AN INTERSECTIONAL IDENTITY APPROACH TO CHRONIC PAIN DISPARITIES USING LATENT CLASS ANALYSIS

by

ANDREA K. NEWMAN

BEVERLY E. THORN, COMMITTEE CHAIR
REBECCA ALLEN, COMMITTEE CO-CHAIR
HEATHER GUNN
JANE DAQUIN
JENNIFER COX

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ABSTRACT

Chronic pain is a highly prevalent and costly condition with substantial negative effects. However, health care differences exist in prevalence, pain assessment, treatment, and outcomes based on demographic characteristics. There has been a recent increase in health disparity research. Many studies have examined the relationships between independent factors of disparity (e.g., race, sex, income, age, etc.) and health outcomes. Research is limited on the interaction of these independent factors (e.g., female Black/African-American, low-income older adult, etc.). Given the high frequency of individuals with multiple disparity factors, applying an intersectional identity approach to chronic pain disparity research is important. Latent class analysis (LCA) examined chronic pain disparities with an intersectional identity theory approach in the Learning About My Pain (LAMP) trial, a randomized comparative effectiveness study of group-based psychosocial interventions (PCORI Contract #941, Beverly Thorn, PI; clinicaltrials.gov identifier NCT01967342) for patients receiving care for chronic pain at low-income clinics in rural and suburban Alabama. LCA results suggested a 5-class model with meaningful differences in factors related to disparities. Cross-sectional results highlighted the importance of SES, age, and race in the experience of chronic pain. The latent disparity profiles varied by pre-treatment chronic pain functioning and there was some evidence that individuals with moderate disparities (i.e., low literacy/education, older Black/African-American adults, and disability) benefited more from Cognitive-Behavioral Therapy (CBT) than Pain Education (EDU). There were no significant heterogeneity of treatment effects when examining CBT or EDU versus Usual-Care (UC). The intersectional identity theory approach provided an integrated

picture of chronic pain disparities and increased information for future treatment adaptations that meet the specific needs of individuals with similar social identities.

DEDICATION

This dissertation is dedicated to those who face inequalities in healthcare. All people deserve the basic human rights to health.

LIST OF ABBREVIATIONS AND SYMBOLS

a	Cronbach's index of internal consistency
$AvePP_k$	Average posterior class probability
BLRT	Bootstrapped likelihood ratio test
CBT	Cognitive-behavioral therapy
CRP	Conditional response probability
EDU	Pain education treatment
OCC_k	Odds of correct classification
df	Degrees of freedom: number of values free to vary after certain restrictions have been placed on the data
F	Fisher's *F* ratio: A ration of two variances
k	Number of latent classes or subgroups
LCA	Latent class analysis
LL	Log likelihood
LMR-LRT	Lo-Mendell-Rubin adjusted likelihood ratio test
M	Mean: the sum of a set of measurements divided by the number of measurements in the set
$mcaP_k$	Modal class assignment probability
npar	Number of parameters
p	Probability associated with the occurrence under the null hypothesis of a value as extreme as or more extreme than the observed value
sBIC	Sample size-adjusted Bayesian Information Criterion

sd	Standard deviation: the amount of variance of a set of data values
$<$	Less than
$>$	Greater than
$=$	Equal to
$\leq$	Less than or equal to
$\geq$	Greater than or equal to
$\hat{\pi}_k$	Model estimated proportion for a given class.

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1. INTRODUCTION

There are widespread disparities in health care for chronic pain. Affecting over 100 million American adults, chronic pain costs up to $635 billion annually, due to the incremental expenses of health care and lost productivity (Institue of Medicine [IOM], 2001). In the US, chronic pain costs society more than cancer, heart disease, and diabetes combined (Institutes of Medicine, 2011). Persistent and unrelieved pain can lead to changes in physical functioning (Ferreira-Valente, Pais-Ribeiro, & Jensen, 2014; R C Tait, Chibnall, & Krause, 1990), interpersonal relationships (Flor, Turk, & Scholz, 1987), employment (Braden, Zhang, Zimmerman, & Sullivan, 2008), and mental health, especially increased risk of depression (Leo, 2005; Means-Christensen, Roy-Byrne, Sherbourne, Craske, & Stein, 2008; Von Korff et al., 2005). Although chronic pain is a growing problem across all populations, there are specific populations more vulnerable to the deleterious effects of chronic pain.

There has been a recent increase in public interest in health disparities. The term "health disparity" has varied in meaning across settings and studies (Carter-Pokras & Baquet, 2002). In order to define health disparity for the purposes of this study, health disparity may be considered differences in prevalence and incidence, access to facilities and services, quality of assessment and treatment, outcomes, and burden of health conditions among specific population groups (Carter-Pokras & Baquet, 2002; Institue of Medicine [IOM], 2001; McGuire, Alegria, Cook, Wells, & Zaslavsky, 2006). There are various factors contributing to disparities, including patient factors (e.g., pain beliefs, nociception, and coping patterns), patient-provider interaction factors (e.g., communication style, practice patterns, discrimination), and the physical and medical environment (e.g., insurance, health plans, public health environment) (Tait & Chibnall, 2014). Disparities have been documented in the following factors (among others not mentioned here): race/ethnicity, sex, age, and socioeconomic status (SES).

Race/ethnicity is one of the most documented areas of disparity research, particularly among Black/African-American individuals. On a patient level, studies typically report lower pain tolerance in Black/African-American individuals versus White/Caucasian individuals, though results vary (Riskowski, 2014). On a patient-provider interaction level, literature continuously demonstrates under-treatment of pain among racial and ethnic minorities regardless of pain type and across health care settings (Green, Baker, Smith, & Sato, 2003). Many studies have shown lower rates of analgesic prescriptions for Black individuals with chronic pain, even after controlling for important factors such as insurance type, income, and access to care (Paulson, Dekker, & Aguilar-Gaxiola, 2007; Ringwalt, Roberts, Gugelmann, & Skinner, 2015). Factors of stereotyping, ageism, bias, and racism contribute to the etiology of health disparities.

There is increasing evidence for sex differences in acute and chronic pain. Across multiple experimental stimulus modalities (e.g., electrical, thermal, mechanical, chemical), women tend to show greater pain sensitivity than men (Bartley & Fillingim, 2013). Population-based research across various geographic regions consistently demonstrates greater prevalence of chronic pain among women than men (Fillingim, King, Ribeiro-Dasilva, Rahim-Williams, & Riley, 2009; Gerdle et al., 2008; Mogil, 2012). The underlying mechanisms contributing to this disparity are currently unclear. It has been suggested that the interaction of biological, psychological, and social mechanisms likely influence sex disparities (Bartley & Fillingim, 2013).

Chronic pain disproportionately affects older adults (Andersson, Ejlertsson, Leden, & Scherstén, 1999; Institue of Medicine [IOM], 2001; Verhaak, Kerssens, Dekker, Sorbi, & Bensing, 1998). The prevalence of chronic pain is higher in older adults, generally defined in chronic pain literature as above 60 or 65 years old (Schopflocher, Taenzer, & Jovey, 2011; Verhaak et al., 1998). However, age differences in the experience of chronic pain are unclear. While some studies suggest a higher pain severity in older adults than younger and middle-aged adults (Manogharan, Kongsted, Ferreira, & Hancock, 2017), other studies suggest lower pain severity (Cook & Chastain, 2001; Riley, Wade, Robinson, & Price, 2000), and others report no age differences in severity (Gagliese & Melzack, 2003). Although older adults typically experience several substantial stressors, such as financial strain, retirement, changes in social support, bereavement, and health decline (Rustøen et al., 2005), multiple studies have concluded that older adults appear more psychologically adept at coping with pain (Boggero, Geiger, Segerstrom, & Carlson, 2015). Controlling for levels of disability, older adults have demonstrated lower levels of depression in comparison to middle aged adults (Manogharan et al., 2017). Overall, the research suggests higher prevalence of chronic pain in older adults, but perhaps less emotional impact (Molton, Hirsh, Smith, & Jensen, 2014).

There are higher rates of chronic pain in low-SES settings (Johannes, Le, Zhou, Johnston, & Dworkin, 2010; Portenoy, Ugarte, Fuller, & Haas, 2004). The factors contributing to pain disparities and SES are complex. SES is multifaceted construct encompassing such factors as income, literacy, education, insurance status, disability status, and employment. With substandard care, fewer resources, limited access to care, and high rates of stress, individuals living in low-income settings are at increased risk of chronic pain and psychiatric conditions (Riskowski, 2014; Vliegenthart et al., 2016). Low literacy has been identified as an important problem in low-income and rural health care settings (Jackson et al., 1991; Kirsch, I. S., Jungeblut, A., Jenkins, L., & Kolstad, 1993; Kuhajda, Thorn, Gaskins, Day, & Cabbil, 2011). Many studies have demonstrated a relationship between low literacy levels and poor health outcomes (Nielsen-Bohlman, L., Panzer, A. M., Kindig, 2004). The various factors of SES likely interact in intricate pathways that influence health behaviors and chronic pain outcomes (Bennett, Chen, Soroui, & White, 2009; Paasche-Orlow & Wolf, 2007; Riskowski, 2014).

Numerous studies have explored disparities in chronic pain through the examination of individual factors influencing the experience of chronic pain, such as SES, race/ethnicity, gender, and age. However, health care systems frequently encounter individuals with multiple factors of disparity. As an example of multiple identities of disparity, consider an individual who is female, Black/African-American, adult, unemployed, with low-literacy levels, and low-income. The research on the individual factors of sex, race, and SES demonstrate unique chronic pain experiences. However, the intersection of these identities paints a picture of specific biological factors (e.g., as mentioned above, studies show increased pain sensitivity among women and Black/African-Americans), obstacles in navigating the health care system, caregiving roles, limited resources, mistrust of health care services, stigma, sexism, racism, discrimination, and invalidation. Therefore, while the examination of individual factors of disparity has been an essential aspect of research, the intersection of these identities now needs to be examined.

Intersectionality Theory

There has been an increasing demand for the application of an intersectionality framework to better understand the characteristics and experiences of individuals with health inequities (Bauer, 2014; Bowleg, 2012; Earnshaw et al., 2018). Rooted in the writings of US

Black feminists (Cole, 2009; Collins, 1992; Crenshaw, 1989; Viruell-Fuentes, Miranda, & Abdulrahim, 2012), intersectionality originated with the argument against a universal gendered experience, and instead argued that the experiences of Black women were shaped by the interactions of gender, race, and class. According to intersectionality theory, distinct social identities work together simultaneously and dynamically to influence self-identity and experiences within society (Cole, 2009; Collins, 1992; Crenshaw, 1991). Inequalities, discrimination, and stigma are not exclusive to individual social categories, but rather involve the intersections of multiple identities. Therefore, to better understand and address disparities, an intersectional approach is essential.

Intersectionality framework has been applied to various fields with influential outcomes. Disparities is not a topic exclusive to psychology, and instead encompasses a diverse range of research and fields. History, philosophy, feminist studies, literature, ethnic studies, queer studies, and legal studies have explored disparities with an intersectional frame (Cho, Crenshaw, & McCall, 2013). In order to target the full picture of disparities, it is important to use a lens that is shared by other fields.

The possibilities associated with applying intersectionality is demonstrated in the legal field. In 1989, Crenshaw wrote a well-known article entitled, “Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics.” The article analyzed multiple legal cases in which Black female claimants unsuccessfully attempted to defend themselves against discrimination in the workforce. The article highlights how the claimants did not fit into categories of Black men or White women. The paradox of being both too similar to and too different from Black men and White women rendered the Black female narratives as unrecognizable, uninterpretable, and separate from established claims of race or gender discrimination in the workplace (Carbado, 2013; Cho et al., 2013; Crenshaw, 1989). Through a myopic lens, in which an individual is seen solely through individual factors of race, ethnicity, class, gender, and other categories, individuals are marginalized and neglected, further deepening and maintaining disparities. Intersectionality helped the field of law challenge and make progress with antidiscrimination laws (Crenshaw, 1991). In order to empower and demarginalize individuals, we must better understand the complexities of the interactions between social identity factors.

Recent theoretical and empirical literature has integrated intersectionality into an array of psychological areas of focus, such as health disparities, discrimination and stereotypes, identity development, victimization, and violence/aggression (Cavanaugh, Martins, Petras, & Campbell, 2013; Cole, 2009; Earnshaw et al., 2018; Galinsky, Hall, & Cuddy, 2013; Gearity & Metzger, 2017; Goodwin et al., 2017; Nylund, Bellmore, Nishina, & Graham, 2007; Thomas, Hacker, & Hoxha, 2011; Thomas, Witherspoon, & Speight, 2008). The recent interest in intersectionality within psychology places the field within an ideal opportunity to be in the forefront of structural change to decrease disparities (Earnshaw et al., 2018). Studies examining discrimination from one's social identity and health outcomes highlight the resulting effects of increased stress response, maladaptive health behaviors, invalidation, and mistrust of health care providers (Kapoor, 2015; Pascoe & Smart Richman, 2009; Vliegenthart et al., 2016; Waugh, Byrne, & Nicholas, 2014; Williams, Neighbors, & Jackson, 2003). There is less understanding of how multiple social determinants might influence health. A risk perspective and double jeopardy hypothesis propose that multiple social identities associated with the experience of discrimination results in worse health outcomes than single social identities (Dowd & Bengtson, 1978; Grollman, 2014; Moradi et al., 2010). Research supporting the risk perspective or the double jeopardy theories originate from the experience of Black women reporting higher levels of discrimination than White women and Black men (Berdahl & Moore, 2006). There is further evidence that a multiply disadvantaged population tends to have worse outcomes than single disparities (Butler, Petterson, Bazemore, & Douglas, 2010; Field, 2000). It might be the case that multiple forms of marginalization result in rejection from communities that typically offer support, validation, and group cohesion to one more homogenous group (Moradi et al., 2010).

Research examining intersectionality theory and disparities tends to explore the interactions of different forms of disadvantage, rather than the roles of strengths and advantages. According to a resilience perspective (Meyer, 2010; Moradi et al., 2010), people with multiple marginalized social identities survive by developing unique resources and coping skills that are protective from the effects of stigma and discrimination. In particular, low-SES communities with predominantly Black residents share similar culture and history that unites and supports community members (Roberts & Jumpper-Black, 2016). Moradi et al. (2010) found that “LGB people of color” had lower levels of perceived stigma than “White LGB participants”. Earnshaw et al. (2018) found similar health outcomes between groups with multiple identities of discrimination to groups with a single identity of discrimination. However, another study found that the resiliency of Black women was found to be a barrier in seeking help (Anyikwa, 2015). This is supported by the finding that Black women encounter greater obstacles in reporting vulvar pain to White providers (Labuski, 2017). Although the majority of research supports the negative effects of multiple identities of disparity, it is possible that people with similar experiences and community develop strengths and advantages to fighting against the effects of discrimination.

The production of health inequalities does not result from social determinants working in isolation, but rather from the interaction of these contextual factors (Crenshaw, 1989; Earnshaw et al., 2018). In order to develop the most effective interventions to address and reduce disparities, it is essential to examine the interaction between social identities (e.g., sex, race, class, etc.) and systems of oppression. The intersection of identities will help to understand how aspects of privilege and disadvantage impact health (Goodwin et al., 2017), target specific subgroups with increased risk of the negative effects of chronic pain, and eventually develop treatments adapted to the specific needs of these subgroups.

Latent Class Analysis

Latent class analysis (LCA) is a type of mixture modeling that can be used to examine intersectionality of identities. Mixture modeling is a statistical technique that identifies subgroups of individuals within a population (Nylund, Asparouhov, & Muthén, 2007). Within behavioral sciences, such as psychology, populations tend to be heterogeneous. For example, when examining academic test results from a population of individuals, there is likely a high degree of variety of test responses (Morovati, 2014). The test results may consist of different subgroups of individuals that tend to have similar response patterns. These subgroups are typically not known *a priori*, but rather are inferred based on the data collected. Subgroups, or subpopulations, are defined as clusters of individuals within a heterogenous population. These subgroups tend to be more homogenous when compared to the overall population (Lubke & Muthén, 2005). Mixture modeling examines the heterogeneity in a sample by uncovering different groups of individuals based on their observed response patterns to a set of items (Nylund et al., 2007). Developed over 60 years ago, LCA is a type of mixture modeling. LCA aims to classify individuals into unobserved (or unknown) latent groups (or classes) based on response patterns to a set of categorical indicators (Nylund et al., 2007).

There are multiple advantages of LCA to classify subgroups of individuals. Latent classification provides a holistic approach to creating groups by accounting for multiple variables simultaneously and the relationships among the set of variables (Morovati, 2014). Accurate classification may allow for the tailoring of interventions to subgroups of individuals that tend to have similar observed characteristics and experiences (Morovati, 2014). For instance, Nylund et al., 2007 identified latent classes of middle school children based on experiences of peer victimization. As evidenced by study results, multiple indicators of victimization were necessary (e.g., severity, frequency, type), rather than one indicator or a cut off score, to best understand the complexities of victimization (Nylund, Bellmore, Nishina, & Graham, 2007). It would be predicted that individuals within the class with the highest peer victimization would perform differently in a given psychosocial intervention, and perhaps need more intensive interventions, than a subgroup of individuals with lower levels of peer victimization. Interventions may benefit from adapting treatment to subgroups with similar characteristics and experiences.

In comparison to other statistical models, LCA provides distinct advantages in identifying subgroups. Cluster analysis is conceptually similar to LCA in that both aim to identify latent classes based on observed response patterns (Nylund et al., 2007). However, LCA is a more robust approach to cluster analysis. Distinct from cluster analysis, LCA determines class membership based on probability and statistical estimates of model fit (Rovner, Vowles, Gerdle, & Gillanders, 2015). Principal component analysis has been used to create latent variables, but they do not describe the intersection of variables (Goodwin, 2017). LCA is also a more robust approach to cluster analysis since profile membership is based on probability and statistical estimates of model fit. LCA also uses maximum likelihood estimates, which better accommodates missing data in contrast to traditional cluster analysis which requires complete data or replacement for missing data (Rovner et al. 2015).

Conceptually, LCA is an advantageous statistical model for intersectionality due to the person-oriented approach. Most statistical models are variable-oriented, meaning that the approach focuses on identifying relationships between variables. A person-oriented approach focuses on the individual as a whole by examining a pattern of individual traits that can provide general conclusions (Morovati, 2014; Nylund et al., 2007). The goal is to identify subgroups of individuals with similar response patterns. In conclusion, LCA presents statistical and conceptual advantages for examining intersectionality.

LCA has been specifically used to examine the interaction of multiple identities in SES. Goodwin et al. (2017) explored disparity profiles in an inner London sample of 1052 participants using indicators of SES, ethnicity, and migration status. The study found seven latent classes that varied by levels of privilege and disadvantage that predicted common mental disorder (CMD). The group that was described as economically inactive, migrant, of mixed ethnicity, and with multiple levels of disadvantage (e.g., receipt of benefits and low education) were found to be most likely to report CMD symptoms (Goodwin et al., 2017). Another group that was described as working, White British, professional/managerial occupations, and homeowners had lower prevalence of CMD. In comparison to individual predictors of CMD, the intersectional approach highlighted the nuanced differences between individuals in economically disadvantaged groups, such as how low-SES renters were at an increased risk of CMD, but low-SES homeowners were not at an increased risk. Additionally, when exploring individual indicators of ethnicity and migration status with CMD, the study found no significant associations. However, when explored with an intersectionality approach with LCA, the study found interactions between SES-indicators and ethnicity and migration status. Result highlighted the key role of various SES factors simultaneously influencing experiences with mental health.

