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Scaling-up Child and Youth Mental Health Services: Assessing Coverage of a County-wide Initiative

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by

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List of Abbreviations

ACS	American Community Survey
CBITS	Cognitive Behavioral Intervention for Trauma in Schools
CPP	Child-Parent Psychotherapy
CPT	Current Procedural Terminology
CSA	Clinic Service Area
EBP	Evidence-based Practice
EBT	Evidence-based Treatment
GIS	Geospatial Information Systems
LACDMH	Los Angeles County Department of Mental Health
MAP	Managing and Adapting Practice
NIMH	National Institute of Mental Health
PEI	Prevention and Early Intervention
SAVA	Small-area Variation Analysis
SPA	Service Planning Area
SS	Seeking Safety
TF-CBT	Trauma Focused Cognitive Behavioral Therapy
TPPP	Triple P Positive Parenting Program

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Abstract of the Dissertation

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Professor Enola K. Proctor, Chair

Over 7 million children and youth have a diagnosable mental illness any given year. There are evidence-based treatments (EBTs) to effectively treat these conditions, but these EBTs reach a very small percentage of their target population with treatment rates between 1-3%.[1] We know very little about what influences these coverage rates. Beginning in 2009, the Los Angeles County Mental Health Department (LACDMH) began an ambitious agenda to scale-up the provision of EBTs in child/youth mental health care. The present study seeks to contribute to the scale-up literature by examining three questions based on LACDMH's initiative: 1) To what extent have the county's selected EBTs reached their target population?; 2) Are there differences in coverage rates within the county?; and 3) What factors are associated with the coverage rates? To answer these questions, the author used small area variation analysis and geospatial methods to create coverage scores at the county, service planning area, and clinic service area levels. The author aggregated community and clinic characteristics to the clinic service area level (n=254) to assess factors related to coverage. The author used LACDMH administrative claims data for FY 2013-2014 with population data from the American Community Survey 2014 5-yr estimates (ACS). The county reached 17% of its target population during FY 2013-2014. Coverage varied

throughout the county. OLS regression results indicated that the proportion of ethnic minorities, immigrants and adults with a college degree were negatively associated with clinic service area coverage scores.

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Chapter 1: Specific Aims

Mental health evidence-based treatments (EBTs) for children and youth have coverage rates as low as 1% to 3%, and we do not know what factors influence those rates.[1] In the US, 50 states/territories have engaged in some effort to implement EBTs in their systems of care, with 36% of those promoting statewide scale-up.[2] Scale-up refers to efforts to sustain and maximize an intervention's impact at a national/regional level.[3] The success of scale-up can be operationalized as the coverage of a given intervention. Coverage refers to "the proportion of the target population who…have received, the service".[4] States have employed various strategies such as mandates, workforce development, funding, and collaboration to scale up EBTs.[2] Notwithstanding these momentous efforts, we do not know the extent to which these EBTs have reached their targeted populations, nor do we know what factors are associated with scale-up success.[5–8] While there are existing measurement frameworks that could address these questions,[4,9,10] the most recent mental health services coverage systematic review found they have not yet been applied to mental health scale-up initiatives in the US.[8] A major challenge in the mental health services field is lack of knowledge about how to integrate available data to appropriately index coverage, particularly within a prevention and early intervention context, to subsequently explore drivers of scale-up success.

The proposed project will help fill these gaps by linking system administrative claims data extracted through the NIMH-funded "4KEEPS" study (R01 MH100134) with publicly-available data from the American Community Survey (ACS) to develop a method to construct the necessary variables to assess coverage and then explore coverage predictors. The ExpandNet framework[11] and other relevant empirical literature guided the selection of coverage predictors (e.g. neighborhood factors, agency factors). The proposed project extends the work of the 4KEEPS study which explored the sustainment of EBTs within the context of a scale-up initiative in LA county.[12] In 2009, LA county rolled out a Prevention and Early Intervention (PEI) initiative which included the scale-up of multiple EBTs for children and youth who presented with early symptoms of a mental illness or were at risk of developing a mental illness.[13,14] This innovative prevention initiative fills an important gap in the public mental health programming landscape.[15] Additionally, the PEI provides a unique opportunity to examine the scale-up of multiple EBTs across the largest county-operated mental health department in the US which has served 87,100 children since PEI's inception.[16] The proposed study will expand the parent grant by examining coverage through the following aims:

Aim 1: <u>Characterize the coverage of the PEI scale-up initiative and assess variability in coverage by geographic locales</u>. Using the empirical and theoretical literature, scale-up measurement frameworks,[4,9] and other services measurement methods,[8,17–19] this project will develop a measurement scheme to calculate coverage and operationalize predictors to assess coverage for fiscal year 2013-2014. Once the scoring scheme is in place, the author will use network analysis and apportionment to create service area buffers around each clinic providing PEI services. The author will then apply the scoring scheme to calculate a coverage score for all of the clinic service area buffers using LA County Mental Health Department claims data, American Community Survey data, and estimates from the epidemiologic and mental health services literature. This aim will generate a coverage score specific to PEI's targeted population for each clinic service area with available data in LA county for fiscal year 2013-2014 and will categorize these locales by degree of coverage.

Aim 2: Examine potential factors associated with coverage. This aim will use LA County Mental Health Department claims data and ACS data to examine the influence of local system and community factors on coverage through an Ordinary Least Square regression.[20] The result will be identification of factors that influence coverage and estimates of their contribution to variance explained.

This study is the first (known to the investigator) U.S.-based study to determine the coverage of a suite of EBTs, along with determinants of scale-up. The methods could offer guidance to others seeking to capture the public health reach of mental health scale-up efforts, and the resultant determinants could serve as targets of further measurement/exploration. In so doing, this proposed study directly aligns with the NIMH's strategic priority 4.4 which is to "develop new capacity for research that evaluates the public health impact of mental health service innovations".[21]

Chapter 2: Background

In the broadest sense, scaling-up refers to the process of extending the reach of an intervention in hopes that more people can receive benefit, to move from a patient-level impact to a population-level impact.[3,11,22,23] Some have gone as far as to suggest that an intervention that does not scale "is of little value".[24] The National Institute of Mental Health (NIMH) has codified its desire to see increased public-level impact in its fourth strategic objective, which is to "strengthen the public health impact of NIMH-supported research".[25] The Institute of Medicine of the National Academies has also convened workshops to address the scaling of interventions to increase the population-level impact.[22,26,27]

2.1 Definitions

The literature has no agreed upon definition of "scale-up" as of this writing. In fact, in the author's review of the mental health service scale-up literature, no empirical articles defined scale-up. There are, however, a number of scale-up definitions in the broader public health and human services literature.[11,23,28–35] However, researchers have not used these definitions consistently in the literature.[27,29,33]

Table 2.1 lists several scale-up definitions from various scale-up frameworks. Whereas there are notable differences between the definitions, there are a number of unifying elements. For example, the definitions address increasing the reach/impact of an intervention. Another unifying theme among the definitions is the concept of sustainability.

