJ, Lance CE. A Review and Synthesis of the Measurement Invariance Literature: Suggestions, Practices, and Recommendations for Organizational Research. *Organ Res Methods*. 2000;3(1):4-70. doi:10.1177/109442810031002

159. Muthén B. Multiple-group structural equation modeling with non-normal continuous variables. *J Math Stat Psychol*. 42:55-62.

160. Ryu E, Cheong J. Comparing Indirect Effects in Different Groups in Single-Group and Multi-Group Structural Equation Models. *Front Psychol*. 2017;8:747. doi:10.3389/fpsyg.2017.00747

161. Lanza ST, Rhoades BL. Latent Class Analysis: An Alternative Perspective on Subgroup Analysis in Prevention and Treatment. *Prev Sci*. 2013;14(2):157-168. doi:10.1007/s11121-011-0201-1

162. Dayton C, Macready G. Concomitant Variable Latent Class Models. *J Am Stat Assoc*. 1988;83:173-178.

163. Asparouhov T, Muthen B. Random Starting Values and Multistage Optimization.

164. Muthen L, Muthen B. *Mplus User's Guide*. 8th ed. Muthen and Muthen

165. Bandalos D. Relative Performance of Categorical Diagonally Weighted Least Squares and Robust Maximum Likelihood Estimation. *Struct Equ Model Multidiscip J*. 2014;21(1). doi:10.1080/10705511.2014.859510

166. Kline RB. *Prinicples and Practice of Structural Equation Modeling*. Fourth. The Guilford Press; 2016.

167. Duncan TE, Duncan SC. The ABC's of LGM: An Introductory Guide to Latent Variable Growth Curve Modeling: The ABC's of LGM. *Soc Personal Psychol Compass*. 2009;3(6):979-991. doi:10.1111/j.1751-9004.2009.00224.x

168. Burant CJ. Latent Growth Curve Models: Tracking Changes Over Time. *Int J Aging Hum Dev*. 2016;82(4):336-350. doi:10.1177/0091415016641692

169. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct Equ Model Multidiscip J*. 1999;6(1):1-55. doi:10.1080/10705519909540118

170. Steiger JH. Structural Model Evaluation and Modification: An Interval Estimation Approach. *Multivar Behav Res*. 1990;25(2):173-180. doi:10.1207/s15327906mbr2502_4

171. Bentler P. Comparative fit indexes in structural models. *Psychol Bull*. 1990;107(2):238-246.

172. Schafer JL, Graham JW. Missing data: Our view of the state of the art. *Psychol Methods*. 2002;7(2):147-177. doi:10.1037/1082-989X.7.2.147

173. Little RJA, Rubin DB. *Statistical Analysis with Missing Data*. Vol 793. John Wiley & Sons; 2019.

174. Little RJA, Rubin DB. *Statistical Analysis with Missing Data*. 21nd ed. Wiley; 2002.

175. Weller BE, Bowen NK, Faubert SJ. Latent Class Analysis: A Guide to Best Practice. *J Black Psychol*. 2020;46(4):287-311. doi:10.1177/0095798420930932

176. Weden MM, Zabin LS. Gender and Ethnic Differences in the Co-occurrence of Adolescent Risk Behaviors. *Ethn Health*. 2005;10(3). doi:10.1080/13557850500115744

177. Bonakdar R, Palanker D, Sweeney MM. Analysis of State Insurance Coverage for Nonpharmacologic Treatment of Low Back Pain as Recommended by the American College of Physicians Guidelines. *Glob Adv Health Med*. 2019;8. doi:10.1177/2164956119855629

178. Turner BJ, Liang Y, Simmonds MJ, Rodriguez N, Bobadilla R, Yin Z. Randomized Trial of Chronic Pain Self-Management Program in the Community or Clinic for Low-Income Primary Care Patients. *J Gen Intern Med*. 2018;33(5):668-677. doi:10.1007/s11606-017-4244-2

179. Roseen EJ, Joyce C, Winbush S, et al. Primary care barriers and facilitators to nonpharmacologic treatments for low back pain: A qualitative pilot study. *PM&R*. Published online May 2, 2024:pmrj.13183. doi:10.1002/pmrj.13183

180. Nguyen LH, Dawson JE, Brooks M, Khan JS, Telusca N. Disparities in Pain Management. *Anesthesiol Clin*. 2023;41(2):471-488. doi:10.1016/j.anclin.2023.03.008

181. Andrews-Cooper IN, Kozachik SL. How Patient Education Influences Utilization of Nonpharmacological Modalities for Persistent Pain Management: An Integrative Review. *Pain Manag Nurs*. 2020;21(2):157-164. doi:10.1016/j.pmn.2019.06.016

182. Rikard SM, Strahan AE, Schmit KM, Guy GP. Prevalence of Pharmacologic and Nonpharmacologic Pain Management Therapies Among Adults With Chronic Pain—United States, 2020. *Ann Intern Med*. 2023;176(11):1571-1575. doi:10.7326/M23-2004

183. Hadjistavropoulos T, Craig KD, Duck S, Cano A. A biopsychosocial formulation of pain communication. *Psychol Bull*. 2011;137(6):910-939.