Study Aims/Objectives

This study aimed to implement an intersectional theory approach to better understand chronic pain disparities. The Learning About My Pain (LAMP) trial is a randomized comparative effectiveness study of group-based psychosocial interventions (PCORI Contract #941, Beverly Thorn, PI; clinicaltrials.gov identifier NCT01967342) for patients receiving care for chronic pain at low-income clinics in rural and suburban Alabama. The LAMP trial includes a population with multiple disparities, including race/ethnicity, SES, age, and sex. The first objective of this study was to identify chronic pain disparity profiles. To better understand the relationships between disparity profiles and health outcomes, the second objective examined cross-sectional relationships between disparity profiles and pre-treatment pain-related and psychological outcomes.

Lastly, the third objective was to explore heterogeneity of treatment effects in the LAMP study using the disparity profiles. Treatment effects vary based on individual differences (Zhang, Wang, Nie, & Soon, 2013). Heterogeneity of treatment effects (HTE) allows for the examination of factors that influence treatment results in order to better personalize and adapt treatments (Kessler et al., 2017). Many studies have examined HTE using moderator analyses, however, few studies have used an intersectional approach with latent classes. Results aim to provide information on the intersectional characteristics of treatment disparities and chronic pain treatment outcomes within a highly disparaged population.

It was first hypothesized that increasing number of disparity factors would predict worsened pain outcomes. Based on prior research, I hypothesized that one latent class would be described by low-SES, Black racial identity, and female sex and due to the intersection of disparities would have the poorest health functioning. Since the LAMP trial is designed to meet the needs of individuals with disparities, I hypothesized that the heterogeneity of treatment effects would suggest that the latent class with highest levels of disparity would receive greater benefits from the trial than those with fewer disparities.

Listed below are the summary of objectives of this study:

(1) Identify disparity profiles/subgroups of individuals with chronic pain.
(2) Examine the cross-sectional relationships of the identified profiles/subgroups at pre-treatment with pain related outcome measures at pre-treatment.
(3) Examine heterogeneity of treatment effects using identified chronic pain profiles/subgroups.

2. METHODS

Participants

A total of 290 participants with chronic pain were recruited within Whatley Health Services (WHS), a privately-owned, nonprofit, network of Community Health Centers serving low-income patients in West and Central Alabama. Recruitment primarily occurred through participant coordinators, but also included flyers and other verbal supplementary recruitment methods. Participants were compensated $45 at the conclusion of each assessment.

Inclusion criteria included (a) at least 19 years of age; (b) at least one chronic pain diagnosis; (c) the experience of pain for more than half of the days for at least 3 months (excluding malignant pain, such as from cancer or HIV); (d) ability to speak and understand English; and (e) access to a method of communication for contact (i.e., telephone) for study purposes.

Exclusion criteria included (a) significant cognitive impairment, as measured by the Short Portable Mental Status Questionnaire (Pfeiffer, 1975); (b) current uncontrolled serious psychological issues (e.g., bipolar disorder, schizophrenia) or active substance abuse; (c) literacy levels below the first-grade; (d) major changes in the four weeks prior to pre-treatment assessment in pain or psychotropic medication regimen; or (e) concurrent psychosocial treatments for any pain condition (however, psychotherapy was allowed for non-pain issues).

Sample Size

There is no commonly accepted method for assessing required sample size to fit an LCA model. Smaller samples run the risk of being underpowered and less able to accurately detect latent classes (Masyn, 2013). In order to assess for the number of classes in an LCA model, Bootstrapped Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000) has been shown to be most helpful and therefore has been used to explore power analyses (Nylund et al., 2007). Power analyses in LCA models are conducted through simulation studies that examine BLRT across multiple sample sizes. Since the researcher can control the risk of incorrectly selecting too many classes through alpha (Type I error, false positive), power analyses are more concerned with the risk of extracting too few classes (Type II error, false negative). For instance, with a selected alpha level of .05, the risk of erroneously extracting too many classes is 5%. However, if the sample size is low, the study is at risk of Type II error, in which the researcher might extract too few classes and not properly reflect the true model of a population (Dziak, Lanza, & Tan, 2014; Nylund et al., 2007). Therefore, power analyses are more concerned with under-extraction of classes.

Recent research through simulation studies have provided guidelines for minimum sample size for extracting an accurate number of latent classes. Dziak, Lanza, and Tan (2014) conducted simulation studies to provide sample size recommendations for power assuming different expected effect sizes. Effect sizes were defined as the magnitude of class separation. Sample size recommendations suggested that with the number of categorical items explored in the current study ($J = 8$), and a medium effect size, LCA requires 293 participants for power of .80. Given a large effect size, LCA requires 106 participants for power of .80 (Dziak et al., 2014).

Prior studies have conducted mixture modeling with relatively small sample sizes. In particular, studies have conducted latent profile analysis and latent class analysis with a sample size less than 300 subjects (Dodd et al., 2011; Flensborg Damholdt, Shevlin, Borghammer, Larsen, & Østergaard, 2012; Kaiser, Brown, & Baumann, 2010; Park, Zimmerman, Sloane, Gruber-Baldini, & Eckert, 2006; Rhee, Belyea, & Elward, 2008; Yamamoto-Mitani, Aneshensel, & Levy-Storms, 2002). A study by Wurps and Geiser (2014) suggested a bare minimum sample size of 70 participants. The study concluded that using more and high quality indicators can compensate for some of the issues associated with small sample size. High quality indicators are variables that demonstrate high probabilities of class membership for an individual (i.e., conditional response probabilities) (Wurpts & Geiser, 2014). For instance, if gender were a high-quality indicator, being male or female would strongly predict membership to a specific *k* class. Therefore, this study will examine conditional response probabilities to identify the quality of indicators and potentially remove poor indicators in order to increase power.

Measures

Data on sociodemographic, pain, and psychological variables were collected through pre-treatment and post-treatment measures. All assessment data were collected by trained assessors. Measures were read out loud to study participants, except for the literacy measures. Data were recorded on portable electronic tablets or paper backups. The Brief Demographics Questionnaire (BDQ) collected information on sex, age, race/ethnicity, income, and highest level of educational attainment. Educational attainment was measured by self-reported highest school grade completed. Poverty status was calculated using self-reported income that was dichotomized into below or above federal poverty line according to the Department of Health and Human Services household-size adjusted poverty threshold (https://aspe.hhs.gov/poverty-guidelines). Other measures utilized in this study are described below.

Literacy

Primary literacy was assessed through the Wide Range Achievement Test-4 Word-Reading subtest (WRAT; Wilkinson & Robertson, 2006). Study participants read aloud/pronounced a series of written words ordered by increasing complexity. Correct pronunciation received a score of 0 and incorrect pronunciation received a score of 1. Scores were converted into grade level equivalency (WRAT GLE) based on a normative sample. The WRAT demonstrates excellent internal consistency reliability ($\alpha = .92$) and alternate-form test-retest (.85) reliabilities (Wilkinson & Robertson, 2006).

Pain Severity and Interference

Pain Severity and Interference were assessed through the Brief Pain Inventory (BPI; Cleeland & Ryan, 1994). For pain severity, participants rated the most severe pain, least severe pain, and average pain over the past week, and current pain on an 11-point Likert Scale ranging from 0 (no pain) to 10 (pain as bad as you can imagine). Pain severity scores were calculated from the mean of these four items. For pain interference, participants rated interference due to pain on 7 domains on an 11-point Likert scale ranging from 0 (no interference) to 10 (complete inference). Pain interference scores were calculated from the mean of these 7 items. The BPI demonstrates concurrent validity with other pain instruments and excellent internal consistency in a variety of pain populations (Raichle, Osborne, Jensen, & Cardenas, 2006).

Disability

Disability was assessed through the Patient-Reported Outcomes Measurement Information System Physical Function v1.0 Short Form 20a (PROMIS PF-20). A 20-item module with possible total scores ranging from 20 to 100, the PROMIS PF-20 was developed by the National Institutes of Health (NIH) to measure self-reported capability in performing various activities, such as walking, self-care, climbing stairs, exercise, and carrying groceries. Participants rate a total of 14 items on the extent of difficulty in performing certain activities on a scale from 1 (unable to do) to 5 (without any difficulty). Participants then rate 6 items on the extent to which health limits certain activities on a scale from 1 (cannot do) to 5 (not at all). The PROMIS PF-20 is calculated by the sum of the 20 items. For the current study, the PROMIS PF-20 was reverse scored to indicate greater impairment or disability in physical functioning with higher scores. Total scale scores range from 20 (highest functioning, lowest disability) to 100 (lowest functioning, highest disability). The PROMIS PF-20 demonstrates excellent internal consistency (Cronbach $\alpha > .90$) in previous research (Bartlett et al., 2015).

Depressive Symptoms.

Depressive symptoms were assessed through the Patient Health Questionaire-9 (PHQ-9; (Kroenke, Spitzer, & Williams, 2001). The PHQ-9 includes 9 items evaluating depressive symptoms, such as changes in appetite, fatigue, and suicidal ideation, measured on a scale of 0 (not at all) to 3 (nearly every day). Scores can range from 0 to 27 in severity with higher scores indicating greater severity of depressive symptoms. The internal reliability of the PHQ-9 is high, with Cronbach's alpha of .89. Test-retest reliability is also reported as excellent (Kroenke, Spitzer, & Williams, 2001).

Pain Catastrophizing.

Pain catastrophizing was assessed through the Pain Catastrophizing Scale (PCS; Sullivan, Bishop, & Pivik, 1995). Pain catastrophizing can be described as highly negative thoughts about pain and its impact on one's life (Quartana, Campbell, & Edwards, 2009). Participants rated 13 items on the degree to which they have specific thoughts and feelings related to experiencing pain. Items were measured on a 5-point Likert scale ranging from 0 (not at all) to 4 (all the time).

An example statement is, “When I have pain I feel I can’t go on.” Higher scores indicate higher levels of catastrophic thinking. The internal reliability of the PCS is excellent, with Cronbach’s alpha of .87 (Sullivan, Bishop, & Pivik, 1995).

Statistical Analysis

Aim 1

A preliminary LCA was conducted using MPlus 6.1 (Muthen & Muthen, 1998) to identify subgroups with similar disparity profiles based on response patterns on observed variables. The analysis derives categorical latent variables to represent the profiles of the disparity subgroups. Parameters for the latent class models were estimated using maximum-likelihood techniques (Nylund et al., 2007). The optimal number of classes were determined through goodness of fit statistics; Akaike Information Criterion (AIC; Akaike, 1974), sample size-adjusted Bayesian Information Criterion (sBIC; Schwarz, 1978), Lo–Mendell–Rubin adjusted Likelihood Ratio Test (LMR-LRT; Lo, Mendell, & Rubin, 2001) and Bootstrapped Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000), The AIC and sBIC are descriptive fit indices for comparing the current complex model with the previous less complex model. Lower scores on AIC and sBIC indicate superior fit in the more complex model. LMR-LRT is a statistic fit index that compares improvement in fit between *k* class and *k-1* class. Another likelihood-based technique that compares LCA models, BLRT is a bootstrapped version of the LMR statistic fit index that empirically generates bootstrap samples to examine whether the current model with *k* classes made statistically significant improvement in model fit than the previous model tested with *k*-1 classes (McLachlan, 1987). If the *p*-value generated for the LMR-LRT and BLRT is significant ($p < .05$), the test suggests that the current more complex model with *k* classes fits significantly better than the previous less complex model with *k*-1 classes

(Asparouhov & Munthen, 2012; Roesch et al., 2010). Research has suggested that BLRT is advantageous over LMR-LRT in the identification of optimal number of classes (K. L. Nylund et al., 2007). In the case of differing results between BLRT and LMR-LRT, the BLRT test statistic was considered the more accurate and meaningful test statistic. Entropy is a statistical indicator of how well the profiles differentiate between groups by calculating the percentage of individuals who were correctly classified by the chosen model (Ramaswamy, DeSarbo, & Reibstein, 1993). Higher entropy scores indicate higher classification accuracy of individuals into identified subgroups. The overall likelihood ratio model chi-square goodness-of-fit chi-square ($\boldsymbol{\chi^2}_{\mathbf{LR}}$) will not be reported in the model fit statistics since the commonly used index of absolute fit is not appropriate in LCA (K. L. Nylund et al., 2007). After identifying the classes, individuals are assigned to their most likely class based on model probabilities (Collins & Lanza, 2009). The best model is determined statistically by examining multiple models with fit indices and substantively by examining the conditional response patterns on each of the item indicators.

After selecting the best fitting model, model classification diagnostics examined the quality of separation/differentiation among the latent classes. Latent classes that are well-separated have high homogeneity in their responses on the observed categorical indicators. The model class diagnostics is not a measure of model fit, but rather, indicates the quality of class separation. Average posterior class probability (AvePP) examines classification uncertainty for each latent class separately and functions as an approximation of internal reliability (Andruff, Carraro, Thompson, Gaudreau, & Louvet, 2009; Little, 2013; D. S. Nagin & Odgers, 2010). Values above .70 to .80 suggest adequate separation and classification precision. Modal class assignment probability ($mcaP_k$) is the proportion of individuals in the sample modally assigned to class k (Little, 2013) . When $mcaP_k$ is similar in value (small discrepancy) to the model estimated proportion for reach class ($\hat{\pi}_k$), results indicate smaller latent class assignment errors.

Therefore, it is desirable to have approximately equivalent $mcaP_k$ and $\hat{\pi}_k$ values. The odds of correct classification (OCC) indicates the odds of correct classification based on random assignment (Nagin, 2005). When $OCC_k = 1.00$, the modal class assignment for class *k* is no better than chance. Nagin (2005) state that OCC values 5.00 or larger indicate a latent class model with good latent class separation and high assignment accuracy.

Variables entered in the LCA included sex, race, age, poverty status, employment, disability status, education, and literacy. Sex was a dichotomous variable, including male (n = 85) and female (n = 205). Race was a dichotomous variable, including White/Caucasian (n = 96) and Black/African-American (n = 194). Poverty status included above (n = 70) and below poverty line (n = 210). Education included 3 categories; no degree (n = 85), high school diploma or GED (n = 112), and education beyond high school (i.e., some college, technical school, college or graduate school) (n = 93). Disability status included 3 categories; on disability (n = 137), seeking disability (n = 103), and not on disability/not seeking disability (n = 50).

Employment was first explored as 4 categories; fully employed (n = 11), partially employed (n = 28), not employed (n = 197), and retired (n = 48). Preliminary results suggested that the categories of employment were poor quality indicators of class membership. Therefore, employment was recategorized as 3 categories; fully employed/partially employed (n = 39), not employed (n = 197), retired (n = 48).

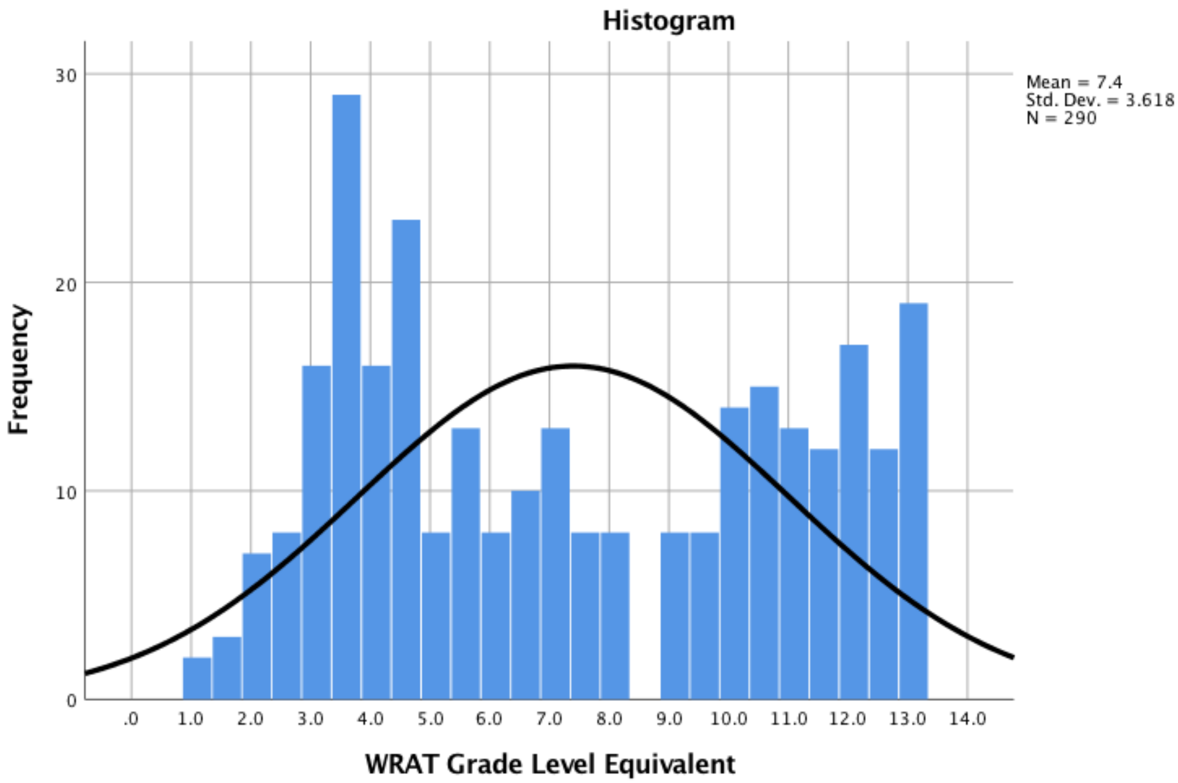
Age was first explored as 4 groups, as seen in previous literature (Boggero et al., 2015); young adults (18 to 30 years old), middle aged adults (30-45 years old), late-middle-aged (45–60 years), and older adults (60+ years old). However, due to the small number of young adults in the LAMP study (n = 7), the young adult group and middle aged adult group were merged into a category labeled early-middle aged adults. Preliminary analyses included the following; early-middle aged adults (18 to 44 years old) (n = 63), late-middle aged adults (45 to 60 years old) (n =

182), and older adults (60+ years old) (n = 45). Preliminary results suggested that the categories of age were poor quality indicators of class membership. Therefore, age was recategorized as a dichotomous variable based on a median split. Age included younger adults (< 51 years old) and older adults (> above 51 years old). Univariate analyses of variance (ANOVAs) were conducted to examine the clinical meaningfulness of the dichotomized age groups. Younger adults reported higher pre-treatment pain severity (M = 6.77, SD = 1.62) than older adults (M = 6.30, SD = 1.61), $F(1, 288) = 6.03$, $p < .05$; higher pre-treatment pain interference (M = 7.01, SD = 1.92) than older adults (M = 6.28, SD = 2.07), $F(1, 288) = 9.74$, $p < .01$; higher pre-treatment depression (M = 11.15, SD = 6.20) than older adults (M = 13.20, SD = 1.62), $F(1, 288) = 7.57$, $p < .01$; and higher pre-treatment pain catastrophizing (M = 32.46, SD = 12.41) than older adults (M = 29.03, SD = 13.72), $F(1, 287) = 4.92$, $p < .05$. Physical disability did not significantly differ by age groups, $F(1, 288) = .547$, $p = .46$. Results suggest some meaningful differences between the created age categories, in which younger adults reported worse chronic pain functioning than older adults, supporting the use of a dichotomous age variable.