Similar to, but distinct from, scale-up is the term "scalability" which is defined as, "the ability of a health intervention shown to be efficacious on a small scale and or under controlled conditions to be expanded under real world conditions to reach a greater proportion of the eligible population, while retaining effectiveness".[32] The difference in terminology between scalability and scale-up is analogous to sustainability and sustainment. In that, one is the ability of something to be sustained (sustainability) and the other is the state of being sustained (sustainment).

Table 2.1 *A selection of scale-up definitions extracted from key scale-up frameworks*

Definition
"…more quality benefits to more people over a wider geographical area more quickly, more equitably and more lastingly" (p.iii-iv)[36]
"Scaling up is defined as expanding, replicating, adapting and sustaining successful policies, programs, or projects in different places and over time to reach a greater number of people" (p.8 citing World Bank)[30]
Involves "the model, innovation or project to be scaled up (what is being scaled up); the methods of going to scale (how of scaling up); the organizational roles involved in scaling up (the who of scaling up); the dimension(s) along which scaling up occurs (loosely speaking, the "where" of scaling up)" (p. 2)[31]
"Scaling up is the process by which health interventions shown to be efficacious on a small scale and or under controlled conditions are expanded under real world conditions into broader policy or practice. The concept of scaling up is different from routine adoption as it involves an explicit intent to expand the reach of an intervention to new settings or target groups and is accompanied by systematic strategy to achieve this objective" (p. 2)[33]
"… the terms "scale up" and "going to scale" refer to intentional efforts to maximize the positive impact of mental health interventions successfully tested in experimental studies in order to benefit mental health care at the national level or at a regional level within a country, and to foster evidence-based mental health policy and program development on a lasting basis."[3]
"… deliberate efforts to increase the impact of successfully tested health innovations so as to benefit more people and to foster policy and programme development on a lasting basis." (p. 2)[11]
"the ambition or process of expanding the coverage of health interventions" (p. 1 citing Mangham & Hanson, 2010)[35]

Coverage refers to “the proportion of the target population who can receive, or have received, the service”.[4] Researchers also use the terms “penetration” and “reach” in the literature in the same or similar ways. Glasgow described reach as,

> “an individual-level measure (e.g., patient or employee) of participation. Reach refers to the percentage and risk characteristics of persons who receive or are affected by a policy or program. It is measured by comparing records of program participants and complete sample or "census" information for a defined population, such as all members in a given clinic, health maintenance organization, or worksite.”[9]

Penetration has been, “defined as the integration of a practice within a service setting and its subsystems”.[37] There is substantial conceptual overlap between these constructs. This paper will use the construct “coverage” and its aforementioned definition. The 4KEEPS study has already assessed the within-service-system penetration of EBTs using the LACDMH claims data (i.e. denominator was clients enrolled in the system).[16] The present study proposes to examine how many children received services relative to the larger targeted population (i.e. total target population, not just enrolled clients); therefore, the term “coverage” seemed more fitting.

For this study, the term evidence-based treatment (EBT) refers to “clearly specified psychological treatments shown to be efficacious in controlled research with a delineated population.”[38] This construct differs from the broader term evidence-base practice (EBP) which refers to, “the integration of the best available research with clinical expertise in the context of patient characteristics, culture, and preferences.”[39] Providers working from an EBP framework would select an EBT based on the best available research which best matches a client’s characteristics, culture and preferences.

2.2 Need for mental health services scale-up

2.2.1 Mental illness

Understanding the nature of the target problem is necessary to develop an effective scale-up strategy. As such, this section aims to elucidate what is known about mental illness. Various surveillance methods spanning multiple decades have found that mental illness is prevalent, severe, has an early onset, is recurrent, is highly co-morbid, and is disabling.[40–49]

In the United States the lifetime retrospective prevalence of any mood or anxiety disorder for individuals 13-years and older is 49.1%; the 12-month retrospective prevalence for any mood or anxiety disorder is 31.6%.[42] For children between 8 and 15, the 12-month prevalence for any disorder is 13.1%.[44] This means that in any given year there are approximately 61,455,800 adults and 7,071,400 children with diagnosable mental illnesses.[43,44,50]

These estimates increase when individuals with symptomatic impairment, a condition in which a person does not meet criteria for a DSM diagnosis yet still experiences "significant psychosocial impairment," are included.[40] Some symptomatic impairment estimates suggest that nearly 50% of children referred for mental health services do not meet the diagnostic threshold, and these rates also increase when they are measured prospectively.[40]

Researchers have also assessed lifetime morbidity rates (LMR) for mental illness.[42] Lifetime morbidity rates reflect the estimated number of people who will contract a disorder at some point in their lifetime. Kessler and colleagues (2012) found that the LMR for mental illnesses exceed their prevalence estimates.[42] This is to say that many people have a mental disorder (prevalence) and even more are going to have one in the future (LMR).