Literacy originally included 3 categories; ≤ 5th grade (n = 125), 6th-11th grade (n = 125), ≥ 12th grade (n = 40). Preliminary results suggested that the categories of literacy were poor quality indicators of class membership. Based on a bimodal distribution of literacy in the LAMP trial, literacy was adjusted to better capture the modes of 3rd-5th grade reading levels and 10th-13th grade reading levels (please see Figure 1). Therefore, literacy was recategorized as 3 different categories; < 5th grade, 5th-8th grade, and ≥ 9 grade reading levels. These new categories also better represent the literacy adaptions for the LAMP study. The CBT and EDU psychosocial intervention patient materials were adapted to literacy levels below the 5th grade.

Figure 1. Histogram representing the number of study participants with specific literacy levels (WRAT). The black curve line represents a normal distribution. The histogram demonstrates a bimodal distribution with clusters of individuals between 3rd to 5th grade reading levels and 10th to 13th grade reading levels.

Aim 2



Differences in identified chronic pain disparity profiles/subgroups on indicators of pre-treatment pain-related outcomes and mental health outcomes were examined using Multivariate Analyses of Variance (MANOVAs). Although many studies examine LCA with distal outcome analyses, MANOVAs are well-established in the field of psychology and demonstrate strengths in accounting for the relationships between dependent variables, potentially increasing power given the moderate correlations found between this study's dependent variables (Olson, 1976). Pain-related outcomes included BPI-severity, BPI-interference, and PROMIS PF-20. Psychological outcomes included PHQ-9 and PCS. Significant omnibus results were followed up with univariate analyses.

Aim 3

Disparity profiles were used to predict treatment outcomes. Multivariate analyses examined the moderation of disparity profiles on treatment outcome. The independent variable was the randomized group assignment (CBT, EDU, or UC) and disparity profile groups. The analysis examined potential interactions between treatment group and disparity profile group on pain-related and psychological functioning trial outcomes. The dependent variables included BPI-Severity, BPI-Interference, PROMIS PF-20, PHQ-9, and PCS. There is currently a debate on the power of using covariates to control for baseline (i.e., posttest would be the outcome and pretest would be the covariate) or using change scores as the outcome variables (i.e., outcome would be defined as posttest minus pretest). Research examining covariates versus change scores in randomized controlled trials suggests that both methods are unbiased approaches and covariates offer more power than change scores (Van Breukelen, 2006). Therefore, this study examined treatment effects with MANCOVAs (Multivariate Analyses of Covariance). The covariate variables were the baseline scores on BPI-Severity, BPI-Interference, PROMIS PF-20, PHQ-9, and PCS.

3. RESULTS

Baseline Characteristics

The sample was characterized by being about 71% female (*N* = 205), 72% below poverty status (*N* = 210), 70% Black/African-American (*N* = 194), 69% not employed (*N* = 197), 47% on disability (*N* = 137), and 29% (*N* = 85) with no High School degree or GED. Participants' mean primary literacy was 7.4 (*SD* = 3.6) and mean age was 50.6 (*SD* = 8.9). See *Table 5* for summary of pre-treatment chronic pain characteristics. The mean pain intensity score at pre-treatment was 6.5 (*SD* = 16), which is categorized as moderate to severe pain (Li, Harris, Hadi, & Chow, 2007). The mean pain interference score was 6.6 (*SD* = 2.0), which is considered severe interference (Shi et al., 2017). The mean t-score of disability (non-reversed PROMIS-PF-20) was 66.9 (*SD* = 5.3), which is about two standard deviations below the PROMIS normative sample. The mean depression score was 12.1 (*SD* = 6.4), which falls in the moderate range of depression (Kroenke et al., 2001). The mean pain catastrophizing score was 30.6 (*SD* = 13.2), suggesting clinically significant levels of pain catastrophizing (Sullivan et al., 1995).

Aim 1

Multiple models were examined iteratively (1-class, 2-class, 3-class... etc.). Model fit indices are reported in *Table 1*. Model fit indices suggested that the 5-class model fit better than the 4-class model. The fit indices also indicated that models beyond 5-classes were a poor fit. The AIC and sBIC values in the 5-class model were lower than the 4-class model, indicating improvement in model fit. In the 5-class model, the LMR-LRT *p*–value was non-significant

(p = .79) and the BLRT p-value was significant ($p < .05$). Due to the discrepancy between LMR-LRT and BLRT, results used the BLRT result suggesting that the 5-class model resulted in significant improvement in model fit in comparison to the 4-class model. Entropy value increased from .767 (4-class model) to .888 (5-class model), suggesting that a greater percentage of individuals were correctly classified in the 5-class model.

Table 1. Overall model fit examined with AIC, sBIC, BLRT, and Entropy for a total of 7 classes.

	LL	**npar**	**AIC**	**sBIC**	**BLRT**	**LMR-LRT**	**Entropy**
1 class	-1875.941	12	3775.883	3781.867	-	-	-
2 classes	-1824.312	25	3698.624	3711.091	<.001	<.001	.718
3 classes	-1788.241	38	3652.482	3671.433	<.001	.137	.688
4 classes	-1768.648	51	3639.295	3664.729	<.001	.930	.767
5 classes	-1750.846	64	3629.693	3661.609	<.05	.790	.888
6 classes	-1736.736	77	3627.472	3665.872	1.00	.907	.818
7 classes	-1723.826	90	3627.652	3672.535	.667	1.00	.847

Note: LL refers to loglikelihood value. npar refers to number of parameters. AIC refers to Akaike Information Criterio. sBIC refers to sample-size adjusted Bayesian value. BLRT refers to the Bootstrapped Likelihood Ratio Test. LMR-LRT refers to Lo–Mendell–Rubin adjusted Likelihood Ratio Test.

Model class diagnostics suggested good quality of separation/differentiation among the latent classes in the 5-class model (*Table 2*). The minimal discrepancies between $\hat{\pi}_k$ and mcaP$_k$ values suggested small latent class assignment errors. All AvePP$_k$ values were above .90, suggesting good separation and classification precision. The OCC$_k$ values were well above 5.00, indicating good latent class separation and high assignment accuracy. In summary, model class diagnostics provide support for the use of a 5-class model.

Table 2. Model class diagnostics for the 5-class model.				
Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	.166	.159	.955	106.622
Class 2	.200	.205	.928	51.556
Class 3	.214	.235	.914	39.035
Class 4	.348	.325	.920	21.546
Class 5	.072	.075	.936	188.500

Note: $\hat{\pi}_k$ refers to model estimated proportion for each class. $mcaP_k$ refers to modal class assignment probability. $AvePP_k$ refers to average posterior class probability. OCC_k refers to odds of correct classification.

Although the 5-class model demonstrated good model fit and quality of class separation, it is important to examine the models with a substantive approach in addition to the statistical approach. The substantive approach examined conditional response patterns in order to assess how well each item predicts class membership. *Table 3* provides the conditional response counts and proportions for each latent class for the 5-class model. Pearson χ^2 tests examined the associations between the 5 latent classes and the socio-demographic categorical variables. All χ^2 tests were significant (p's < .05), suggesting that the socio-demographic characteristics vary significantly by each latent class. Although class 5 (n = 21, 7.24% of total sample) included few participants, there is a lack of consensus about a minimum class size rule. Instead, statisticians emphasize the importance of examining whether the classes add substantive information. In other words, a small class size is acceptable if the characteristics of the class add meaningful information about the subgroups within the sample (Muthén & Muthén, 2002; K. L. Nylund et al., 2007). It is clear that class 5 has unique conditional response counts and proportions, especially among employment and gender. Based on the statistical and substantive analyses, the 5-classes model was the best fit for the data with meaningful classes and therefore was selected as the final model.

Table 3. Conditional response proportions by latent classes within the 5-class model.							
Characteristics	Overall Sample (n = 290)	Class 1 (n = 48, 16.6%)	Class 2 (n = 58, 20.0%)	Class 3 (n = 62, 21.4%)	Class 4 (n = 101, 34.8%)	Class 5 (n = 21, 7.2%)	Pearson χ^2
Race							
White/Caucasian	96 (33.1%)	30 (31.3%)	28 (29.2%)	12 (12.5%)	14 (14.6%)	12 (12.5%)	52.42**
Black/African-American	194 (66.9%)	18 (9.3%)	30 (15.5%)	50 (25.8%)	87 (44.8%)	9(4.6%)	
Sex							
Male	85 (29.3%)	10 (11.8%)	22 (25.9%)	20 (23.5%)	33 (38.8%)	0 (0.0%)	13.26*
Female	205 (70.7%)	38 (18.5%)	36 (17.6%)	42 (20.5%)	68 (33.2%)	21 (10.2%)	
Poverty Status							
Above	70 (25.0%)	16 (22.9%)	6 (8.6%)	2 (2.9%)	33 (47.1%)	13 (18.6%)	44.38**
Below	210 (75.0%)	30 (14.3%)	50 (23.8%)	58 (27.6%)	64 (30.5%)	8 (3.8%)	
Employment Status							
Employed	39 (13.7%)	0 (0.0%)	5 (12.8%)	3 (7.7%)	11 (28.2%)	20 (51.3%)	174.25**
Not Employed	197 (69.4%)	36 (18.3%)	50 (25.4%)	55 (27.9%)	56 (28.4%)	0 (0.0%)	
Retired	48 (16.9%)	12 (25.0%)	1 (2.1%)	3 (6.3%)	32 (66.7%)	0 (0.0%)	
Disability Status							
On disability	137 (47.2%)	26 (19.0%)	26 (19.0%)	0 (0.0%)	85 (62.0%)	0 (0.0%)	240.01**
Seeking disability	103 (35.5%)	16 (15.5%)	21 (20.4%)	62 (60.2%)	0 (0.0%)	4 (3.9%)	
Not on/Not seeking disability	50 (17.2%)	6 (12.0%)	11 (22.0%)	0 (0.0%)	16 (32.0%)	17 (34.0%)	
Literacy							
< 5th grade literacy	104 (35.9%)	0 (0.0%)	0 (0.0%)	35 (33.7%)	67 (64.4%)	2 (1.9%)	249.47**
5^{th}-8th grade literacy	76 (26.2%)	0 (0.0%)	8 (10.5%)	27 (35.5%)	34 (44.7%)	7 (9.2%)	
≥ 9th grade literacy	110 (37.9%)	48 (43.6%)	50 (45.5%)	0 (0.0%)	0 (0.0%)	12 (10.9%)	
Mean (SD)	7.4 (3.6)	11.7 (1.0)	10.7 (1.9)	5.0 (1.7)	4.5 (1.8)	9.4 (3.1)	
Age							
Younger (< 51 years)	116 (40.0%)	0 (0.0%)	58 (50.0%)	35 (30.2%)	16 (13.8%)	7 (6.0%)	150.94**
Older (≥ 51 years)	174 (60.0%)	48 (27.6%)	0 (0.0%)	27 (15.5%)	85 (48.9%)	14 (8.0%)	
Mean (SD)	50.6 (8.86)	55.5 (5.1)	41.7 (7.0)	47.6 (6.7)	55.1 (7.4)	51.1 (10.2)	
Education							
No degree	85 (29.3%)	4 (4.7%)	16 (18.8%)	25 (29.4%)	37 (43.5%)	3 (3.5%)	44.47**
High School Diploma/GED	112 (38.6%)	18 (16.1%)	14 (12.5%)	26 (23.2%)	47 (42.0%)	7 (6.3%)	
> High School	93 (32.1%)	26 (28.0%)	28 (30.1%)	11 (11.8%)	17 (18.3%)	11 (11.8%)	

** Significant at the 0.05 level.
* Significant at the 0.01 level.
Note: The percentages reported in the overall sample column reflect the number of individuals in the identified "characteristic" category out of the total sample. The percentages reported in classes 1-5 reflect the number of individuals in the identified "characteristic" category out of the total number of individuals within the same "characteristic" category (e.g., There were 30 White/Caucasian individuals categorized to class 1 out of a total of 96 White/Caucasian individuals, resulting in the 31.3%).

Table 4 and *Figure 2* depicts the latent class profiles for the 5-class model. *Figures 3-5* depict comparisons of specific latent class profiles. The conditional response probabilities (CRP) allows for the examination of indicators that have strong or weak relationships to the latent class variable (i.e., CRPs close to one or zero). Following Collins and Wugalter (1992) (also see Wurpts & Geiser, 2014), high-quality indicators include CRPs of 0.9 or 0.1, moderate-quality indicators include CRPs of 0.8 and 0.2, and low-quality indicators include CRPs of 0.7 or 0.3. Higher quality indicators better predict class membership and provide for better understanding of the profiles of each class. This study only analyzed moderate to high quality indicators for class membership characterization (see *Table 5*).

The largest class (n = 101, 34.8%; class 4) demonstrated moderate levels of disparities (as compared to other groups within this study sample; within national standards, this would be considered severe levels of disparities). The highest and lowest probabilities for class membership (CRPs $\geq$ .80 and CRPs $\leq$ .20) suggested high probabilities for being Black/African-American (.85), on disability (.83), and older ($\geq$ 51 years) (.86), and low probabilities for being employed (.11), at or above 9th grade literacy (.00), and having education beyond High School (.18). Class 4 was labeled “moderate disparity” (MD) group and is distinguished by being older, Black/African-American, lower literacy/education, and on disability.

The second largest class (n = 62, 21.4%; class 3) demonstrated the overall highest levels of disparities and therefore was labeled “severe disparity” (SD) group. The CRPs suggested high probabilities for being Black/African-American (.82), below poverty status (.96), not employed (.92), and seeking disability (.89), and low probabilities for having literacy levels at or above the 9th grade literacy (.06) and having education beyond High School (.17). The SD group differs from the MD group in terms of greater likelihood of a group member being below poverty status

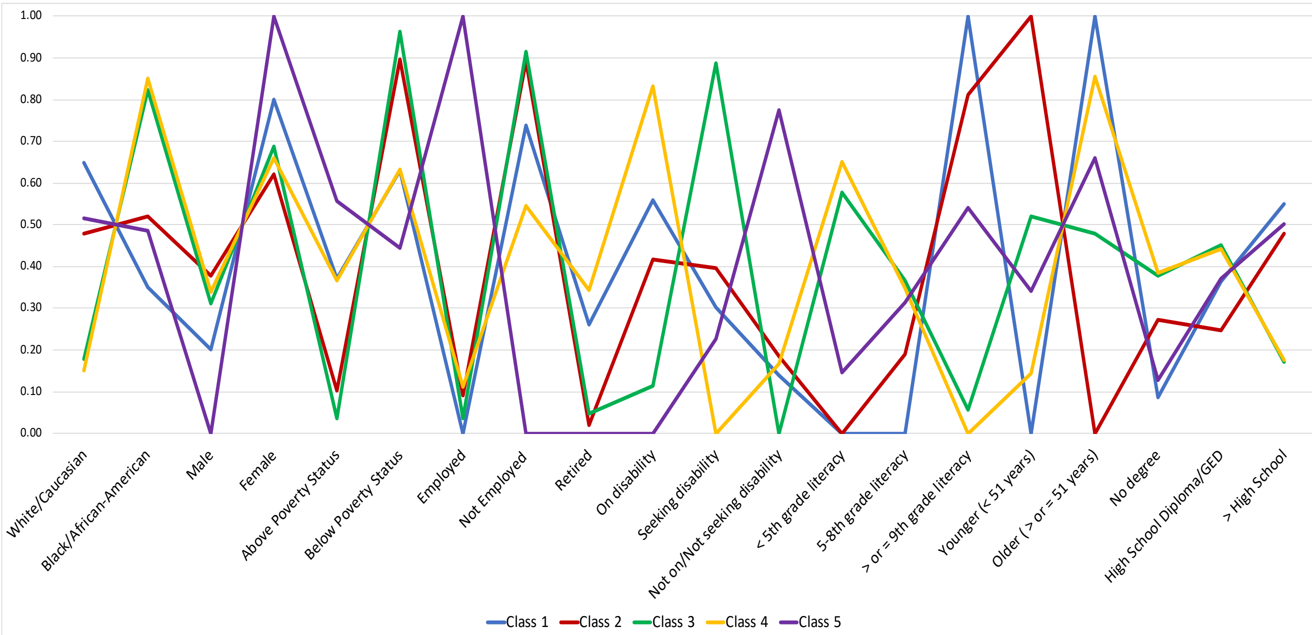
Table 4. Conditional response probabilities.

	Class 1 (n = 48)	Class 2 (n =58)	Class 3 (n = 62)	Class 4 (n = 101)	Class 5 (n = 21)
Race					
White/Caucasian	0.65	0.48	0.18	0.15	0.52
Black/African-American	0.35	0.52	0.82	0.85	0.49
Sex					
Male	0.20	0.38	0.31	0.34	0.00
Female	0.80	0.62	0.69	0.66	1.00
Poverty Status					
Above Poverty Status	0.37	0.10	0.04	0.37	0.56
Below Poverty Status	0.63	0.90	0.96	0.63	0.44
Employment					
Employed	0.00	0.09	0.04	0.11	1.00
Not Employed	0.74	0.89	0.92	0.55	0.00
Retired	0.26	0.02	0.05	0.34	0.00
Disability Status					
On disability	0.56	0.42	0.11	0.83	0.00
Seeking disability	0.30	0.40	0.89	0.00	0.23
Not on/Not seeking disability	0.14	0.19	0.00	0.17	0.77
Literacy					
< 5th grade literacy	0.00	0.00	0.58	0.65	0.15
5^{th}-8th grade literacy	0.00	0.19	0.37	0.35	0.31
≥ 9^{th} grade literacy	1.00	0.81	0.06	0.00	0.54
Age					
Younger (< 51 years)	0.00	1.00	0.52	0.14	0.34
Older (≥ 51 years)	1.00	0.00	0.48	0.86	0.66
Education					
No degree	0.09	0.27	0.38	0.38	0.13
High School Diploma/GED	0.37	0.25	0.45	0.44	0.37
> High School	0.55	0.48	0.17	0.18	0.50

Table 5. Moderate to high quality conditional response probabilities (≥.80 or ≤.20) that characterize disparity profiles.

Class	*N* (%)	Label	Description	
1	48 (16.6%)	Moderate-Older Adults	High CRPs	female (.80), having at or above 9th grade literacy levels (1.00), and older (≥ 51 years) (1.00)
			Low CRPs	employed (.00), not on/not seeking disability (.14), and no educational degree (.09)
2	58 (20.0%)	Moderate – Younger Adults	High CRPs	poverty status (.90), not employed (.89), ≥ 9th grade literacy levels (.81), and younger (< 50 years of age; 1.00)
			Low CRPs	not on/not seeking disability (.19).
3	62 (21.4%)	Severe Disparity	High CRPs	Black/African-American (.82), below poverty status (.96), not employed (.92), and seeking disability (.89)
			Low CRPs	≥ 9th grade literacy levels (.06) and education beyond High School (.17)
4	101 (34.8%)	Moderate Disparity	High CRPs	Black/African-American (.85), on disability (.83), and older (≥ 51 years) (.86)
			Low CRPs	Employed (.11), at or above 9th grade literacy (.00), and education beyond High School (.18)
5	21 (7.2%)	Low Disparity	High CRPs	female (1.00) and employed (1.00)
			Low CRPs	on disability (.00), having below 5th grade literacy (.15), and lacking an educational degree (.13).

Figure 2. Latent class profiles for the five-class model.



and seeking disability (see *Figure 3* for a comparison). Research has suggested that seeking disability is associated with poor health functioning and therefore is considered a greater disadvantage than being on disability (Gebauer, Scherrer, Salas, Burge, & Schneider, 2015; Sayer, Spoont, & Nelson, 2004). In this study, disability status serves as a proxy variable for health care access. When patients are seeking disability, it is likely that there is an overall lack of access to health care services. In addition, the MD group is unique in terms of age (higher likelihood of being in the older age category).

Class 2 (n = 58, 20.0%) was distinguished by age and low-SES. There were high probabilities for being below poverty status (.90), not employed (.89), at or above 9th grade literacy levels (.81), and younger (< 50 years of age; 1.00). The only low probability included not on/not seeking disability (.19). Therefore, class 2 was labeled "moderate disparity – younger adult" (MD-YA) group. When comparing MD-YA (class 2) and SD (class 3), both groups have high probabilities of an individual being below poverty status and not employed. However, MD-

YA (class 2) is distinguished by age (younger) and higher literacy levels. SD (class 3) is also more distinguished by race (Black/African-American) and seeking disability status (see *Figure 4* for further comparison).

Figure 3. Comparison of latent class profiles 3 and 4.

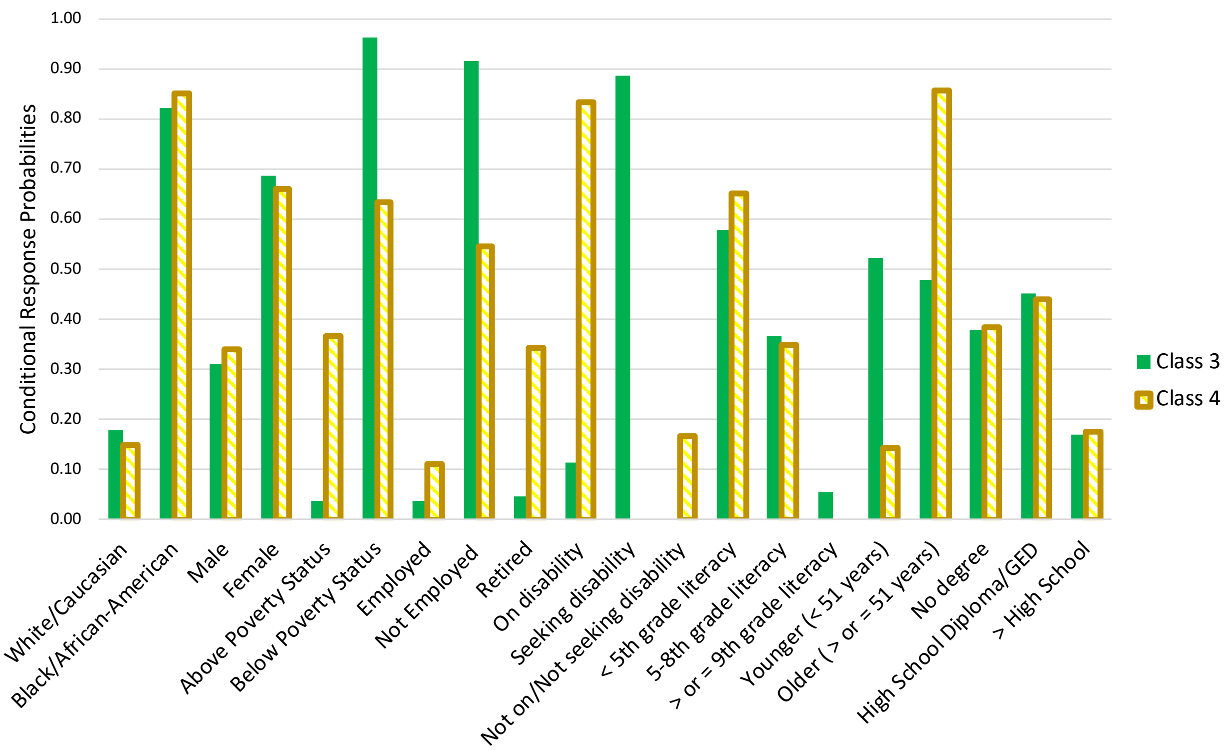
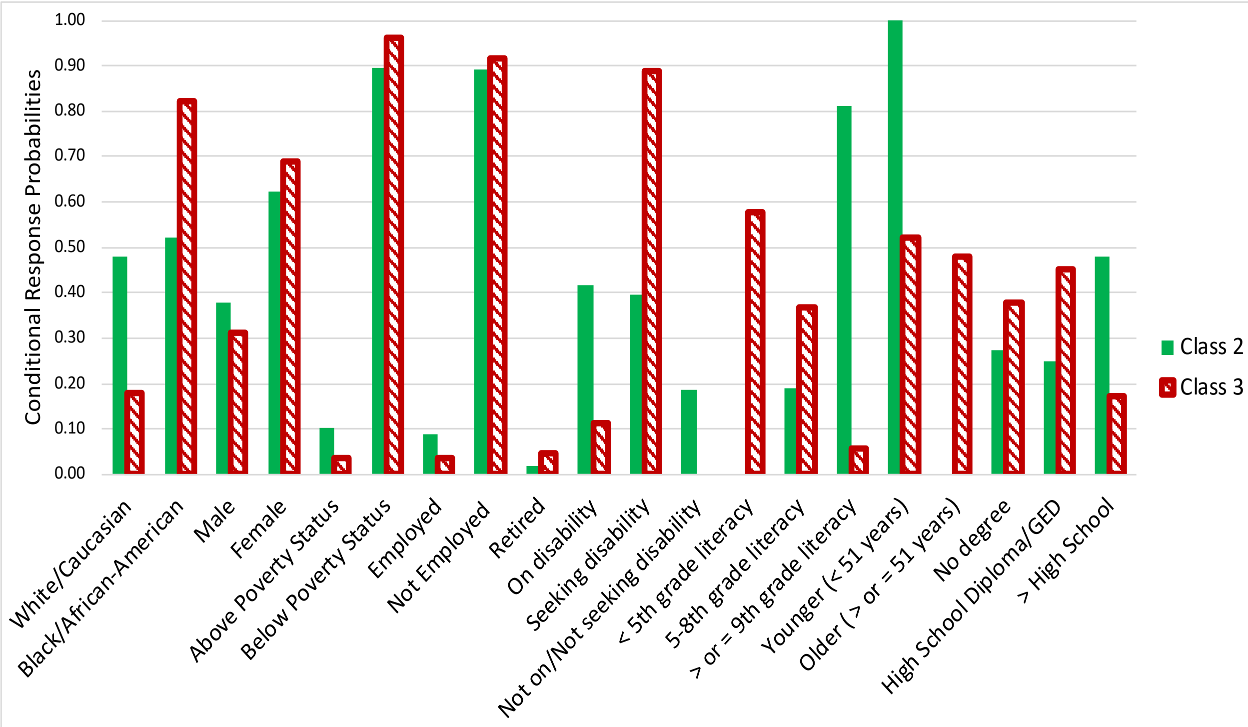


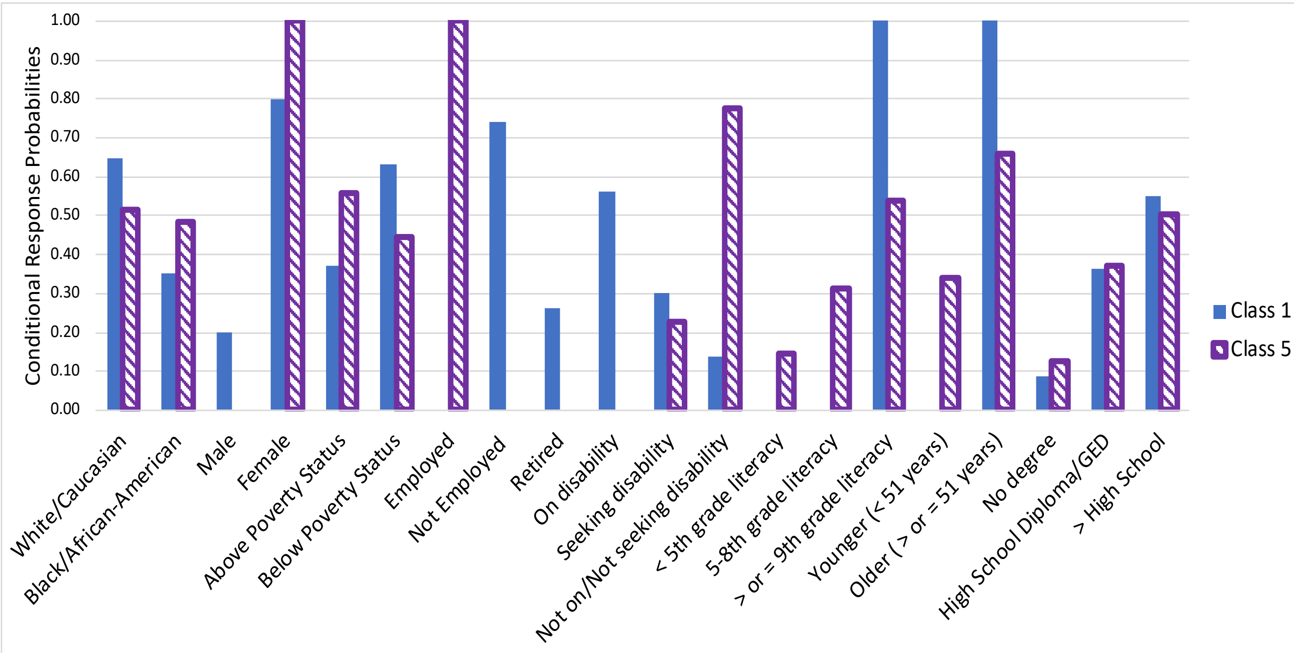
Figure 4. Comparison of latent class profiles 2 and 3.



Class 1 (n = 48, 16.6%) demonstrated high probabilities for being female (.80), having at or above 9th grade literacy levels (1.00), and older (≥ 51 years). Class 1 had low probabilities for being employed (.00), not on/not seeking disability (.14), and no educational degree (.09). Therefore, class 1 was labeled "moderate disparity – older adults" (MD-OA) group.

The smallest class (n = 21, 7.2%; class 5) was strongly characterized by being female (1.00) and employed (1.00). Class 5 demonstrated low probabilities for being on disability (.00), having below 5th grade literacy (.15), and lacking an educational degree (.13). Therefore, class 5 was labeled "low disparity" (LD) group. When comparing MD-OA (class 1) with LD (class 5), both classes have high probabilities of a class member being female. However, MD-OA is distinguished by lack of employment, age (older), and higher literacy. Class 5 is more specified in terms of all class members being employed (see *Figure 5* for further comparison).

Figure 5. Comparison of latent class profiles 1 and 5.



Aim 2

A one-way Multivariate Analysis of Variance (MANOVA) examined the associations between chronic pain disparity subgroups (latent classes) and chronic pain functioning. Dependent variables included Pain Severity (BPI-Severity), Pain Interference (BPI-Interference), Disability (PROMIS-PF-20), Depression (PHQ-9), and Pain Catastrophizing (PCS). Correlations between dependent variables are within a moderate range (see *Table 6*), which is ideal for optimal power to detect differences through multivariate analyses (French, A., Macedo, M., Poulsen, J., Waterson, T., & Yu, 2008; Huberty & Morris, 1992). Descriptive statistics of the means and standard deviations among dependent variables per latent class are provided in *Table 7*. The assumption of homogeneity of covariance was not met, Box's M = 83.75, F(60, 35338.20) = 1.32, p = .047, suggesting that covariance matrices of the dependent variables were not equal across groups. The assumption of homogeneity of variance (levene's test) was met for all dependent variables (p's > .05), expect PCS, $F(4, 284) = 2.93$, $p < .05$. PCS demonstrated a non-normal distribution and was analyzed separately using non-parametric testing (see the end of Aim 2). After removing PCS, the assumption of homogeneity of covariance was met, Box's M = 39.39, $F(40, 37821.79)$, $p = .57$, and the assumption of variance was met for all dependent variables (p's > .05). The multivariate main effects were significant, Roy's largest root = .21, $F(4, 285) = 15.21$, $p < .001$. Results suggest that pre-treatment chronic pain functioning varied by latent classes.

Table 6. Bivariate correlations among chronic pain related variables at pre-treatment.

	1	2	3	4	5
1. Pain Severity (BPI- Severity)	-	-	-	-	-
2. Depression (PHQ-9)	.355**	-	-	-	-
3. Pain Catastrophizing (PCS)	.445**	.638**	-	-	-
4. Pain Interference (BPI-Interference)	.599**	.530**	.527**	-	-
5. Physical Disability (PROMIS-PF-20)	.425**	.471**	.414**	.572**	-

**. Correlation is significant at the 0.01 level (2-tailed).

Table 7. Descriptive statistics of pre-treatment dependent variables among chronic pain disparity subgroups (latent classes).

Dependent Variable	Latent Class	Mean	Std. Deviation
BPI-Severity	1.000	5.82	1.43
	2.000	6.41	1.43
	3.000	7.44	1.47
	4.000	6.48	1.66
	5.000	5.81	1.77
	Total	6.51	1.63
PHQ-9	1.000	10.85	6.15
	2.000	13.47	6.63
	3.000	15.58	6.15
	4.000	10.59	5.78

	5.000	8.71	5.39
	Total	12.14	6.42
PCS	1.000	23.58	12.36
	2.000	31.56	12.51
	3.000	40.08	9.02
	4.000	29.59	12.79
	5.000	21.43	12.52
	Total	30.64	13.21
BPI-Interference	1.000	6.14	1.99
	2.000	6.90	1.67
	3.000	7.79	1.64
	4.000	6.28	2.08
	5.000	5.07	2.04
	Total	6.62	2.03
PROMIS-PF-20	1.000	60.52	9.55
	2.000	59.88	12.37
	3.000	66.02	12.67
	4.000	56.79	12.85
	5.000	51.19	8.95
	Total	59.59	12.59

Follow-up analyses were completed with two distinct approaches. The first approach involves multivariate t-tests with orthogonal contrasts. The first approach offers the advantage of preserving the multivariate environment. The second approach was proposed in the preliminary proposal and involves univariate analyses. The univariate analyses do not preserve the multivariate environment but allow for more in-depth analyses.

Multivariate t-tests with orthogonal contrasts were performed to compare latent classes on chronic pain functioning at pre-treatment. Class 3 reported significantly worse chronic pain functioning (higher pain severity, pain interference, physical disability, and depression) than the average of the other classes, Roy's Largest Root = .154 $F(4, 285) = 10.96$, $p < .001$. Class 2 reported significantly worse chronic pain functioning than the average of classes 1, 4, and 5, Roy's Largest Root = .059, $F(4, 223) = 3.26$, $p < .001$. Class 4 reported significantly worse chronic pain functioning than the average of classes 1 and 5, Roy's Largest Root = .062, $F(4, 165) = 2.57$, $p < .05$. Class 1 reported significantly worse chronic pain functioning than class 5, Roy's Largest Root = .263, $F(4, 64) = 4.21$, $p < .01$.

Univariate analyses examined the main effects on each dependent variable. The main effects were significant for BPI-Severity, $F(4, 285) = 8.99$, $p < .001$; PHQ-9, $F(4, 285) = 9.40$, $p < .001$; BPI-Interference, $F(4, 285) = 11.36$, $p < .001$; and PROMIS-PF-20, $F(4, 285) = 8.52$, $p < .001$. Post-hoc Tukey tests were examined among each dependent variable (see *Table 8*). Below is a summary of significant results.

Table 8. Tukey post-hoc tests examining pre-treatment chronic pain functioning between latent classes.

Dependent Variable	Latent Class (I)	Latent Class (J)	Mean Difference (I-J)	Std. Error	Sig.
BPI Severity	1	2	-0.63	0.30	0.24
		3	-1.61	0.30	0.00
		4	-0.66	0.27	0.11
		5	0.01	0.41	1.00
	2	3	-0.99	0.28	0.01
		4	-0.03	0.26	1.00
		5	0.64	0.39	0.49
	3	4	0.95	0.25	0.00
		5	1.63	0.39	0.00
	4	5	0.67	0.37	0.37
PHQ-9	1	2	-2.51	1.19	0.22
		3	-4.73	1.17	0.00
		4	0.26	1.06	1.00

		5	2.14	1.59	0.66
	2	3	-2.22	1.11	0.27
		4	2.77	1.00	0.05
		5	4.65	1.55	0.02
	3	4	4.99	0.98	0.00
		5	6.87	1.53	0.00
	4	5	1.88	1.46	0.70
BPI-Interference	1	2	-0.81	0.37	0.19
		3	-1.65	0.37	0.00
		4	-0.14	0.33	0.99
		5	1.07	0.50	0.20
	2	3	-0.84	0.35	0.11
		4	0.67	0.31	0.21
		5	1.88	0.48	0.00
	3	4	1.51	0.31	0.00
		5	2.72	0.48	0.00
	4	5	1.21	0.46	0.06
Physical Disability	1	2	0.76	2.33	1.00
		3	-5.50	2.30	0.12
		4	3.73	2.10	0.39
		5	9.34	3.13	0.03
	2	3	-6.26	2.19	0.04
		4	2.97	1.97	0.56
		5	8.57	3.05	0.04
	3	4	9.22	1.93	0.00
		5	14.83	3.02	0.00
	4	5	5.61	2.87	0.29

Pain Severity (BPI-Severity)

Class 3 reported significantly higher scores on BPI-Severity ($M = 7.44$, $SD = 1.47$) than Class 1 ($M = 5.82$, $SD = 1.43$), $p < .001$, Class 2 ($M = 6.45$, $SD = 1.45$), $p < .01$, Class 4 ($M = 6.48$, $SD = 1.66$), $p < .01$, and Class 5 ($M = 5.81$, $SD = 1.77$), $p < .001$.

Depression (PHQ-9)

Class 2 reported significantly higher scores on PHQ-9 ($M = 13.36$, $SD = 6.62$) than Class 4 ($M = 10.59$, $SD = 5.78$), $p < .05$, and Class 5 ($M = 8.71$, $SD = 5.39$), $p < .05$. Class 3 reported significantly higher scores on PHQ-9 ($M = 15.58$, $SD = 6.15$) than Class 1 ($M = 10.85$, $SD = 6.15$), $p < .01$, Class 4 ($M = 10.59$, $SD = 5.78$), $p < .001$, and Class 5 ($M = 8.71$, $SD = 5.39$), $p < .001$.

Pain Interference (BPI-Interference)

Class 2 reported significantly higher scores on BPI-Interference ($M = 6.95$, $SD = 1.69$) than class 5 ($M = 5.07$, $SD = 2.04$), $p < .01$. Class 3 reported significantly higher scores on BPI-Interference ($M = 7.79$, $SD = 1.64$) than class 1 ($M = 6.14$, $SD = 1.99$), $p < .001$, class 4 ($M = 6.28$, $SD = 2.08$), $p < .001$, and class 5 ($M = 5.07$, $SD = 2.04$), $p < .001$.

Physical Disability (PROMIS-PF-20)

Class 1 reported higher scores on PROMIS-PF-20 (greater physical disability) ($M = 60.52$, $SD = 9.55$) than class 5 ($M = 51.19$, $SD = 8.95$), $p < .05$. Class 2 reported higher scores on PROMIS-PF-20 ($M = 59.76$, $SD = 12.30$) than class 5 ($M = 51.19$, $SD = 8.95$), $p < .05$. Class 3 reported higher scores on PROMIS-PF-20 ($M =66.02$, $SD = 12.67$) than class 2 ($M = 60.52$, $SD = 9.55$), $p < .05$, class 4 ($M = 56.79$, $SD = 12.85$), $p < .001$, and class 5 ($M = 51.19$, $SD = 8.95$), $p < .001$.