Severity estimates of disorders vary. Kessler & Wang (2008) estimated that 22.3% of 12-month prevalence disorders in adults were serious.[43] Merikangas et al. (2010) estimated that 11.3% of 12-month disorders in children were serious.[44] SAMHSA uses the legislative definition of serious mental illness and estimated that there are around 10 million adults with serious mental illness (SMI).[46,47]

The age of onset varies by disorder but, generally, 50% of disorders have onset prior to age 14 and 75% have onset by age 24.[40,42,43] In one longitudinal, prospective study, investigators found that 90% of children had either a diagnosable mental illness or symptomatic impairment by the time they reached young adulthood, deeming distress caused by mental disorders or impairing symptoms almost a universal experience.[40]

The rates of recurrence in mental illness are high. For example, a systematic review found that adults with depression who receive treatment in a specialized mental healthcare clinics had recurrence rates ranging from 42% after 5 years to 85% after 15 years.[51] The rate for the general population after 15 years was 35%.[51] Another review found a recurrence rate of 39% for those with depression who had received treatment.[52] Anxiety had recurrence rates of 23.5% after two years in one sample,[53] and recurrence of mood episodes in bipolar disorder was 44% within the first year.[54] Recurrence rates have also been noted for children.[55,56]

Mental illnesses are highly co-morbid with other mental illnesses and chronic health conditions.[41,43,57] The lifetime prevalence of two or more mental disorders in adults was 27.7%.[43] The 12-month prevalence of any disorder from one analysis was 26.2%, from that group, 11.8% had two or more disorders.[43] A nationally representative survey found that 40% of affected youth had more than one disorder.[57] When other chronic health conditions (e.g. diabetes) are included with mental illnesses, the range of individuals with one or more disorder ranges from 83.6% to 96.5%, with a mean number of additional disorders ranging from 2.7 to 4.6.[41]

One of the major contributors to years lived with a disability (YLD) is mental illness, and their influence has increased the number of YLD by 37.5% from 1990 to 2010.[49] YLD has been defined as, "time lived in health states worse than perfect health."[58] Vos and colleagues calculated YLD by multiplying the prevalence of a health sequela by a disability weight.[49] Based on data from 2010, mental illness was the leading contributor to YLD for individuals ages 10 to 65, for those ages 22 to 29 the contribution is the highest (36%).[49] In North America, Major Depressive Disorder and Anxiety Disorder are the second and fifth leading causes of YLD.[49] Four of the top five most burdensome illnesses (measured by YLDs) at the individual level were mental illnesses versus physical illness (e.g., cancer, chronic pain, arthritis, diabetes, cardiovascular disorders).[41] After accounting for co-morbidity, mental illnesses still account for two of the top five most burdensome disorders.[41]

Total disability (disability-adjusted life years, DALYs) which is the combination of years lived with disability (YLD) and years of life lost (YLL) is another measure of the impact of mental illness. The top five mental illnesses/substance abuse disorders account for 153.727 million DALYs.[45] In North America, five out of the top 25 DALY contributors are mental illnesses, with Major Depressive Disorder ranking #5.[45] Mental illness DALY contributions are significant, and they are growing, DALYs have increased by 37.6% between 1990 and 2010.[45]

Mental illness also takes a significant economic toll. The United States spent more money on mental disorders than any other medical condition.[59] Health care spending for mental disorders was approximately $200 billion, heart conditions ($150 billion), trauma ($148 billion), cancer ($120 billion), and pulmonary conditions ($98 billion) followed.[59] Mental health treatment spending is projected to be $238 billion by 2020.[60] Medicaid (30%) or private insurance (25%) will cover the majority of the projected spending.[60]

Individuals and society also experience significant economic tolls due to mental illness. Individuals with serious mental illness (SMI) in the U.S. made, on average, $16,306 less than someone without SMI, which at the society-level equals $193.2 billion lost.[61] Combining high income countries, mental illness will result in a $9 trillion burden due to loss of economic output by 2030, which is higher than any other non-communicable disease.[62]

In summary, the collective impact of mental health need is wide (high prevalence), deep (severe), and growing (LMR and disability). These disorders not only result in significant burdens for individuals and families, they also represent substantial economic impacts to society. The need and costs are high.

2.2.2 Mental health services

Fortunately, there are treatments to address mental illnesses. Mental health service outcome research has demonstrated that psychotherapy is effective.[63–65] Approximately 67% of treated adults will receive the intended clinical benefit.[65] Psychotherapy is also effective for children and adolescents.[66] While some researchers have challenged psychotherapy effect sizes due to publication bias favoring positive trial results, there remains a general agreement that psychotherapy is beneficial.[67]

Efforts to integrate evidence-based treatments (EBTs) have burgeoned to enhance the efficacy of psychotherapy.[64] Researchers have developed and tested hundreds of evidence-based treatment protocols for a variety of mental illnesses.[64,66] Providers and researchers have increased their efforts to transfer these EBTs from clinical trials to real-world settings.[7,64,68]

Mental health service use has increased over time.[69,70] The Epidemiologic Catchment Area Study (ECAS) in the 1980s reported treatment rates of 19%; the National Comorbidity Study (NCS) reported rates of 25% in 1990; the National Comorbidity Study Replication (NCS-R) reported rates of 41% in 2000.[70] SAMHSA's National Survey on Drug Use and Health (NSDUH) found that treatment rates were 44.7% in 2013, with rates as high as 68.5% for those individuals with serious mental illness (SMI).[46] Treatment for those with SMI dipped slightly in 2015 to 65.3%.[47]

These estimates have varied and are based on different data sources.[69] All of these data are retrospective in nature, and more recent research comparing self-reported rates to actual rates based on insurance claims shows that respondents underreport their mental health service use.[71] This suggests that service use may be even higher than these estimates. Reports suggest that the increase in mental health service use is largely due to the increase of psychopharmacology.[64]

Notwithstanding the gains in treatment receipt, there has not been the anticipated decrease in the prevalence of mental illness.[15,72,73] In fact, some prevalence estimates show increases in prevalence rates.[73] These results are puzzling given the statistically significant increases in the use of psychotropic medications and psychosocial treatments.[73] The clinical trials for these mental health treatments have resulted in shorter episode durations and lower rates of recurrence. Given this, why is there not the same population-level response?[15,72] Researchers offer a number of hypotheses to explain this discrepancy. The following section explains five of those hypotheses.

First, the prevalence of mental illness appears to be increasing over time and the expansion of service receipt is buffering those increases.[73] An evaluation found that prevalence was, in fact, growing and it was primarily due to the aging of the population.[74] People's attitudes towards disclosing mental health information has changed over time, making people more willing to seek treatment, discuss their problems, and less likely to feel embarrassed if someone found out they received services.[75] Such a shift may also have led to self-reported prevalence increases.[75]

Second, the epidemiological methods deployed to measure population-level change may not detect small decreases in prevalence.[72,74] One simulation showed that scaling-up services resulted in a decreased prevalence of about 5%.[74,76] A change of that magnitude may not be captured by the current epidemiologic sampling methods. While 5% does not seem like much of a decrease, that would be more than 3 million fewer adults with a mental illness[74], a number larger than the population of 21 states in the U.S.

Third, this decrease may not have been detected because there are still such large unmet needs. Unmet need rates vary in the literature.[46,47,69,70,77–79] The most recent service data in the U.S. for individuals with SMI suggest that 34.7% had not received services.[47] 58% of those with any 12-month disorder reported not receiving services in the last NCS-R study.[70] The argument of unmet need is often coupled with issues related to mental health workforce shortages and client-level barriers.

The US has a shortage in the mental health workforce, it is growing, and the shortage impacts some communities disproportionately.[80–87] The Health Resources and Services Administration (HRSA) projects that the mental health workforce will be short by over 47,000 providers by 2025.[83] This estimate is a replacement estimate, the number of providers required to continue business as usual. However, business as usual currently does not provide services to all those in need. The workforce would need at least 253,000 additional providers by 2025 to meet all mental health needs.[83]

Even with sufficient workforce, there are client-level barriers that inhibit service receipt and treatment completion.[64,77,84] In a review of the world mental health services literature, Andrade et al. (2014) found that only 27.9% of those with a 12-month disorder received care.[77] Of those who did not receive care, 61.5% did not perceive a need for care; perceived need is a substantial barrier to mental health service utilization.[77,79] The 38.5% who did perceive a need and did not receive care reported both attitudinal (e.g. want to handle on their own, view that problem is not severe, would get better on their own, etc.), and structural barriers (cost, transportation, etc.).[69,77] Attitudinal barriers were larger of the two.[77] Sadly, there is a pattern that the most serious cases had the highest perceived need, and the highest attitudinal and structural barriers.[77]

The fourth hypothesis about why mental health service utilization has increased but mental illness prevalence has not decreased is that the services which have been provided have not been of high quality, not adhering to treatment recommendations.[15,26,73] Guideline concordant care has been operationalized in epidemiologic studies as number of psychotherapy sessions, and number of days with a prescription (if prescribed).[69,70,88,89] The rates of meeting those bare-minimum standards are very low, 13% to 32%.[69,70,88] Researchers have found higher rates of concordant care with specialized mental health providers.[70,89] The general medical sector provides the majority of mental health services, and unfortunately, that sector has the lowest concordance rates.[69,70,79,89] Furthermore, some have argued that even specialized mental health settings are not using evidence-based treatments.[26]

The fifth hypothesis is that some have cited service system inefficiencies as a possible explanation about why the prevalence of mental illness has not decreased.[73] These inefficiencies are manifest in the number of resources used to provide care to those who may not have mental illnesses.[70,79] In their nationally representative study, Wang et al. (2005) found that 10% of those who received care had no disorder.[70] Mechanic & Binder (2004) found that 61% of those surveyed without a mental illness received care, 29% were even prescribed psychotropic medications.[79] It is certainly possible that these individuals needed care even though they did not meet criteria for a disorder.[40] Priorities may be misplaced: there was a percentage of individuals with severe diagnoses who received no care while those with no discernable diagnosis did receive care.[47,79]

These inefficiencies are also manifested by the inequitable access to care.[73] Racial, educational, and socioeconomic disparities in access to care exist, which indicates that certain segments of the population who need care are systematically not receiving it.[46,69,81,89–91] This pattern is in part a symptom of service break-downs.

There are effective tools to mitigate the deleterious impacts of mental illness. More people are receiving services than before; yet, there has not been a shift in population-level prevalence. As such, making a public-level impact is a key priority to the National Institute of Mental Health.[25] Understanding coverage is a key component to understanding impact.[4]

2.2.3 Factors associated with access to mental health services

Research identifying keep determinants of mental health services coverage is very sparse.[8] The most recent systematic review on the subject found seven articles, worldwide, who measured the coverage of a behavioral health intervention or service.[8] Among the seven articles, only one analyzed the impact of predictors on coverage.[92] They found that clinics who were affiliated with the larger government agency, who were open more hours per day, and who provided more than two types of comprehensive services had better coverage rates for their methadone program.[92] There are no other predictors, this author is aware of, in the mental health coverage literature.

While empirical research about the determinants of mental health service coverage is sparse, a substantial body of research examines the determinants of mental health service access, utilization, and engagement. These constructs, though conceptually different from coverage, are necessary precursors to coverage.[4] In order to receive a mental health intervention, the client must have access to it and choose to engage. Those who use the service (utilization) become the numerator in the coverage calculation. Utilization, however, says nothing about the denominator of the target population nor the subsequent proportion of the population receiving the services. It is possible that the determinants of access, engagement, and utilization may ultimately be associated with coverage. As such, the author reports determinants associated with these proximal coverage constructs.

Researchers have identified characteristics, which have community-level implications, associated with residents' mental health and mental health service use[93–96] and have hypothesized others to test.[97,98] For example, Cook and colleagues found that neighborhood characteristics like minority density and mental health specialist density impact mental health service initiation.[93] Researchers have noted that ethnic minority youth are less likely to receive mental health services compared to white youth.[99–102] Researchers have found that immigrant status is associated with lower service utilization.[103–107] Neighborhood deprivation and lower socioeconomic status are connected with higher risk for mental disorders,[95] and, even after controlling for individual characteristics, neighborhood disadvantage remains associated with limited access to healthcare[96] including mental healthcare.[108] Scores of other researchers have found associations between deprivation and negative mental health service outcomes.[108–115] Not having access to transportation negatively impacts access to mental health care.[116–118] Agencies who provide transportation remove distance barriers for clients.[117] Education level concentration in a neighborhood has been associated with lower mental health service utilization.[93] Higher education levels have been associated with greater utilization,[119–122] and higher service utilization is associated with parents having higher education.[121] Having low English proficiency has been associated with longer periods of being untreated and lower mental health service utilization.[123–125] There are also determinants of mental health service access at the agency/provider level.