Pain Catastrophizing

Due to the violation of assumption of heterogeneity in the MANOVA, disparity profile differences on PCS were explored through the non-parametric Mann-Whitney testing. Mann-Whitney tests require dichotomous independent variables and therefore latent classes were directly compared with each other (see *Table 9*). Bonferroni corrections were applied (adjusted alpha = .005). Class 1 reported lower PCS (M = 23.58, SD = 12.36) than Class 2 (M = 31.56, SD = 12.51), Mann-Whitney = 872.5, p < .005. Class 3 reported higher PCS (M = 40.08, SD = 9.02) than Class 1 (M = 23.58, SD = 12.36), Mann-Whitney = 436.5, Class 2 (M = 31.56, SD = 12.51), Mann-Whitney = 1079.0, Class 4 (M = 29.59, SD = 12.79), Mann-Whitney = 1628.5, and Class 5 (M =21.43, SD = 12.52), Mann-Whitney = 157.5, p's < .005. Class 5 reported lower PCS (M =21.43, SD = 12.52) than Class 2 (M = 31.56, SD = 12.51), Mann-Whitney = 340.0, p < .005.

Table 9. Mann-Whitney tests examining pre-treatment pain catastrophizing between latent classes.

Dependent Variable	Latent Class (I)	Latent Class (J)	Mean Difference (I-J)	Std. Error	Mann-Whitney	Sig.
Pain Catastrophizing	1	2	-0.60	0.18	872.5	0.001*
		3	-1.25	0.17	436.5	0.000*
		4	-0.46	0.16	1771.0	.008
		5	0.16	0.24	448.5	.469
	2	3	-0.65	0.17	1079.0	.000*
		4	0.15	0.15	2599.0	.311
		5	0.77	0.23	340.0	.004*
	3	4	0.79	0.15	1628.5	.000*
		5	1.41	0.23	157.5	.000*
	4	5	0.62	0.22	682.5	.010

* Indicates p-values that are significant with a Bonferroni correction.

Aim 3

Preliminary analyses examined potential treatment group differences on latent classes. A Chi-square analysis suggested no significant relationship between treatment group assignment and latent class, χ^2 (8) = 12.69, p = .12. A 2 (Randomized Treatment Group) x 2 (Latent Classes) Multivariate Analysis of Covariance (MANCOVA) examined post-treatment outcome variables. Treatment groups included CBT, EDU, and UC. Latent classes included the 5 identified chronic pain disparity profiles. Dependent variables included the following at post-treatment: BPI-Severity, BPI-Interference, PROMIS-PF-20, PHQ-9, and PCS. Covariates included the following at pre-treatment: BPI-Severity, BPI-Interference, PROMIS-PF-20, PHQ-9, and PCS. Correlations between dependent variables at post-treatment suggest moderate to high correlations (see *Table 10*). The assumption of homogeneity of covariance was not met, Box's M = 304.03, F(195, 9089.77) = 1.28, p <.01, suggesting that covariance matrices of the dependent variables were not equal across groups. The assumption of homogeneity of variance was met for all dependent variables (p's > .05), expect PCS, p < .05. Based on violations of assumptions, PCS was removed from analyses. After removing PCS, the test of homogeneity of covariance suggested a violation, Box's M = 191.21, F(130, 9599.78), p < .05. However, the assumption of homogeneity of variance was met; Levene's test was non-significant for each dependent variable (p's > .05). Given the difference observed in p-values between Box's M and the Levene's test, the relative consistency in standard deviations among latent classes and group treatment, the tendency for heterogeneity in the within-group covariance matrices to increase with the number of groups, and the established doubt of the validity of Box's M test (Tabachnick & Fidell, 2013), the study concluded that multivariate assumptions were met.

Table 10. Bivariate correlations among chronic pain related variables at post-treatment.

	1	2	3	4	5
1. PCS Post-treatment	-				
2. BPI-Interference Post-Treatment	.603**	-	-	-	-
3. PROMIS-PF-20	.480**	.590**	-	-	-
4. BPI-Severity Post-Treatment	.453**	.777**	.502**	-	-
5. PHQ-9 Post-Treatment	.710**	.604**	.545**	.513**	-

**. Correlation is significant at the 0.01 level (2-tailed).

The multivariate main effect of treatment was significant, Roy's largest root = .06, $F(4, 219) = 3.02$, $p < .05$. Main effect of latent classes was significant, Roy's largest root = .08, $F(4, 221) = 4.21$, $p < .01$. The interaction effect of treatment and latent classes was not significant, Roy's largest root = .06, $F(8, 221) = 1.65$, $p = .12$. Since this study is not interested in the main effect of treatment (see Thorn et al., 2018) for details on the main outcomes paper, only the main effect of latent classes was further explored. Follow-up univariate analyses suggested significant main effects for BPI-Severity, $F(4, 221) = 2.64$, $p < .05$, and PHQ-9, $F(4, 221) = 3.06$, $p < .05$. Post hoc analyses were conducted with Bonferonni correction (see *Tables 8* and *9)*. Class 3 reported significantly higher post-treatment BPI-Severity scores ($M = 6.47$, $SD = .25$) than Class 1 ($M = 5.34$, $SD = .26$), $p < .05$. Class 3 reported significantly higher post-treatment PHQ-9 scores ($M = 11.80$, $SD = .72$) than Class 4 ($M = 8.64$, $SD = .57$), $p < .01$. Descriptive statistics of post-treatment outcomes are provided in *Table 11*.

Table 11. Descriptives of post-treatment outcome variables by latent classes and treatment group. Means are adjusted by pre-treatment variables entered as covariates.					
Dependent Variable	Latent Class	Treatment	Mean	Std. Deviation	N
BPI Severity	1	UC	5.69	1.57	17
		CBT	5.12	1.75	13
		EDU	4.19	2.15	12
		Total	5.08	1.87	42
	2	UC	6.45	1.74	20
		CBT	5.88	2.23	8
		EDU	4.92	2.14	16
		Total	5.79	2.06	44
	3	UC	7.25	1.53	15
		CBT	7.03	2.21	18
		EDU	7.26	1.07	20
		Total	7.18	1.63	53
	4	UC	6.10	1.64	20
		CBT	4.81	2.20	39
		EDU	5.60	1.80	25
		Total	5.35	2.02	84
	5	UC	4.33	2.31	6
		CBT	4.19	2.31	4
		EDU	5.71	1.95	7
		Total	4.87	2.15	17
	Total	UC	6.19	1.81	78
		CBT	5.42	2.29	82
		EDU	5.68	2.04	80
		Total	5.75	2.07	240
PHQ-9	1	UC	9.76	5.23	17
		CBT	10.62	5.52	13
		EDU	9.75	7.24	12
		Total	10.02	5.81	42

	2	UC	13.85	6.18	20
		CBT	9.50	6.12	8
		EDU	8.13	3.79	16
		Total	10.98	5.94	44
	3	UC	15.67	7.12	15
		CBT	12.11	6.62	18
		EDU	14.10	7.07	20
		Total	13.87	6.95	53
	4	UC	7.95	5.05	20
		CBT	7.49	4.80	39
		EDU	7.24	3.95	25
		Total	7.52	4.58	84
	5	UC	9.00	7.07	6
		CBT	5.50	6.45	4
		EDU	8.14	6.49	7
		Total	7.82	6.42	17
	Total	UC	11.42	6.56	78
		CBT	9.10	5.79	82
		EDU	9.59	6.12	80
		Total	10.02	6.22	240
PCS	1	UC	19.29	11.69	17
		CBT	19.08	7.53	13
		EDU	16.67	13.55	12
		Total	18.48	10.98	42
	2	UC	34.35	12.40	20
		CBT	16.50	12.55	8
		EDU	19.88	11.42	16
		Total	25.84	14.22	44
	3	UC	36.27	11.23	15
		CBT	31.22	13.87	18
		EDU	35.60	14.99	20
		Total	34.30	13.57	53

	4	UC	22.00	13.65	20
		CBT	20.44	11.63	39
		EDU	20.68	10.97	25
		Total	20.88	11.82	84
	5	UC	15.50	14.54	6
		CBT	13.75	11.93	4
		EDU	18.14	12.17	7
		Total	16.18	12.31	17
	Total	UC	26.82	14.48	78
		CBT	21.88	12.61	82
		EDU	23.43	14.28	80
		Total	24.00	13.90	240
BPI-Interference	1	UC	5.75	2.60	17
		CBT	4.92	1.86	13
		EDU	4.26	2.67	12
		Total	5.07	2.44	42
	2	UC	6.98	1.84	20
		CBT	4.36	2.74	8
		EDU	4.84	2.55	16
		Total	5.72	2.52	44
	3	UC	6.90	2.26	15
		CBT	6.79	2.20	18
		EDU	7.20	2.01	20
		Total	6.98	2.11	53
	4	UC	5.68	2.55	20
		CBT	4.52	2.90	39
		EDU	5.14	1.88	25
		Total	4.98	2.57	84
	5	UC	3.69	3.27	6
		CBT	2.68	2.38	4
		EDU	5.16	2.60	7
		Total	4.06	2.83	17

	Total	UC	6.11	2.52	78
		CBT	4.98	2.73	82
		EDU	5.46	2.43	80
		Total	5.51	2.59	240
PROMIS-PF-20	1	UC	57.82	9.80	17
		CBT	58.15	7.85	13
		EDU	58.75	9.95	12
		Total	58.19	9.07	42
	2	UC	60.30	16.88	20
		CBT	60.25	13.12	8
		EDU	47.81	14.10	16
		Total	55.75	16.13	44
	3	UC	66.13	15.07	15
		CBT	62.39	15.93	18
		EDU	62.40	12.04	20
		Total	63.45	14.14	53
	4	UC	50.55	10.82	20
		CBT	54.69	13.69	39
		EDU	53.16	12.93	25
		Total	53.25	12.79	84
	5	UC	46.00	17.67	6
		CBT	44.75	16.68	4
		EDU	54.00	13.87	7
		Total	49.00	15.52	17
	Total	UC	57.28	14.84	78
		CBT	56.99	13.90	82
		EDU	55.31	13.39	80
		Total	56.53	14.02	240

The lack of significant interaction effects in the MANCOVA may be a result of the limitations of sample size with high number of groups (multiple conditions had less than 10 participants; see *Table 8*), high correlations among dependent variables, and likely non-normal distributions of data. Therefore, this study conducted additional analyses using Bootstrapping through Hayes' PROCESS macro in SPSS Version 25.0 with 5000 bootstrapped samples (IBM SPSS; Preacher & Hayes, 2008). Bootstrapping is a nonparametric resampling procedure without assumptions of multivariate normality. In order to limit the number of analyses, dependent variables were limited to the primary (BPI-Severity) and secondary (BPI-Interference and PHQ-9) outcome variables at post-treatment (Thorn et al., 2018). Pre-treatment scores were controlled as covariates. Independent variables were examined as CBT versus EDU, CBT versus UC, and EDU versus UC.

Results suggested that the disparity profiles significantly moderated the relationship between treatment groups and BPI-Severity post-treatment, $F(1, 157) = 5.75$, $p < .05$ (see *Table 12* for all results). Within the MD group (latent class 4), participants in the CBT group reported lower BPI-Severity scores than participants in the EDU group, $B = -.75$, $SE = .36$, $p < .05$. Within the LD group (latent class 5), participants in the CBT group reported lower BPI-Severity scores than participants in the EDU group, $B = -1.31$, $SE = .54$, $p < .05$ (see *Table 13* and *Figure 6*). However, due to the small N in each cell for class 5 (CBT had 4 participants and EDU had 7 participants), results are considered uninterpretable. A one-way ANOVA was conducted to examine BPI-Severity mean differences within each treatment group across latent classes (see *Figure 7*). Within CBT treatment group, the one-way ANOVA was significant, $F(4, 76) = 2.72$, $p < .05$, suggesting differences across latent classes in pain severity. Post hoc analyses were conducted with Bonferroni corrections (*Table 14*). Class 3 reported significantly higher BPI-Severity ($M = 6.43$, $SD = .43$) than Class 4 at post-CBT treatment ($M = 4.87$, $SD = .28$), $p < .05$. Within EDU treatment group, the one-way ANOVA was significant, $F(4, 74) = 3.29$, $p < .05$.

Class 3 reported significantly higher BPI-Severity (*M* = 6.80, *SD* = .40) than Class 1 at post-EDU treatment (*M* = 4.55, *SD* = .50), $p < .05$. Latent classes did not significantly moderate the relationship between treatment groups and BPI-Interference or PHQ-9.

Table 12. Bootstrap analyses examining the interaction between treatment group and latent classes on treatment outcome variables.

Independent Variable	Moderator	Dependent Variable	Interaction *F*(df, df)	p-value
CBT vs EDU	Latent Classes	BPI-Severity	$F(1, 157) = 5.75$	< .05
CBT vs UC	Latent Classes	BPI-Severity	$F(1, 155) = 1.60$	0.21
EDU vs UC	Latent Classes	BPI-Severity	$F(1, 153) = 2.21$	0.14
CBT vs EDU	Latent Classes	BPI-Interference	$F(1, 158) = 2.56$	0.11
CBT vs UC	Latent Classes	BPI-Interference	$F(1, 156) = .30$	0.58
EDU vs UC	Latent Classes	BPI-Interference	$F(1, 153) = 1.44$	0.23
CBT vs EDU	Latent Classes	PROMIS PF-20	$F(1, 158) = 2.82$	0.1
CBT vs UC	Latent Classes	PROMIS PF-20	$F(1, 156) = .79$	0.38
EDU vs UC	Latent Classes	PROMIS PF-20	$F(1, 153) = .78$	0.38
CBT vs EDU	Latent Classes	PHQ-9	$F(1, 158) = 2.82$	0.1
CBT vs UC	Latent Classes	PHQ-9	$F(1, 156) = 1.04$	0.31
EDU vs UC	Latent Classes	PHQ-9	$F(1, 153) = .58$	0.45
CBT vs EDU	Latent Classes	PCS	$F(1, 158) = 2.15$	0.14
CBT vs UC	Latent Classes	PCS	$F(1, 156) = .60$	0.44
EDU vs UC	Latent Classes	PCS	$F(1, 153) = .69$	0.41

Table 13. Follow-up analyses on the significant interaction between latent classes and CBT vs. EDU on BPI-Severity at post-treatment.

Latent Class	Effect	SE	95% CI	p-value
1	0.95	0.57	-.16 to 2.07	0.09
2	0.39	0.38	-.36 to 1.13	0.31
3	-.18	0.28	-.74 to .38	0.52
4	-.75	0.36	-1.45 to -.04	0.04
5	-1.31	0.54	-2.37 to -.26	0.02

Figure 6. Significant moderation of latent classes and psychosocial interventions (EDU vs. CBT) on BPI-Severity at post-treatment. Analysis controls for pre-treatment BPI-Severity. Moderation is significant for disparity profiles 4 and 5, in which CBT demonstrates lower pain severity than EDU.

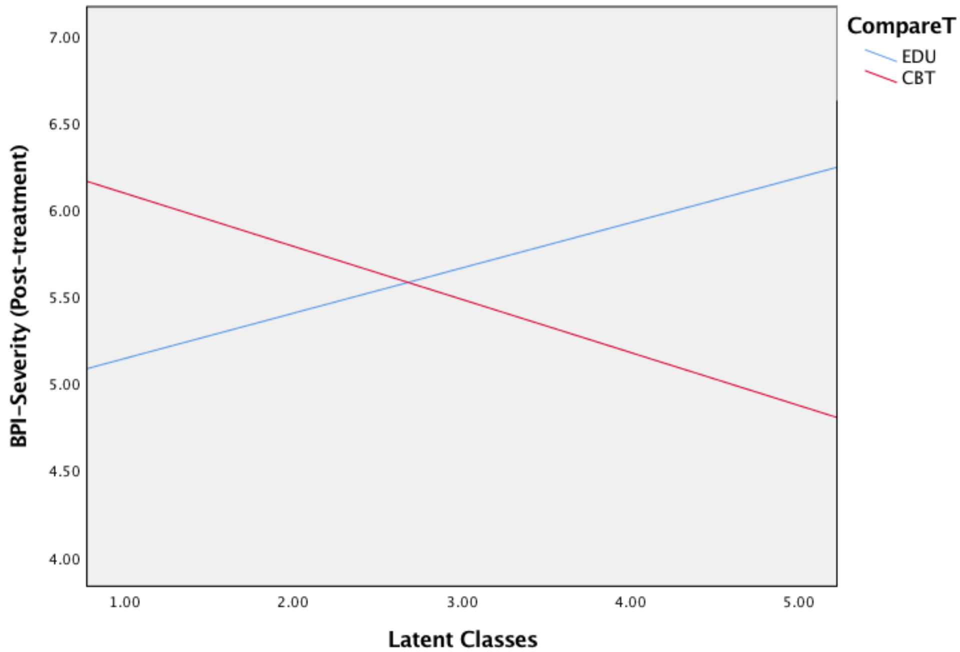


Figure 7. Simple effects testing for BPI-Severity at post-treatment. Estimated means from covariates are provided above graph bar lines.

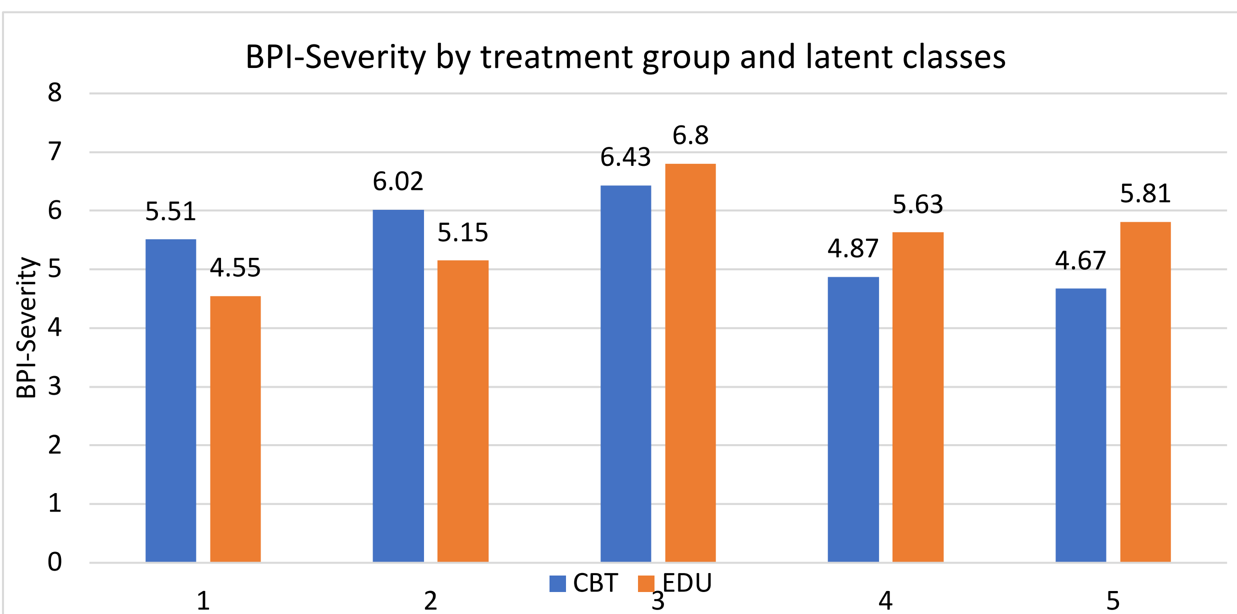


Table 14. Bonferonni corrected post hoc tests examining post-treatment outcomes variables between latent classes.