Additional determinants of mental health service utilization/access include service location, staff ethnicity and staff language. Youth are more likely to receive mental health services if they are provided in a school compared to other settings.[112,126–128] Matching client and provider ethnicity has resulted in improved mental health service outcomes like utilization, satisfaction, and positive perception of the therapist.[129–131] The literature suggests that being a child/youth with lower English proficiency was associated with lower mental health service utilization,[106,125,132,133] and that services are more effective when the therapist provides the services in the clients' native language.[134] Researchers have included language-match between therapist and client (i.e. client receiving services in their preferred language) in models assessing the effectives of psychotherapy.[134,135] The author will include these provider/agency determinants and community-level determinants in the analysis.

2.2.4 The need for mental health scale-up research

Given the plight of mental illness and the availability of tools, dozens of states have tried to scale-up evidence based psychosocial treatments.[3,6,7,136,137] These efforts, however, have been understudied and perhaps are not guided by research.[3,6] McHugh & Barlow (2010, p. 83) succinctly expressed, "Governments, public health authorities, and individuals suffering from psychological problems around the world are demanding increased access to psychological treatments, and the urgency of this demand has gotten ahead of the determination of best practices to achieve it."[7] Solid scale-up research is needed to meet this demand and guide these efforts to increase the impact of mental health care.[3,29]

2.3 Current study

In 2009, the LA County Department of Mental Health (LACDMH) embarked on an ambitious initiative to scale-up the provision of mental health evidence-based treatments for children, adolescents, and transition-age youth.[12–14,16] This initiative is called the Prevention and Early Intervention (PEI) program.[12,14,16] It focuses on a providing mental health services to children and youth who are showing the first signs of a mental illness.[12,13,16]

One of the key components of the scale-up strategy for PEI is that providers can only be reimbursed if they utilize one of the 52 approved EBTs.[16] LACDMH also selected six of the 52 interventions of which to provide additional technical assistance and training.[12,16] Those EBTs include: Child-Parent Psychotherapy (CPP), Cognitive Behavioral Intervention for Trauma in

School (CBITS), Managing and Adapting Practices (MAP), Seeking Safety (SS), Trauma-Focused Cognitive Behavioral Therapy (TF-CBT), and Triple P Positive Parenting Program (TPPP).[12,16] Though the county provided additional implementation support for these six interventions, clinicians could still be reimbursed as long as the intervention was on the list of 52 approved EBTs.

PEI is a herculean undertaking. LACDMH is the largest county mental health provider in the United States.[12,16,138] Every year LACDMH provides services to approximately 250,000 residents.[138] These services are provided through a combination of county-managed clinics and contracts with other agencies and individuals.[138] During the first five years of PEI, 87,000 unique children received services.[16] Previous LACDMH scale-up research has explored the sustainment and adaptation of the six supported EBTs[12] and the penetration of those six interventions within the service-provider-system.[16]

The current study seeks to expand their work[12,16] by addressing the following research questions:

(1) To what degree has PEI reached its target population?

(2) What variation is there in how well PEI has reached its target population?

(3) What factors are associated with the coverage of the targeted population?

2.3.1 Conceptual frameworks

Two frameworks guide this study: the Health Services Coverage Framework and the ExpandNet framework.[4,11] The Health Services Coverage framework provides guidance on how to operationalize and measure the coverage of scale-up efforts, which is the principal outcome for this study, and the ExpandNet framework provides broad categories of determinants that influence the scale-up of an intervention.[4,11]

The first framework is the Health Services Coverage framework.[4] This framework is an evaluation framework because it specifies what outcome to measure and how to do so.[139] The framework posits an "intervention needs to be: (i) physically available (available), (ii) financially and geographically accessible (accessible), (iii) acceptable, (iv) used (contact coverage), and (v) delivered appropriately and effectively (effective coverage)" to obtain a population-level impact.[8]

The current study will be measuring the fourth level of the Health Services Framework, contact coverage. Contact coverage refers to the proportion of the target population who receive the intervention.[4] The current study will not be measuring the other levels within the framework due to limitations in the existing dataset. However, the author used levels two and three (accessibility and acceptability) to locate proximal determinants of contact coverage.

Tanahashi suggests that an intervention will not be used if the target population finds it to be inaccessible and/or unacceptable.[4] Given the dearth of research on the determinants of contact coverage, the author searched for determinants that were associated with constructs that fit within the second or third levels of the Health Services Coverage framework (the levels immediately preceding contact coverage). Constructs like access, engagement, utilization and their attending determinants—explicated in section 2.2.3—are viable targets given their theoretical connection to contact coverage.[4] The Health Services Coverage framework does not, however, provide guidance on the category of constructs that would be associated with coverage or any of the other levels. The author used a second framework to guide the selection of possible determinant categories.

The World Health Organization's (WHO) ExpandNet framework is the second framework. It complements the Health Services Coverage framework by providing categories of constructs that are associated with scale-up success.[11] ExpandNet is both a process model because it provides a sequence of steps to guide scale-up efforts, and a determinants framework because it identifies key constructs that influence scale-up.[11,139] Scale-up work by Simmons & Shiffman form the basis of the framework.[140] Simmons & Shiffman developed their initial framework using a literature review, case studies, a series of meetings held with other scale-up experts, and their own professional experience.[140] The framework is divided into three parts: the elements of scaling up, strategic choice areas, and the steps for developing a scaling-up strategy. For the purposes of this study, the author used constructs contained within the "elements of scaling up" section.

There are five main constructs in the elements of scaling up section of the ExpandNet framework: the innovation, the resource team, the scaling up strategy, the user organizations and the environment.[11] See figure 2.1 for an adapted version of the ExpandNet framework. The innovation refers to the intervention/practice/technology/policy/etc. that the resource team is scaling up. In the current study, the innovation refers to the LACDMH approved EBTs for the PEI initiative. The resource team are those "individuals and organizations who promote and facilitate wider use of the innovation."[11] The LACDMH, treatment developers, and trainers serve as the resource team. The scaling-up strategy includes the "plans and actions necessary to fully establish the innovation in policies, programmes, and service delivery."[11] The LACDMH have deployed a number of strategies to scale-up PEI EBTs: fiscal mandates in the form of reimbursement for providing approved EBTs, training in the EBTs, technical assistance in the EBTs, implementation teams, etc. User organizations are the entities who will adopt the innovation. In LA, this includes the mental health agencies and their providers. And, the environment refers to “the conditions and institutions ... [which are] external to the user organizations but fundamentally affect the prospects for scaling up.”[11] Environment includes constructs like “socio-economic and cultural conditions” and “people’s needs, perspectives and rights.”[11] Community characteristics for LA county fit within the “environment” construct.