Dependent Variable	Latent Class (I)	Latent Class (J)	Mean Difference (I-J)	Std. Error	Sig.[b]
T3 BPI Severity composite (mean: 0-10)	1	2	-0.44	0.38	1.00
		3	-1.135*	0.37	0.02
		4	-0.33	0.33	1.00
		5	-0.20	0.50	1.00
	2	3	-0.70	0.36	0.55
		4	0.11	0.34	1.00
		5	0.24	0.51	1.00
	3	4	0.81	0.32	0.13
		5	0.94	0.51	0.69
	4	5	0.13	0.46	1.00
T3 PHQ-9 Total Score (0-27)	1	2	0.62	1.10	1.00
		3	-1.11	1.08	1.00
		4	2.06	0.96	0.33
		5	1.02	1.46	1.00
	2	3	-1.72	1.06	1.00
		4	1.45	0.98	1.00
		5	0.40	1.49	1.00
	3	4	3.168*	0.94	0.01
		5	2.12	1.50	1.00
	4	5	-1.05	1.34	1.00
Based on estimated marginal means					
*. The mean difference is significant at the					
b. Adjustment for multiple comparisons: Bonferroni.					

4. DISCUSSION

An intersectional approach provided unique information about chronic pain disparities. Although individual factors of disparities have been explored in research, there is limited information on the intersection of multiple identities of disparity and differential outcomes in chronic pain. To the author's knowledge, this is the first research study to examine chronic pain disparity profiles with LCA. Although the heterogeneity of treatment effects analyses (Aim 3) were largely non-significant, most likely due to being underpowered, results suggest some areas for specializing and adapting psychosocial treatments for specific subgroups.

The latent class analysis (LCA) was successful in establishing chronic pain disparity subgroups. Results suggested statistical and substantive support for a 5-class model. Other studies using LCA within intersectionality have also found a high number of classes (Goodwin et al., 2017; Laska, Pasch, Lust, Story, & Ehlinger, 2009; Leigh, Hudson, & Byles, 2015; van Lang, Ferdinand, Ormel, & Verhulst, 2006; Yu, Mahendran, Abdullah, Kua, & Feng, 2017). The 5-class model fits with prior work demonstrating the importance of sociodemographic traits in the experience of chronic pain and highlights the complexities of the interactions between these social identities. Results provide support for the utility of a sophisticated statistical approach in understanding complex relationships between multiple aspects of identity. The following sections discuss an analysis of indicators from the LCA, an analysis of each disparity profile, major themes, heterogeneity of treatment results, and an overall summary.

Analysis of indicators

This study provides information on the complex ways in which the intersections of sex, age, race/ethnicity, and SES influence health and chronic pain. An examination of the quality of indicators through conditional response probabilities (CRPs) provides information about the factors that best define disparity profiles. Overall, SES factors strongly predicted class membership. Employment status, disability status, and literacy tended to be high quality indicators. Given the research suggesting that SES is among the most robust determinants in health outcomes in the health experience (Hayward, Miles, Crimmins, & Yang, 2000; World Health Commision, 2008), it is not surprising that multiple indicators of SES were important for class membership. Employment and disability status directly impact insurance and access to health care services, and literacy has been shown to be a highly important factor in treatment outcomes (Baker et al., 2002; Briggs et al., 2010). Although age was dichotomized by a median split, it proved to be a high-quality indicator. Race was an important indicator for two classes (SD group and MD group; classes 3 and 4) and sex was important for two classes (MD-OA and LD; class 1 and 5). Given that the majority of the sample was Black/African-American and female, it is surprising that race and sex were not consistently high-quality indicators. This finding may be attributed to the multiple indicators of SES that help account for homogeneity within each latent class and differentiate between latent classes. In sum, N (Williams, Priest, & Anderson, 2016).

Disparity Profiles and Chronic Pain

Results suggest meaningful patterns of chronic pain functioning by disparity profiles. The intersectional approach provides a holistic picture of the advantages and disadvantages associated with the sociodemographic traits of each subgroup that contribute to the experience of chronic pain. With a more accurate image of disparities, treatments can be tailored to better meet the unique needs of subgroups with similar social identities, potentially reducing the gap in health inequalities.

The SD group (class 3) was distinguished as Black/African-American and low-SES (below poverty status, not employed, seeking disability, and low literacy/education levels). The SD group reported the lowest pre-treatment chronic pain functioning (highest pain severity, pain interference, disability, depression, and pain catastrophizing). This subgroup of individuals with chronic pain present with substantial barriers to obtaining adequate health care services. The combination of SES factors portrays a picture of individuals severely financially limited and without access to health care services (i.e., not receiving care through disability status or employment). Even when health care services are provided, transportation difficulties, higher stress levels, and the increased cognitive demands associated with lower literacy levels and chronic pain itself, potentially diminish biomedical treatment outcomes. The intersection of these SES factors with race, then increase the obstacles to obtaining adequate treatment. Factors such as racial discrimination in medicinal treatment, experiences of invalidation, oppression, and racism contribute to these chronic pain disparities. The SD group highlights the worsened health outcomes associated with multiple disparities.

The MD group (class 4) was best described as older Black/African-American individuals with low-SES (on disability, not employed, and literacy/education below High School levels). With the intersection between age, race, and SES, this subgroup presents with some unique disadvantages and advantages. Similar to SD group, the MD group also exhibits multiple factors of low-SES that are associated with higher stress and present obstacles to obtaining adequate health care services. However, the MD group has better access to health care through being on disability, as well as a greater likelihood of having basic needs met, such as food, housing, and clothing. Providing low-income individuals with access to healthcare services through Medicaid and providing people with even minimal financial aid to provide for basic needs, may help to mitigate the harmful effects of chronic pain. In sum, the MD group demonstrates the unique facets of SES and the complex intersections of various identities that present advantages and disadvantages.

The MD-OA group (class 1) was best described by being older, female, with literacy levels at or above the 9^{th} grade, with a Highschool degree/GED or higher, and either on disability or seeking disability status. In contrast to the MD-YA group (class 2), the MD-OA group is an average of about 14 years older, is less impoverished, and has slightly higher literacy/educational levels. The MD-OA group was distinguished by significantly lower levels of pain catastrophizing than the MD-YA group. There was a non-significant trend for lower pain severity, depression, and pain interference in the MD-OA group than the MD-YA group. The results add to the general theme of age being an essential contributor to chronic pain. Age is further discussed in greater depth later in this discussion.

Overall, the MD-OA performed most similarly to the MD group. Given that the MD group is characterized by racial and literacy disparities, and the MD-OA is characterized by sex disparities, one might predict that the MD group would report higher levels of chronic pain. An explanatory piece of the similar chronic pain functioning between the MD-OA and MD groups may be accounted for by age, in which the advantages of having chronic pain as an older adult reduces some of the negative effects of chronic pain (to be explored later in this document). In addition, although the MD group includes racial disparities, the access to care through disability (most likely Medicare), potentially provides enough advantage through health care access to result in similar chronic pain functioning to the MD-OA group. Alternatively, a resilience perspective may suggest that the combination of disparities in both groups with older age may result in greater ability to cope, adapt, obtain resources, and endure suffering. Overall, the similar levels of pain functioning suggest that SES and age may be more robust than sex and race as determinants of chronic pain.

The MD-YA group (class 2) was characterized by being below poverty status, not employed, high literacy levels, and young-middle age. An individual in this group has a high likelihood of either being on disability status or seeking disability status. Although the MD-YA group reported similar levels of pain severity, pain interference, and disability to the other moderate disparity groups, the MD-YA exhibited poorer psychological functioning. Depressive symptoms were in the moderate-severe range and pain catastrophizing was clinically significant. Similar to the SD group, the MD-YA class exhibits substantial financial difficulties and obstacles in obtaining access to health care services. However, the MD-YA group benefits from higher literacy levels than the SD group, suggesting greater potential for better health outcomes, as well as potentially more employment opportunities. The discrepancy between younger age and higher literacy with lack of employment and poverty may create an environment of stigma and shame. The poorer psychological functioning in this younger disparity group highlights the potential impact of age in the experience of chronic pain, which is later explored in this discussion.

The smallest class, the LD group (class 5), is interpreted with caution due to the small group size. A very distinct class due to all group members being women and employed, the class has the highest levels of SES advantage in contrast to the other disparity profiles. Overall, the LD group demonstrated the best chronic pain functioning in contrast to all other groups. Since all individuals in this class are employed, it would be expected that chronic pain functioning would be higher than other classes. Nevertheless, pain severity and pain interference are within moderate levels, suggesting that this group must have protective factors to help manage pain. One of the protective factors might be working itself through higher levels of physical movement, increased social interactions, the potential for health insurance, and increased financial security. It may be the case that being female is also a factor of resilience. Women in this group are working even with substantial levels of chronic pain, suggesting that sex may also be associated with potential factors of resilience in this sample. In sum, the distinctly higher SES status of this subgroup highlights the major influence of SES in the experience of chronic pain.

The complexity of SES

The interaction between various aspects of SES support the complexity of the construct of SES. Often, SES is measured as one variable, such as income. When accounting for various factors of SES, research captures a more accurate picture of SES. For example, among the classes with strong indicators of low-SES (classes 1-4; moderate and severe levels of disparity groups), there were differences among levels of literacy and education, disability status, and poverty status. There was a consistent pattern of individuals not being employed in classes 1-4, and yet each class told a different story. The MD-OA (class 1) and MD-YA (class 2) groups had higher literacy levels than the MD (class 4) and SD (class 3) groups, potentially providing greater resources in processing and implementing health related information. The MD-YA and SD groups were distinguished by being below poverty status, adding severe financial barriers to health care. The MD group was unique because there was a high likelihood for a class member being on disability, thereby providing greater access to resources. Therefore, the various facets of SES are important to examine and contribute to health functioning in intricate manners.

Age

Given that the median age of study participants was 51 years old, and that the younger and older age groups continued to center around middle age, it is interesting that this study implied age as an important factor in the chronic pain experience. Middle age is typically associated with juggling responsibilities (e.g., caregiving, finances, home maintenance, health of self and others...), as well as "peak times" of positions at work or within social relationships (e.g., family or community) (Lachman, Teshale, & Agrigoroaei, 2015). Within this study, stressors of midlife are compounded by various factors of low-SES, inequalities in treatments for chronic pain, and various levels of oppression. Therefore, middle age may be an especially stressful period for individuals in this sample. This study emphasizes the potential protective factors of older-middle age and the potential risk factors associated with younger-middle age within a low-resourced context.

In comparison to older adults, a developmental time period in which chronic pain is more prevalent, expected, and normalized, younger adults may experience a discrepancy between personal experiences and developmental norms (Boggero et al., 2015). Chronic pain poses the risk of interference with ability to work, engage in physical activities, and socialize with others. As seen in the MD-YA group, younger adults reported high levels of unemployment and poverty status, suggesting that individuals are not approaching or meeting the societal expectations for career or social advancements. Younger-middle age adults may feel frustration and shame for not meeting these societal norms, and may also be in a state of worry about future decline in functioning (Kapoor, 2015).

Younger-middle age adults with chronic pain may also have a loss of sense of control during a less typical developmental period. Aging is associated with natural physical and cognitive changes, decreasing sense of control and contributing to stress (Dickerson & Kemeny, 2004). However, when sense of control decreases due to chronic pain, during a less normative developmental period, younger adults may be left with low sense of self-efficacy in managing pain and motivation for social and physical activities (Lachman et al., 2015). This sense of helplessness and loss of control may contribute to overall poorer functioning within this age group.

The socioemotional selectivity theory has been applied to understand the strengths of aging. As individuals age, there is a tendency to attend to and remember positive over negative information, also known as the *positivity effect* (Kennedy, Mather, & Carstensen, 2004; Mather, 2016). Older age is associated with higher levels of optimism (Lachman, Röcke, Rosnick, & Ryff, 2008), potentially increasing motivation to facilitate change in lifestyle. The socioemotional selectivity theory implies that older adults prioritize present-oriented goals and younger adults prioritize future-oriented goals (Carstensen, 1995, 2006). The higher catastrophizing in younger adults supports the theory of attending to future functioning with chronic pain. In contrast, older adults may focus more on meaningful activities and social relationships. Individuals in the MD and MD-OA groups have significant levels of chronic pain, but may be more successful in engaging in meaningful activities, thereby increasing quality of life. Due to the advantages associated with older age, it may be the case that older-middle age is the ideal time period for interventions.

Disparities and Health

The study provides information on how multiple social determinants influence health. Consistent with research suggesting a risk perspective or double jeopardy theory, this study demonstrates that latent classes with higher levels of disparity reported worsened chronic pain functioning. The SD group demonstrated the lowest chronic pain functioning. It may be the case that the intersection of race (Black/African-American) and various factors of low-SES resulted in a complex additive effects of patient factors, patient-provider factors, and environmental factors. The MD groups (classes 1, 2, and 4) overall had similar levels of chronic pain that fell between the SD and LD groups, providing evidence that greater factors of disparity result in worse health outcomes. However, there was some variability within the moderate groups that highlights nuanced differences between subgroups of disparity profiles.

Resilience was potentially identified through older age, as seen by the higher functioning of the MD and MD-OA groups. It may also be the case that being female was associated with resilience, as seen by MD-OA group and the LD group. Although women with chronic pain tend to have more pain conditions and comorbidities (Bartley & Fillingim, 2013; Fillingim et al., 2009), multiple studies have identified resiliency in managing chronic health issues among Black/African-American women, as a result of surviving multiple adversities, creating strong social networks, and developing adaptive strategies (Dale & Safren, 2018; DeNisco, 2011; Holden, Bradford, Hall, & Belton, 2013). The study provides support for the worsened health outcomes with multiple disparities and also sheds light on resilience with aging and potentially with gender.

Heterogeneity of Treatment Effects (HTE)

Analyses provide important insights into the complexities of intersectionality in HTE and some information for targeting health interventions among individuals with multiple disparities. Given the widely established disparities in chronic pain, it is essential that research examines the intersection of disparity factors so that evidence-based treatments can be tailored to subgroups of individuals. This study examined HTE for CBT, EDU, and UC for chronic pain. The multivariate analyses revealed no significant moderation of latent classes between treatment and outcome variables. The multivariate analyses may have been non-significant due to the high number of factors with small numbers of participants in each cell. Univariate tests conducted through bootstrap analyses suggested one significant moderation between psychosocial treatments (CBT vs. EDU) and pain severity. Although the significant moderation may be due to chance given the number of other analyses conducted with non-significant results, analyses were overall largely underpowered. Therefore, the significant moderation found through bootstrap is interpreted with caution.

Participants in the MD group reported lower post-treatment pain severity within CBT than EDU. Results suggested that individuals who are Black/African-American, mid-older adults (above 50 years old), with low-SES and lower levels of literacy and education, benefited more from CBT than EDU for chronic pain treatment. The specific interaction of social identities related to race, age, and SES, may create an environment in which patients benefit more from CBT specific skills. Within the MD group, patients potentially exhibit higher coping skills and emotion regulation, and greater normalization of chronic pain as a function of older age. These psychological advantages, along with greater access to health care services through Medicaid or Medicare, may provide patients with the greater ability to learn and implement additional coping skills for pain management. The more directive and structured CBT intervention that provides concrete skills may have better met the need of individuals with lower literacy and education levels. The resiliency of the MD group may also have provided individuals with an ideal time period for creating change. With the greater psychological functioning associated with older age, access to resources through disability, and racial inequalities, individuals in this group have a longer history of overcoming substantial obstacles related to SES and race. A resilience perspective suggests that this subgroup may have greater capacity than other subgroups for application of psychosocial skills. Given that low literacy often results in exclusion from research studies, and often from CBT interventions, it is noteworthy that this subgroup proved to benefit more from literacy adapted-CBT.

There was a lack of additional moderation of chronic pain disparities in treatment outcome. When examining the treatment outcome means, it is clear that there is heterogeneity among disparity groups by treatment. However, the high number of factors (5 latent classes with treatment groups) resulted in conditions with small number of participants, substantially limiting power. This dissertation brings up a major difficulty in examining HTE within a lens of intersectionality. With multiple conditions dividing the number of participants, it is necessary to have a sample size that can meet power requirements. Since the researcher cannot predict the best fitting model with *k* groups, it is impossible to conduct moderation power analyses *apriori*. This presents a problem in future randomized controlled trials planning to examine HTE with intersectionality and LCA.

Consistent with pre-treatment chronic pain, the SD group exhibited the highest levels of post-treatment chronic pain. Visual and statistical examination of the post-treatment means suggest clinically similar levels of pain across treatment groups among the SD group. This study highlights a group of individuals with multiple forms of disparity who did not respond well to the psychosocial treatments. With severely low-SES, patients likely struggle with obtaining basic necessities, such as food, clothing, and housing. Consistent with Maslow's hierarchy of needs, when physiological and safety levels are not met, targeting physical and psychological aspects of health are substantially more difficult (Maslow, 1943). The lack of improvement within the SD group suggests systemic problems with the current health care system that neglects individuals with multiple disparities, and especially severely low-SES.

Although not statistically significant, a visual examination of post-treatment functioning among the MD-YA group suggests heterogeneity among outcome means across treatment groups. For example, there was substantial variability among all outcome variables for the MD-YA group (e.g., post-treatment depressive scores were 13.85 for UC, 9.50 for CBT, and 8.13 for EDU). Potentially significant results may have been obscured by small cell sizes. A visual examination of post-treatment means suggests less heterogeneity among outcome means within the MD-OA profile. It is unclear if non-significant results reflect actual lack of differential treatment responses, or if the results are due to small cell sizes. Therefore, further research is needed to better understand treatment differences among individuals in the MD-YA and MD-OA group.

Collapsing across treatment groups, there is overall decreased variability in post-treatment chronic pain functioning by disparity profiles. Results are in part influenced by differences in more conservative post hoc alpha corrections than pre-treatment analyses (due to post hoc limitations in SPSS when covariates are included), as well as reduced total sample size at post-treatment. The decreased variation among post-treatment outcomes may also suggest that interventions reduced some of the influence of disparities on health outcomes. Although one might expect to see consistent levels of pain functioning among the UC group, usual care involved medical treatment as well as chronic pain assessments as part of the LAMP trial. It may be the case that the assessments themselves offered a time period for patients to tell their stories, feel heard, and decrease feelings of invalidation, all potentially decreasing some of the negative health effects associated with disparities. The decreased variability among post-treatment chronic pain functioning by disparity groups may suggest the importance of integrated and interdisciplinary care in reducing health disparities.

In order to examine the utility of an intersectional approach using LCA, study results were compared to the independent HTE results reported in Van Dyke et al. (in press). The Van Dyke et al. (in press) study examined independent socio-demographic factors as moderators of pain severity, pain interference, and depression (primary and secondary outcome variables in the LAMP trial). Independent analyses found that patients with less education or literacy levels benefited more from CBT than EDU. The intersectional approach also supported the finding that individuals with lower education and literacy benefited more from CBT than EDU, as seen by the MD group. However, the lack of significant results for the SD group, a group with low literacy levels, highlights nuanced information about the intersection between race, SES, and age. Based on the intersectional approach, an individual with low literacy, racial/ethnic minority status, and severely low-SES may need additional resources for pain management beyond group-based psychosocial interventions (e.g., greater access to health care, social services, disability), whereas, an individual with low literacy, racial/ethnic minority status, older age, and more stable low-SES may benefit more from CBT than EDU.