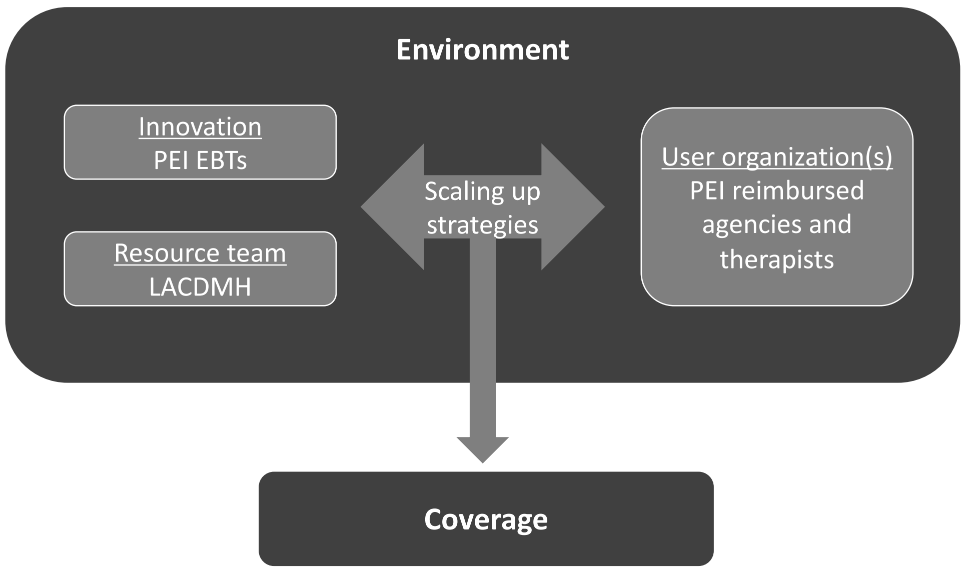


Figure 2.1 *Adapted ExpandNet and Health Services Coverage frameworks for the current LACDMH PEI initiative scale-up study.*[4,11]

The determinants explicated in the section 2.2.3 all fit within one of the broad constructs within the ExpandNet framework. Figure 2.2 presents the analytic framework for the current study. The determinant constructs come from the ExpandNet framework. The author operationalized the variables associated with those constructs based on guidance from the literature outlined in section 2.2.3. The framework combines the proximal determinants of scale-up, nested within the ExpandNet construct categories “environment” and “user organization” with the attending outcome constructs from the Health Services Coverage framework, of which “contact coverage” is the prime target.

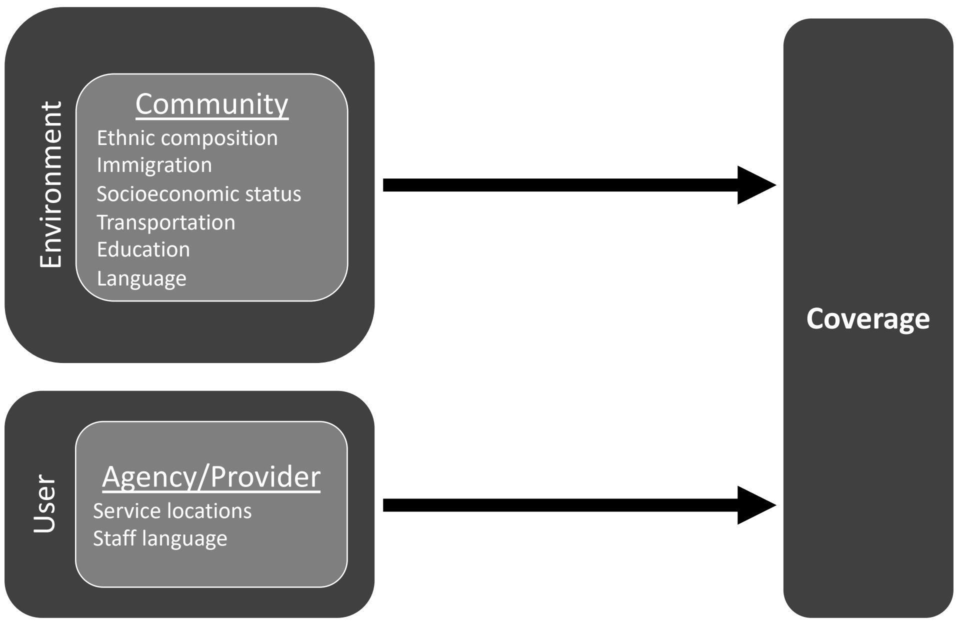


Figure 2.2 An analytic framework which guides the current study based on ExpandNet and the Health Services Coverage frameworks

Chapter 3: Methods

3.1 Data sources

Data for this study came from three sources: LACDMH administrative claims data for the PEI initiative, LA county population data from the American Community Survey (ACS), and geographic files from the census and LA county. There is precedent in the health services literature for combining census data with claims data[141] and using geographic files in combination with census data.[142–144]

The administrative claims data included information about the client, provider, agency, and intervention for each PEI-eligible claim.[145] Mental health providers who sought reimbursement from PEI funds submitted a claim demonstrating that the client met criteria for PEI services (e.g. age, presenting problem, diagnosis, etc.) and that the clinician used one of the approved EBTs (e.g. MAP, TF-CBT, etc.).[16] Client and staff reimbursement eligibility criteria varied depending on the intervention being used.[146] For example, CPP could be provided to children ranging in age from 0 to 5 years-and-11-months.[146] Overarching PEI eligibility criteria included: Medi-Cal eligible and the presenting mental health issue problem was a first-episode (early-intervention). While the claims data included multiple fiscal years, this study only examined one fiscal year.

This study used administrative claims data for fiscal year (FY) 2013-2014. Cleaning and analyzing the data for nine fiscal years is beyond the scope of this project. The author selected FY 2013-2014 because it represented a mid-point in the PEI scale-up initiative and was the fiscal year LACDMH provided services to the highest number of PEI child/transitional age youth clients. This coverage score would be the highest coverage score for the duration of the PEI initiative.

The analytic sample for this study included all qualified claims. Following precedent set by others,[16] qualified claims included psychotherapy claims for clients ages 0 to 25, who received an approved EBT. Similar to others, the author excluded claims for services like medication management, evaluation and assessment, and case management.[16] Limiting to psychotherapy claims focuses the analysis on the active psychosocial treatment of the EBTs. The National Academies has highlighted the need to understand the scale-up of psychosocial interventions.[26]

Most mental health insurance claims data have diagnostic codes, CPT procedurals codes, and varying degrees of information about the provider and setting. The LACHMD claims include that information and provide additional details about the specific EBT the therapists used during the treatment encounter.[145] Table 3.1 lists data fields this study isolated.

Table 3.1 *Variables contained in the LACDMH administrative data used in this study*

Variable	Description
Client ID Staff ID Agency/clinic ID	Unique research-generated ID numbers for each level
Service location address	Postal address for service location
Service location zip code	Postal zip code for service location
Date of service	Date when client received a service from provider
EBT code	Nominal – six categories (the approved EBIs)
CPT Procedure code	ICD procedural code
Client ethnicity	Nominal – White, Latino/a, African American, Asian, American Indian/Alaska Native, Native Hawaiian/Pacific Islander, Other, and not reported.
Client language	Nominal – English, Spanish, Other
Client diagnosis	Nominal – Mood, anxiety, disruptive behavior, trauma, attention/hyperactive, adjustment, autism/ppd, substance use, and other
Client age	Continuous – years
Staff language	Nominal – English, Spanish, Other
Service setting	Nominal – office, school, home, residential, unlisted

The American Community Survey (ACS) is the second data source this study utilized. The ACS began in 2005 and is a key continuous population survey administered by the United States Census Bureau.[147] Through monthly samples, the survey produces population characteristic estimates for varying geographic units (e.g. block, census tract, zip code tabulation area). The survey calculates these population characteristic estimates by sampling approximately 3 million addresses per year. Households receive a survey, phone-call follow-up, and/or field visits to complete the survey. The survey includes questions about the house (e.g. number of rooms, type of home), transportation, income and household costs, and household member relationships and demographics.[148]

This study used the 2014 ACS 5-year estimates given their increased accuracy and their match with FY 2013-2014 claims data. These ACS estimates are the average of data collected from January 2010 to December of 2014.[149] The ACS dataset was at the block group level specific to LA county. There are 6,425 block groups in LA county. The author used block groups because they were the smallest geographic size with available census data and could be used to aggregate to higher geographic levels for subsequent analyses. Others have used the block group level as a proxy for neighborhoods to assess community-level predictors of mental health service disparities.[93] See table 3.2 for community characteristics this study used from LA county ACS data.

Table 3.2 *Community characteristic estimates extracted from the American Community Survey specific to LA county at the group block level, then aggregated to clinic service areas.*

Variable	Description
Ethnic composition	Continuous – proportion of individuals who identify as an ethnic minority
Immigration	Continuous – proportion of individuals born outside the U.S.
Socioeconomic status	Continuous – proportion of individuals below poverty line
Means of transportation	Continuous – proportion of households with no access to a vehicle
Adult education level	Continuous – proportion of adults (>=25 y/o) with at least college degree
Language spoken in home	Continuous – proportions of households considered limited English
Population density	Continuous – number of 0 to 24-year-old per square mile living in the clinic service area

The author combined various geographic shapefiles to create the maps for this study. The county block group and service planning area files created the geographic boundaries and the road file facilitated the calculation of distance to the clinics. The clinic addresses from the LACMDH file served as the center point for the service area buffers, and the street address file helped located the addresses on the map. Table 3.3 lists geographic files

Table 3.3 *List of data sources for the geospatial analysis*

File name	Type	Source	Description
DRP_COUNTY_BOUNDARY.shp	Polygon	https://egis3.lacounty.gov/dataportal/drp_county_boundary/	LA County boundary file including Catalina & San Clemente islands. From LA county GIS portal
tl_2014_06_bg.shp	Polygon	https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2014&layergroup=Block+Groups	California census block groups TIGER shapefile for 2014
Service_Planning_Areas_2012.shp	Polygon	https://egis3.lacounty.gov/dataportal/2012/03/01/service-planning-areas-spa-2012/	Service planning areas for LA county. These areas are used by the department of mental health. These are aggregated from 2010 census tracts and the file was created in 2012.
tl_2014_06037_roads.shp	Line	https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2014&layergroup=Roads	All roads LA county from 2014 TIGER/Line shapefile
Street_Addresses_US.lox	Point	ESRI	ESRI ArcMap 2012 address database to match clinic addresses
DISS-lacmhd-program-addresses.csv	Point	LACDMH claims data	LA County Department of Mental Health agencies who provided PEI services during fiscal year 2013-2014

3.2 Unit of analysis

This study used three different geographic units to answer the study's research questions see table 3.4 To determine the coverage of a particular intervention, one must know the number of individuals who received the service (numerator), the number of the service's target population (denominator), and the geography on which these numbers are based. The first coverage score used the county as the geographic unit. The numerator was all the distinct clients who received PEI services and the denominator was the PEI target population for the county. This score does not account for boundary crossers--individuals from a neighboring county who traveled to LA county to receive services. This score answered the research question about the extent to which the target population has received PEI services. The county-level, however, did not allow for any comparisons within the county.

Table 3.4 *Unit of analysis and numerator/denominator calculations for each research question.*

Research question	Unit of analysis (n)	Coverage numerator	Coverage denominator
#1 – PEI coverage	County (n=1)	Distinct clients who received at least one psychotherapy session within the county	PEI target population within county
#2 - Coverage variation	Service Planning Areas (SPA) (n=8)	Distinct clients who received at least one session within the SPA, clients assigned to the SPA where they received most of their care.	PEI target population within SPA
#3 - Factors associated with coverage	Clinic Service Areas (CSA) (n=254)	Distinct clients who received at least one session from the clinic.	PEI target population within CSA

The next geographic unit was the service planning area (SPA). LACDMH has divided the county into eight SPAs (n=8).[150] Others have noted the utility of using service areas as a meaningful geographic level to support behavioral health service planning.[151] The coverage numerator was the number of distinct clients who received services in clinics assigned to each SPA. County data analysts designed the borders of the SPAs to coincide with census tracts, so the author used census data for these geographic areas to calculate a denominator for each SPA. Like the county, this scoring approach assumed that clients lived within the SPA where they received services. The SPA-level coverage scores permitted a descriptive-level comparison, but the sample size was too small for inferential statistics.