In addition, the independent results did not find significant moderations for sex or race/ethnicity (Van Dyke et al., in press). The lack of moderations may be a limitation of univariate analyses that fail to examine the interaction of sex, race/ethnicity, with other social identity factors. For example, this study found that the intersection of low-SES and race jointly influences the chronic pain experience, as seen by the worsened chronic pain functioning in the SD group. The influence of sex on chronic pain functioning was less clear in this study. Overall, results did not suggest that women had worsened chronic pain functioning than men, as seen by the LD group exhibiting the lowest levels of chronic pain (highest chronic pain functioning). However, the intersectional approach leaves some uncertainty of the role of sex in the chronic pain experience. This uncertainty emphasizes the helpful aspects of independent analyses in understanding the unique contributions of each variable to an outcome, while intersectional approaches are more interested in the combination of factors, in which the whole is greater than sum of its parts. The significant moderation of disparity profiles with treatment for pain severity underscore the potential for intersectional analyses to unveil the complexities of social identities that influence health and interventions.

Similar to Van Dyke et al. (in press), this study also found a lack of significant moderation between treatment and depression and lack of significant results when examining CBT and UC and EDU and UC. As pointed out by Van Dyke et al. (in press), other psychosocial factors may better account for heterogeneity of treatment effects in depression (i.e., self-efficacy, pain catastrophizing, etc...). The lack of significant moderation between treatments groups and usual care is intriguing and may be attributed to the main effects of psychosocial interventions independent of disparity profiles.

Limitations

Limitations of the study include limited generalizability beyond low-income federally qualified clinics in Alabama. The LAMP study includes a multiply disparaged population that has been severely under resourced and understudied. Therefore, results on disparity profiles may not translate to less disadvantaged populations. In addition, the study includes a combination of study participants living in rural and suburban settings. Rurality is an important factor in health disparities. However, this study was limited in measuring rurality and therefore was not included in analyses. The main limitation of the HTE analyses included sample size. The combination of five disparity profiles with three treatment groups rendered cell sizes with less than 10 or 20 subjects. The multiple non-significant moderations with the low power suggest the need for future research that collaborates across multiple medical sites.

Summary/Implications

When considering interventions for individuals with chronic pain, it is essential to consider the intersection of social identities and environmental contexts that influence health and treatment outcomes. This study demonstrates that within low-resource neighborhoods, patients present with varying levels of socioeconomic status, such as literacy, employment, disability status, and access to health care. In addition to the various SES indicators, the interactions with race, sex, and age are meaningful in the experience of chronic pain. With increasing number of identities related to disparities, there is an overall greater likelihood of receiving inadequate health care and multiple barriers to access (Jha, Orav, & Epstein, 2011; Schoen, Osborn, Squires, & Doty, 2013). Within an overall low-SES environment, additional factors of oppression and discrimination tend to worsen health outcomes. Although the study provides overall support for the negative effects of multiple disparities, study results also emphasize the protective aspects of older age in the psychological functioning of chronic pain.

HTE results suggested that the specific needs of individuals in the MD group were best met through CBT versus EDU. Patients presenting with the intersection of low literacy and education, disability, older age, and racial/ethnic minority status may benefit more from group-based CBT more so than education groups. The health effects associated with low literacy/education and racial/ethnic minority status were potentially mitigated by access to care through disability status (i.e., Medicare), and older age. In comparison to the SD group, results highlight the nuances of two low-SES subgroups characterized by being Black/African-American and with low literacy and education levels with substantially different pre- and post-treatment chronic pain experiences. The novel differences emphasize the importance of the examination of multiple factors related to disparities that contribute to health.

There has been an increasing demand for integrating intersectionality into culturally adapted evidenced-based treatments (American Psychological Association, 2017). Research examining intersectionality overall focuses on individual treatment (Kivlighan et al., 2019; Smith & Trimble, 2016). Integrating an intersectional approach to group-based interventions has been less discussed. Based on the findings from this study, there is some evidence that groups with similar patterns in social identity factors would benefit from treatment specifically adapted to needs related to disparities. For example, the MD group benefits most from group-based literacy-adapted CBT versus EDU. It could be hypothesized that the SD group needs social services to help with the severe low-SES prior to starting psychosocial treatments and that the MD-YA group would benefit from interventions focusing on emotional and cognitive aspects of pain treatment. The MD-YA group may benefit from a focus on acceptance of pain and ways to manage pain catastrophizing. Given that older age presents with unique advantages, it is interesting that there is a gap in the literature on the benefits or disadvantages of having groups with participants of mixed ages. It may be the case that younger adults can learn from older adults. It may also be the case that the future-directed versus present-directed orientations of younger versus older adults would provide for an invalidating environment. Future group-based interventions would benefit from the examination of outcome differences between mixed-age versus age-specific groups.

Future research should examine group-based interventions that are adapted with an intersectional approach. The difficulties associated with HTE with an intersectional approach emphasize the need for large sample sizes, likely from the combination of data from multiple studies. Although this study is unique and provides important information about various facets of SES within a low-resourced population, future research examining intersectionality with greater variability in SES would provide a wider breadth of information. Beyond SES, race, and sex, factors of immigration status, religion, English-speaking status, and sexual orientation would be beneficial for future latent class analysis replication.

REFERENCES

Akaike, H. (1974) A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*(6), 716-723.

Andersson, H. I., Ejlertsson, G., Leden, I., & Scherstén, B. (1999). Impact of chronic pain on health care seeking, self care, and medication. Results from a population-based Swedish study. *Journal of Epidemiology and Community Health*, *53*(8), 503–9. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10562870

Andruff, H., Carraro, N., Thompson, A., Gaudreau, P., & Louvet, B. (2009). Latent class growth modelling: a tutorial. *Tutorials in Quantitative Methods for Psychology*, *5*(1), 11–24.

Anyikwa, V. A. (2015). The Intersections of Race and Gender in Help-Seeking Strategies Among a Battered Sample of Low-Income African American Women. *Journal of Human Behavior in the Social Environment*, *25*(8), 948–959. https://doi.org/10.1080/10911359.2015.1047075

Association, A. P. (2017). Multicultural Guidelines: An Ecological Approach to Context, Identity, and Intersectionality. Retrieved October 3, 2019, from http://www.apa.org/about/policy/multicultural-guidelines.pdf

Baker, D. W., Gazmararian, J. A., Williams, M. V, Scott, T., Parker, R. M., Green, D., … Peel, J. (2002). Functional health literacy and the risk of hospital admission among Medicare managed care enrollees. *American Journal of Public Health*, *92*(8), 1278–83. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12144984

Bartlett, S. J., Orbai, A.-M., Duncan, T., DeLeon, E., Ruffing, V., Clegg-Smith, K., & Bingham, C. O. (2015). Reliability and Validity of Selected PROMIS Measures in People with Rheumatoid Arthritis. *PLOS ONE*, *10*(9), e0138543. https://doi.org/10.1371/journal.pone.0138543

Bartley, E. J., & Fillingim, R. B. (2013). Sex differences in pain: a brief review of clinical and experimental findings. *British Journal of Anaesthesia*, *111*(1), 52–58. https://doi.org/10.1093/bja/aet127

Bauer, G. R. (2014). Incorporating intersectionality theory into population health research methodology: Challenges and the potential to advance health equity. *Social Science & Medicine*, *110*, 10–17. https://doi.org/10.1016/j.socscimed.2014.03.022

Bennett, I. M., Chen, J., Soroui, J. S., & White, S. (2009). The contribution of health literacy to disparities in self-rated health status and preventive health behaviors in older adults. *Annals of Family Medicine*, *7*(3), 204–211. https://doi.org/10.1370/afm.940

Berdahl, J. L., & Moore, C. (2006). Workplace harassment: Double jeopardy for minority women. *Journal of Applied Psychology*, *91*(2), 426–436. https://doi.org/10.1037/0021-9010.91.2.426

Boggero, I. A., Geiger, P. J., Segerstrom, S. C., & Carlson, C. R. (2015). Pain Intensity Moderates the Relationship Between Age and Pain Interference in Chronic Orofacial Pain Patients. *Experimental Aging Research*, *41*(4), 463–74. https://doi.org/10.1080/0361073X.2015.1053770

Bowleg, L. (2012). The Problem With the Phrase *Women and Minorities:* Intersectionality—an Important Theoretical Framework for Public Health. *American Journal of Public Health*, *102*(7), 1267–1273. https://doi.org/10.2105/AJPH.2012.300750

Braden, J. B., Zhang, L., Zimmerman, F. J., & Sullivan, M. D. (2008). Employment Outcomes of Persons With a Mental Disorder and Comorbid Chronic Pain. *Psychiatric Services*, *59*(8), 878–885. https://doi.org/10.1176/ps.2008.59.8.878

Briggs, A. M., Jordan, J. E., Buchbinder, R., Burnett, A. F., O'Sullivan, P. B., Chua, J. Y. Y., … Straker, L. M. (2010). Health literacy and beliefs among a community cohort with and without chronic low back pain. *Pain*, *150*(2), 275–283. https://doi.org/10.1016/j.pain.2010.04.031

Carbado, D. W. (2013). Colorblind Intersectionality. *Signs: Journal of Women in Culture and Society*, *38*(4), 811–845. https://doi.org/10.1086/669666

Carstensen, L. L. (1995). Evidence for a Life-Span Theory of Socioemotional Selectivity. *Current Directions in Psychological Science*, *4*(5), 151–156. https://doi.org/10.1111/1467-8721.ep11512261

Carstensen, L. L. (2006). The Influence of a Sense of Time on Human Development. *Science (New York, N.Y.)*, *312*(5782), 1913. https://doi.org/10.1126/SCIENCE.1127488

Carter-Pokras, O., & Baquet, C. (2002). What is a "Health Disparity"? *Public Health Reports*, *117*(5), 426–434. https://doi.org/10.1093/phr/117.5.426

Cavanaugh, C. E., Martins, S. S., Petras, H., & Campbell, J. C. (2013). Mental disorders associated with subpopulations of women affected by violence and abuse. *Journal of Traumatic Stress*, *26*(4), 459–66. https://doi.org/10.1002/jts.21821

Cho, S., Crenshaw, K. W., & McCall, L. (2013). Toward a Field of Intersectionality Studies: Theory, Applications, and Praxis. *Signs: Journal of Women in Culture and Society*, *38*(4), 785–810. https://doi.org/10.1086/669608

Cleeland, C. S., & Ryan, K. M. (1994). Pain assessment: global use of the Brief Pain Inventory. *Annals of the Academy of Medicine, Singapore*, *23*(2), 129–38.

Cole, E. R. (2009). Intersectionality and research in psychology. *The American Psychologist*, *64*(3), 170–80. https://doi.org/10.1037/a0014564

Collins, P. H. (1992). *Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment*. Hyman.

Cook, A. J., & Chastain, D. C. (2001). The classification of patients with chronic pain: age and sex differences. *Pain Research & Management*, *6*(3), 142–51.

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex: a black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics. *University of Chicago Legal Forum*, *1989*(1), 8.

Crenshaw, K. (1991). Mapping the Margins: Intersectionality, Identity Politics, and Violence against Women of Color. *Stanford Law Review*, *43*(6), 1241. https://doi.org/10.2307/1229039

Dale, S. K., & Safren, S. A. (2018). Resilience takes a village: black women utilize support from their community to foster resilience against multiple adversities. *AIDS Care*, *30*(sup5), S18–S26. https://doi.org/10.1080/09540121.2018.1503225

DeNisco, S. (2011). Exploring the relationship between resilience and diabetes outcomes in African Americans. *Journal of the American Academy of Nurse Practitioners*, *23*(11), 602–10. https://doi.org/10.1111/j.1745-7599.2011.00648.x

Dickerson, S. S., & Kemeny, M. E. (2004). Acute Stressors and Cortisol Responses: A Theoretical Integration and Synthesis of Laboratory Research. *Psychological Bulletin*, *130*(3), 355–391. https://doi.org/10.1037/0033-2909.130.3.355

Dodd, M. J., Cho, M. H., Cooper, B. A., Petersen, J., Bank, K. A., Lee, K. A., & Miaskowski, C. (2011). Identification of Latent Classes in Patients Who Are Receiving Biotherapy Based on Symptom Experience and Its Effect on Functional Status and Quality of Life. *Oncology Nursing Forum*, *38*(1), 33–42. https://doi.org/10.1188/11.ONF.33-42

Dowd, J. J., & Bengtson, V. L. (1978). Aging in minority populations. An examination of the double jeopardy hypothesis. *Journal of Gerontology*, *33*(3), 427–36.

Dziak, J. J., Lanza, S. T., & Tan, X. (2014). Effect Size, Statistical Power and Sample Size Requirements for the Bootstrap Likelihood Ratio Test in Latent Class Analysis. *Structural*

Equation Modeling : A Multidisciplinary Journal, *21*(4), 534–552. https://doi.org/10.1080/10705511.2014.919819

Earnshaw, V. A., Rosenthal, L., Gilstad-Hayden, K., Carroll-Scott, A., Kershaw, T. S., Santilli, A., & Ickovics, J. R. (2018). Intersectional experiences of discrimination in a low-resource urban community: An exploratory latent class analysis. *Journal of Community & Applied Social Psychology*, *28*(2), 80–93. https://doi.org/10.1002/casp.2342

Ferreira-Valente, M. A., Pais-Ribeiro, J. L., & Jensen, M. P. (2014). Associations between psychosocial factors and pain intensity, physical functioning, and psychological functioning in patients with chronic pain: a cross-cultural comparison. *The Clinical Journal of Pain*, *30*(8), 713–23. https://doi.org/10.1097/AJP.0000000000000027

Fillingim, R. B., King, C. D., Ribeiro-Dasilva, M. C., Rahim-Williams, B., & Riley, J. L. (2009). Sex, Gender, and Pain: A Review of Recent Clinical and Experimental Findings. *The Journal of Pain*, *10*(5), 447–485. https://doi.org/10.1016/j.jpain.2008.12.001

Flensborg Damholdt, M., Shevlin, M., Borghammer, P., Larsen, L., & Østergaard, K. (2012). Clinical heterogeneity in Parkinson's disease revisited: a latent profile analysis. *Acta Neurologica Scandinavica*, *125*(5), 311–318. https://doi.org/10.1111/j.1600-0404.2011.01561.x

Flor, H., Turk, D. C., & Scholz, O. B. (1987). Impact of chronic pain on the spouse: marital, emotional and physical consequences. *Journal of Psychosomatic Research*, *31*(1), 63–71.

French, A., Macedo, M., Poulsen, J., Waterson, T., & Yu, A. (2008). Multivariate Analysis of Variance (MANOVA). Retrieved March 30, 2019, from http://userwww.sfsu.edu/efc/classes/biol710/manova/manovanewest.htm

Gagliese, L., & Melzack, R. (2003). Age-related differences in the qualities but not the intensity of chronic pain. *Pain*, *104*(3), 597–608. https://doi.org/10.1016/S0304-3959(03)00117-9

Galinsky, A. D., Hall, E. V., & Cuddy, A. J. C. (2013). Gendered Races. *Psychological Science*, *24*(4), 498–506. https://doi.org/10.1177/0956797612457783

Gearity, B. T., & Metzger, L. H. (2017). Intersectionality, Microaggressions, and Microaffirmations: Toward a Cultural Praxis of Sport Coaching. *Sociology of Sport Journal*, *34*(2), 160–175. https://doi.org/10.1123/ssj.2016-0113

Gebauer, S., Scherrer, J. F., Salas, J., Burge, S., & Schneider, F. D. (2015). Disability and disability benefit seeking in chronic low back pain: Discovery Service for The University of Alabama Libraries. *OCCUPATIONAL MEDICINE -OXFORD*, *4*, 309.

Gerdle, B., Björk, J., Cöster, L., Henriksson, K., Henriksson, C., & Bengtsson, A. (2008). Prevalence of widespread pain and associations with work status: a population study. *BMC Musculoskeletal Disorders*, *9*(1), 102. https://doi.org/10.1186/1471-2474-9-102

Goodwin, L., Gazard, B., Aschan, L., MacCrimmon, S., Hotopf, M., & Hatch, S. L. (2017). Taking an intersectional approach to define latent classes of socioeconomic status, ethnicity and migration status for psychiatric epidemiological research. *Epidemiology and Psychiatric Sciences*, 1–12. https://doi.org/10.1017/S2045796017000142

Green, C. R., Baker, T. A., Smith, E. M., & Sato, Y. (2003). The effect of race in older adults presenting for chronic pain management: a comparative study of black and white Americans. *The Journal of Pain : Official Journal of the American Pain Society*, *4*(2), 82–90.

Grollman, E. A. (2014). Multiple Disadvantaged Statuses and Health. *Journal of Health and Social Behavior*, *55*(1), 3–19. https://doi.org/10.1177/0022146514521215

Hayward, M. D., Miles, T. P., Crimmins, E. M., & Yang, Y. (2000). The Significance of Socioeconomic Status in Explaining the Racial Gap in Chronic Health Conditions. *American Sociological Review*, *65*(6), 910. https://doi.org/10.2307/2657519

Holden, K. B., Bradford, L. D., Hall, S. P., & Belton, A. S. (2013). Prevalence and correlates of depressive symptoms and resiliency among African American women in a community-based primary health care center. *Journal of Health Care for the Poor and Underserved*, *24*(4 Suppl), 79–93. https://doi.org/10.1353/hpu.2014.0012

Huberty, C. J., & Morris, J. D. (1992). Multivariate analysis versus multiple univariate analyses. In *Methodological issues & strategies in clinical research.* (pp. 351–365). Washington: American Psychological Association. https://doi.org/10.1037/10109-030

IBM, C. (n.d.). IBM SPSS Statistics for Mac (Version 24.0) [Computer software]. Armonk, NY: IBM Corp; 2016.

Institue of Medicine [IOM]. (2001). *Relieving Pain in America: A Blueprint for Transforming Prevention, Care, Education, and Research*. Washington, DC: The National Academies Press.

Jackson, R. H., Davis, T. C., Bairnsfather, L. E., George, R. B., Crouch, M. A., & Gault, H. (1991). Patient reading ability: an overlooked problem in health care. *Southern Medical Journal*, *84*(10), 1172–5. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1925713

Jha, A. K., Orav, E. J., & Epstein, A. M. (2011). Low-Quality, High-Cost Hospitals, Mainly In South, Care For Sharply Higher Shares Of Elderly Black, Hispanic, And Medicaid Patients. *Health Affairs*, *30*(10), 1904–1911. https://doi.org/10.1377/hlthaff.2011.0027

Johannes, C. B., Le, T. K., Zhou, X., Johnston, J. A., & Dworkin, R. H. (2010). The Prevalence of Chronic Pain in United States Adults: Results of an Internet-Based Survey. *The Journal of Pain*, *11*(11), 1230–1239. https://doi.org/10.1016/j.jpain.2010.07.002

Kaiser, B. L., Brown, R. L., & Baumann, L. C. (2010). Perceived Influences on Physical Activity and Diet in Low-Income Adults From Two Rural Counties. *Nursing Research*, *59*(1), 67–75. https://doi.org/10.1097/NNR.0b013e3181c3bd55

Kapoor, S. (2015). *Perceived stigma, illness invalidation, sleep difficulties, and psychological distress in emerging adults in college with persistent pain*. University of Alabama, Tuscaloosa.

Kennedy, Q., Mather, M., & Carstensen, L. L. (2004). The Role of Motivation in the Age-Related Positivity Effect in Autobiographical Memory. *Psychological Science*, *15*(3), 208–214. https://doi.org/10.1111/j.0956-7976.2004.01503011.x

Kessler, R. C., van Loo, H. M., Wardenaar, K. J., Bossarte, R. M., Brenner, L. A., Ebert, D. D., … Zaslavsky, A. M. (2017). Using patient self-reports to study heterogeneity of treatment effects in major depressive disorder. *Epidemiology and Psychiatric Sciences*, *26*(1), 22–36. https://doi.org/10.1017/S2045796016000020

Kirsch, I. S., Jungeblut, A., Jenkins, L., & Kolstad, A. (1993). Adult Literacy in America: A First Look at the Findings of the National Adult Literacy Survey. Retrieved from https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=93275

Kivlighan, D. M., Hooley, I. W., Bruno, M. G., Ethington, L. L., Keeton, P. M., & Schreier, B. A. (2019). Examining therapist effects in relation to clients' race-ethnicity and gender: An intersectionality approach. *Journal of Counseling Psychology*, *66*(1), 122–129. https://doi.org/10.1037/cou0000316

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–13.

Kuhajda, M. C., Thorn, B. E., Gaskins, S. W., Day, M. A., & Cabbil, C. M. (2011). Literacy and cultural adaptations for cognitive behavioral therapy in a rural pain population. *Translational Behavioral Medicine*, *1*(2), 216–23. https://doi.org/10.1007/s13142-011-0026-2

Labuski, C. M. (2017). A black and white issue? Learning to see the intersectional and racialized dimensions of gynecological pain. *Social Theory & Health*, *15*(2), 160–181. https://doi.org/10.1057/s41285-017-0027-4

Lachman, M. E., Röcke, C., Rosnick, C., & Ryff, C. D. (2008). Realism and Illusion in Americans' Temporal Views of Their Life Satisfaction. *Psychological Science*, *19*(9), 889–897. https://doi.org/10.1111/j.1467-9280.2008.02173.x

Lachman, M. E., Teshale, S., & Agrigoroaei, S. (2015). Midlife as a Pivotal Period in the Life Course: Balancing Growth and Decline at the Crossroads of Youth and Old Age. *International Journal of Behavioral Development*, *39*(1), 20–31. https://doi.org/10.1177/0165025414533223

Laska, M. N., Pasch, K. E., Lust, K., Story, M., & Ehlinger, E. (2009). Latent class analysis of lifestyle characteristics and health risk behaviors among college youth. *Prevention Science : The Official Journal of the Society for Prevention Research*, *10*(4), 376–86. https://doi.org/10.1007/s11121-009-0140-2

Leigh, L., Hudson, I. L., & Byles, J. E. (2015). Sleeping difficulty, disease and mortality in older women: a latent class analysis and distal survival analysis. *Journal of Sleep Research*, *24*(6), 648–657. https://doi.org/10.1111/jsr.12324

Leo, R. J. (2005). Chronic pain and comorbid depression. *Current Treatment Options in Neurology*, *7*(5), 403–12. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/16079044

Li, K. K., Harris, K., Hadi, S., & Chow, E. (2007). What Should be the Optimal Cut Points for Mild, Moderate, and Severe Pain? *Journal of Palliative Medicine*, *10*(6), 1338–1346. https://doi.org/10.1089/jpm.2007.0087

Little, T. D. (2013). *The Oxford handbook of quantitative methods. Vol. 2, Statistical analysis*. Oxford University Press. Retrieved from https://books.google.com/books/about/The_Oxford_Handbook_of_Quantitative_Meth.html?id=bCFwAgAAQBAJ

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Lubke, G. H., & Muthén, B. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods*, *10*(1), 21–39. https://doi.org/10.1037/1082-989X.10.1.21

Manogharan, S., Kongsted, A., Ferreira, M. L., & Hancock, M. J. (2017). Do older adults with chronic low back pain differ from younger adults in regards to baseline characteristics and prognosis? *European Journal of Pain*, *21*(5), 866–873. https://doi.org/10.1002/ejp.989

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, *50*(4), 370–396. https://doi.org/10.1037/h0054346

Masyn, K. E. (2013). *Latent Class Analysis and Finite Mixture Modeling*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199934898.013.0025

Mather, M. (2016). The Affective Neuroscience of Aging. *Annual Review of Psychology*, *67*(1), 213–238. https://doi.org/10.1146/annurev-psych-122414-033540

McGuire, T. G., Alegria, M., Cook, B. L., Wells, K. B., & Zaslavsky, A. M. (2006). Implementing the Institute of Medicine Definition of Disparities: An Application to Mental Health Care. *Health Services Research*, *41*(5), 1979–2005. https://doi.org/10.1111/j.1475-6773.2006.00583.x

McLachlan, G. J. (1987). On Bootstrapping the Likelihood Ratio Test Stastistic for the Number of Components in a Normal Mixture. *Applied Statistics*, *36*(3), 318. https://doi.org/10.2307/2347790

Means-Christensen, A. J., Roy-Byrne, P. P., Sherbourne, C. D., Craske, M. G., & Stein, M. B. (2008). Relationships among pain, anxiety, and depression in primary care. *Depression and Anxiety*, *25*(7), 593–600. https://doi.org/10.1002/da.20342

Meyer, I. H. (2010). Identity, Stress, and Resilience in Lesbians, Gay Men, and Bisexuals of Color. *The Counseling Psychologist*, *38*(3), 442–454. https://doi.org/10.1177/0011000009351601

Mogil, J. S. (2012). Sex differences in pain and pain inhibition: multiple explanations of a controversial phenomenon. *Nature Reviews Neuroscience*, *13*(12), 859–866. https://doi.org/10.1038/nrn3360

Molton, I. R., Hirsh, A. T., Smith, A. E., & Jensen, M. P. (2014). Age and the role of restricted activities in adjustment to disability-related pain. *Journal of Health Psychology*, *19*(8), 1025–1034. https://doi.org/10.1177/1359105313483156

Moradi, B., Wiseman, M. C., DeBlaere, C., Goodman, M. B., Sarkees, A., Brewster, M. E., & Huang, Y.-P. (2010). LGB of Color and White Individuals' Perceptions of Heterosexist Stigma, Internalized Homophobia, and Outness: Comparisons of Levels and Links. *The Counseling Psychologist*, *38*(3), 397–424. https://doi.org/10.1177/0011000009335263

Morovati, D. (2014). *The Intersection of Sample Size, Number of Indicators, and Class Enumeration in LCA: A Monte Carlo Study - ProQuest Dissertations & Theses Full Text - ProQuest*. University of California, Santa Barbara. Retrieved from https://search-proquest-com.libdata.lib.ua.edu/pqdtft/docview/1617402700/56EA8F309FD64707PQ/1?accountid=14472

Muthén, L. K., & Muthén, B. O. (2002). How to Use a Monte Carlo Study to Decide on Sample Size and Determine Power. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(4), 599–620. https://doi.org/10.1207/S15328007SEM0904_8

Muthen, L., & Muthen, B. (1998). Mplus. Los Angeles: Muthén &Muthén.

Nagin, D. (2005). *Group-based modeling of development*. Harvard University Press. Retrieved from http://www.hup.harvard.edu/catalog.php?isbn=9780674016866

Nagin, D. S., & Odgers, C. L. (2010). Group-Based Trajectory Modeling in Clinical Research. *Annual Review of Clinical Psychology*, *6*(1), 109–138. https://doi.org/10.1146/annurev.clinpsy.121208.131413

Nylund, K., Bellmore, A., Nishina, A., & Graham, S. (2007). Subtypes, severity, and structural stability of peer victimization: what does latent class analysis say? *Child Development*, *78*(6), 1706–22. https://doi.org/10.1111/j.1467-8624.2007.01097.x

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Olson, C. L. (1976). On choosing a test statistic in multivariate analysis of variance. *Psychological Bulletin*, *83*(4), 579–586. https://doi.org/10.1037/0033-2909.83.4.579

Paasche-Orlow, M. K., & Wolf, M. S. (2007). The causal pathways linking health literacy to health outcomes. *American Journal of Health Behavior*, *31 Suppl 1*, S19-26. https://doi.org/10.5555/ajhb.2007.31.supp.S19

Park, N. S., Zimmerman, S., Sloane, P. D., Gruber-Baldini, A. L., & Eckert, J. K. (2006). An empirical typology of residential care/assisted living based on a four-state study. *The Gerontologist*, *46*(2), 238–48.

Pascoe, E. A., & Smart Richman, L. (2009). Perceived discrimination and health: A meta-analytic review. *Psychological Bulletin*, *135*(4), 531–554. https://doi.org/10.1037/a0016059

Paulson, M. R., Dekker, A. H., & Aguilar-Gaxiola, S. (2007). Eliminating disparities in pain management. *The Journal of the American Osteopathic Association*, *107*(9 Suppl 5), ES17-20.

Pfeiffer, E. (1975). A short portable mental status questionnaire for the assessment of organic brain deficit in elderly patients. *Journal of the American Geriatrics Society*, *23*(10), 433–41.

Portenoy, R. K., Ugarte, C., Fuller, I., & Haas, G. (2004). Population-based survey of pain in the united states: Differences among white, african american, and hispanic subjects. *The Journal of Pain*, *5*(6), 317–328. https://doi.org/10.1016/j.jpain.2004.05.005

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Quartana, P. J., Campbell, C. M., & Edwards, R. R. (2009). Pain catastrophizing: a critical review. *Expert Review of Neurotherapeutics*, *9*(5), 745–758. https://doi.org/10.1586/ern.09.34

Raichle, K. A., Osborne, T. L., Jensen, M. P., & Cardenas, D. (2006). The Reliability and Validity of Pain Interference Measures in Persons With Spinal Cord Injury. *The Journal of Pain*, *7*(3), 179–186. https://doi.org/10.1016/j.jpain.2005.10.007

Rhee, H., Belyea, M. J., & Elward, K. S. (2008). Patterns of asthma control perception in adolescents: associations with psychosocial functioning. *The Journal of Asthma : Official*

Journal of the Association for the Care of Asthma, *45*(7), 600–6. https://doi.org/10.1080/02770900802126974

Riley, J. L., Wade, J. B., Robinson, M. E., & Price, D. D. (2000). The stages of pain processing across the adult lifespan. *The Journal of Pain*, *1*(2), 162–170. https://doi.org/10.1016/S1526-5900(00)90101-9

Ringwalt, C., Roberts, A. W., Gugelmann, H., & Skinner, A. C. (2015). Racial Disparities Across Provider Specialties in Opioid Prescriptions Dispensed to Medicaid Beneficiaries with Chronic Noncancer Pain. *Pain Medicine*, *16*(4), 633–640. https://doi.org/10.1111/pme.12555

Riskowski, J. L. (2014). Associations of Socioeconomic Position and Pain Prevalence in the United States: Findings from the National Health and Nutrition Examination Survey. *Pain Medicine*, *15*(9), 1508–1521. https://doi.org/10.1111/pme.12528

Roberts, T. L., & Jumpper-Black, C. J. (2016). Promoting public health through community engagement: Embracing the journey. *Journal of Human Behavior in the Social Environment*, *26*(7–8), 565–574. https://doi.org/10.1080/10911359.2016.1236000

Rovner, G., Vowles, K. E., Gerdle, B., & Gillanders, D. (2015). Latent Class Analysis of the Short and Long Forms of the Chronic Pain Acceptance Questionnaire: Further Examination of Patient Subgroups. *The Journal of Pain*, *16*(11), 1095–1105. https://doi.org/10.1016/j.jpain.2015.07.007

Rustøen, T., Wahl, A. K., Hanestad, B. R., Lerdal, A., Paul, S., & Miaskowski, C. (2005). Age and the experience of chronic pain: Differences in health and quality of life among younger, middle-aged, and older adults. *Clinical Journal of Pain*, *21*(6), 513–523. https://doi.org/10.1097/01.ajp.0000146217.31780.ef

Sayer, N. A., Spoont, M., & Nelson, D. (2004). Veterans seeking disability benefits for post-traumatic stress disorder: who applies and the self-reported meaning of disability compensation. *Social Science & Medicine (1982)*, *58*(11), 2133–43. https://doi.org/10.1016/j.socscimed.2003.08.009

Schoen, C., Osborn, R., Squires, D., & Doty, M. M. (2013). Access, Affordability, And Insurance Complexity Are Often Worse In The United States Compared To Ten Other Countries. *Health Affairs*, *32*(12), 2205–2215. https://doi.org/10.1377/hlthaff.2013.0879

Schopflocher, D., Taenzer, P., & Jovey, R. (2011). The Prevalence of Chronic Pain in Canada. *Pain Research and Management*, *16*(6), 445–450. https://doi.org/10.1155/2011/876306

Schwarz, G. (n.d.). Estimating the Dimension of a Model. *The Annals of Statistics*. Institute of Mathematical Statistics. https://doi.org/10.2307/2958889

Shi, Q., Mendoza, T. R., Dueck, A. C., Ma, H., Zhang, J., Qian, Y., … Cleeland, C. S. (2017).

Determination of mild, moderate, and severe pain interference in patients with cancer. *PAIN*, *158*(6), 1108–1112. https://doi.org/10.1097/j.pain.0000000000000890

Smith, T. B., & Trimble, J. E. (2016). *Foundations of multicultural psychology: Research to inform effective practice.* Washington: American Psychological Association. https://doi.org/10.1037/14733-000

Sullivan, M. J. L., Bishop, S. R., & Pivik, J. (1995). The Pain Catastrophizing Scale: Development and validation. *Psychological Assessment*, *7*(4), 524–532. https://doi.org/10.1037/1040-3590.7.4.524

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. Pearson Education.

Tait, R. C., & Chibnall, J. T. (2014). Racial/ethnic disparities in the assessment and treatment of pain: Psychosocial perspectives. *American Psychologist*, *69*(2), 131–141. https://doi.org/10.1037/a0035204

Tait, R. C., Chibnall, J. T., & Krause, S. (1990). The Pain Disability Index: psychometric properties. *Pain*, *40*(2), 171–82. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/2308763

Thomas, A. J., Hacker, J. D., & Hoxha, D. (2011). Gendered Racial Identity of Black Young Women. *Sex Roles*, *64*(7–8), 530–542. https://doi.org/10.1007/s11199-011-9939-y

Thomas, A. J., Witherspoon, K. M., & Speight, S. L. (2008). Gendered racism, psychological distress, and coping styles of African American women. *Cultural Diversity & Ethnic Minority Psychology*, *14*(4), 307–14. https://doi.org/10.1037/1099-9809.14.4.307

Thorn, B. E., Eyer, J. C., Van Dyke, B. P., Torres, C. A., Burns, J. W., Kim, M., … Tucker, D. H. (2018). Literacy-Adapted Cognitive Behavioral Therapy Versus Education for Chronic Pain at Low-Income Clinics. *Annals of Internal Medicine*, *168*(7), 471. https://doi.org/10.7326/M17-0972

Van Breukelen, G. J. P. (2006). ANCOVA versus change from baseline had more power in randomized studies and more bias in nonrandomized studies. *Journal of Clinical Epidemiology*, *59*(9), 920–925. https://doi.org/10.1016/J.JCLINEPI.2006.02.007

van Lang, N. D. J., Ferdinand, R. F., Ormel, J., & Verhulst, F. C. (2006). Latent class analysis of anxiety and depressive symptoms of the Youth Self-Report in a general population sample of young adolescents. *Behaviour Research and Therapy*, *44*(6), 849–860. https://doi.org/10.1016/J.BRAT.2005.06.004

Verhaak, P. F., Kerssens, J. J., Dekker, J., Sorbi, M. J., & Bensing, J. M. (1998). Prevalence of chronic benign pain disorder among adults: a review of the literature. *Pain*, *77*(3), 231–9. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/9808348

Viruell-Fuentes, E. A., Miranda, P. Y., & Abdulrahim, S. (2012). More than culture: Structural racism, intersectionality theory, and immigrant health. *Social Science & Medicine*, *75*(12), 2099–2106. https://doi.org/10.1016/J.SOCSCIMED.2011.12.037

Vliegenthart, J., Noppe, G., van Rossum, E. F. C., Koper, J. W., Raat, H., & van den Akker, E. L. T. (2016). Socioeconomic status in children is associated with hair cortisol levels as a biological measure of chronic stress. *Psychoneuroendocrinology*, *65*, 9–14. https://doi.org/10.1016/j.psyneuen.2015.11.022

Von Korff, M., Crane, P., Lane, M., Miglioretti, D. L., Simon, G., Saunders, K., … Kessler, R. (2005). Chronic spinal pain and physical–mental comorbidity in the United States: results from the national comorbidity survey replication. *Pain*, *113*(3), 331–339. https://doi.org/10.1016/j.pain.2004.11.010

Waugh, O. C., Byrne, D. G., & Nicholas, M. K. (2014). Internalized Stigma in People Living With Chronic Pain. *The Journal of Pain*, *15*(5), 550.e1-550.e10. https://doi.org/10.1016/j.jpain.2014.02.001

Williams, D. R., Neighbors, H. W., & Jackson, J. S. (2003). Racial/ethnic discrimination and health: findings from community studies. *American Journal of Public Health*, *93*(2), 200–8. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12554570

Williams, D. R., Priest, N., & Anderson, N. B. (2016). Understanding associations among race, socioeconomic status, and health: Patterns and prospects. *Health Psychology : Official Journal of the Division of Health Psychology, American Psychological Association*, *35*(4), 407–11. https://doi.org/10.1037/hea0000242

World Health Commision. (2008). Closing the gap in a generation: health equity through action on the social determinants of health.

Wurpts, I. C., & Geiser, C. (2014a). Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study. *Frontiers in Psychology*, *5*, 920. https://doi.org/10.3389/fpsyg.2014.00920

Yamamoto-Mitani, N., Aneshensel, C. S., & Levy-Storms, L. (2002). Patterns of family visiting with institutionalized elders: the case of dementia. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *57*(4), S234-46. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12084793

Yu, J., Mahendran, R., Abdullah, F. N. M., Kua, E.-H., & Feng, L. (2017). Self-reported sleep problems among the elderly: A latent class analysis. *Psychiatry Research*, *258*, 415–420. https://doi.org/10.1016/J.PSYCHRES.2017.08.078

Zhang, Z., Wang, C., Nie, L., & Soon, G. (2013). Assessing the heterogeneity of treatment effects via potential outcomes of individual patients. *Journal of the Royal Statistical Society. Series C, Applied Statistics*, *62*(5), 687–704. https://doi.org/10.1111/rssc.12012

APPENDIX

Office for Research

Institutional Review Board for the Protection of Human Subjects

THE UNIVERSITY OF ALABAMA
RESEARCH

July 12, 2013

Beverly Thorn, Ph.D.
Department of Psychology
College of Arts & Sciences
The University of Alabama

Re: Medical IRB Protocol # 10-021-ME-R3
"Reducing Disparities with Literacy-Adapted Psychosocial Treatments for Chronic Pain: A Comparative Trial"

Dr. Thorn:

The University of Alabama Medical IRB has received the revisions requested by the full board on 6/14/13. The board has reviewed the revisions and your protocol renewal application is now approved for a one year period.

Your application will expire on June 13, 2014. You will receive a notice of the expiration date 90 days in advance. If your research will continue beyond this date, complete the renewal portions of the FORM: IRB Renewal Application. If you need to modify the study, please submit FORM: Modification of An Approved Protocol. Changes in this study cannot be initiated without IRB approval, except when necessary to eliminate apparent immediate hazards to participants. When the study closes, please complete the FORM: Request for Study Closure.

Should you need to submit any further correspondence regarding this application, please include the above application number.

Good luck with your research.

Sincerely,

John C. Higginbotham, Ph.D., MPH
Medical IRB Chair
The University of Alabama

358 Rose Administration Building
Box 870127
Tuscaloosa, Alabama 35487-0127
(205) 348-8461
FAX (205) 348-7189
TOLL FREE (877) 820-3066