The final geographic unit was the clinic-service-area (CSA). Ideally, the study would base contact coverage scores on the clients' residence aggregated to meaningful communities. However, for privacy reasons, LACDMH did not include client geographic identifiers (e.g. zip code) in the dataset. To generate a proxy, the author created a buffer around each clinic based on network distance. Walker and colleagues used a similar approach when they assessed mental health services across Washington State,[152] and Guerrro and colleagues used this approach to assess access to substance abuse treatment in LA County.[142,143] Network distance is one measure geospatial researchers have used to derive meaningful distances for behavioral health service access.[152–154]

The author used service area network analysis to create the CSAs.[152–155] Ballas and colleagues define a spatial network as "…any representation of movement in a directed space."[155] Service area network analysis is a method to construct an area within a specified distance from a service location like a mental health clinic.[155] The network accounts for how the subjects can move throughout the area. In the present study, the author used LA county streets to create the service area networks. This street network approach differs from the Euclidean ('as the crow flies') approach, which creates geography by drawing straight-lines from the service location rather than accounting for the network of roads.[155] Figure 3.1 provides an example of a clinic service area using network analysis compared to the equivalent Euclidean area.

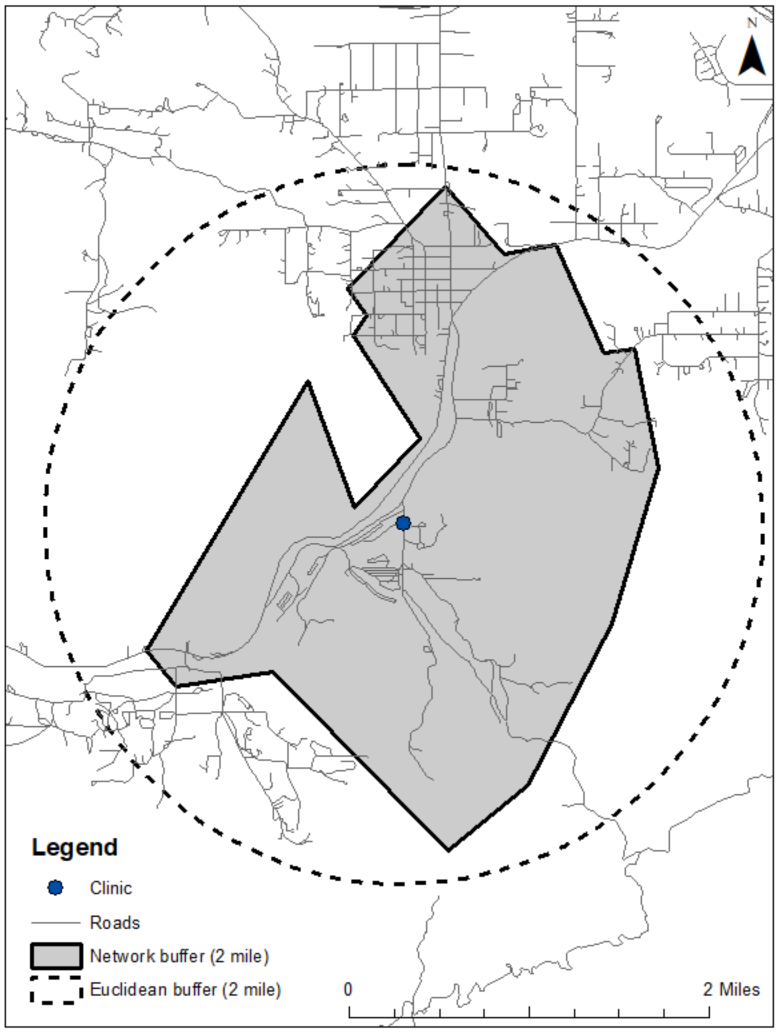
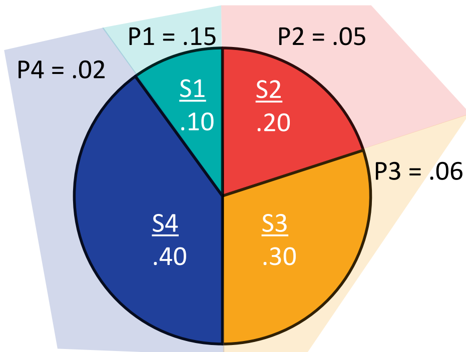


Figure 3.1 *An example of the clinic service area buffer used for this study, compared to a Euclidian buffer.*

To make the clinic service areas, the author geocoded the clinics in ARCMap 10.6 using the clinic's address and then calculated a 2-mile service area around each clinic using LA County census street maps. The length of street network service area buffers vary in the health services literature (e.g. .3 miles, .6 miles, 1.2 miles, 1.9 miles, 2.73 miles, 10 miles, 20 miles).[154,156] The author based the 2-mile buffer for this study on research conducted in LA county which found that survey respondents traveled 1.9 miles to receive behavioral health services.[157] There was overlap with some CSAs. The author retained the overlap because the mental health clinics do not have prescribed geographic boundaries that determine who they can serve like a school. Retaining the overlap assumes that if a potential client lived within close proximity (less than 2 miles) to two clinics, the client could elect to receive services from either.

To create the outcome variable and the predictors, the author used apportionment to aggregate both the census and clinic data to the CSA-level.[158] Apportionment is the process by which a geographic shape (e.g. CSA) is overlaid onto other geographic shapes (e.g. census block groups) and is assigned the portion of data covered by the overlaid shape. For example, in figure 3.2, the circle is overlaid onto four other polygons. Each of the four polygons contains geographically-constrained data (e.g. proportion of people living below the poverty line within the polygon). Apportionment assumes that the population characteristics of the underlying polygons are evenly distributed across the polygon (e.g. proportion of people living below the poverty line are evenly distributed across the area of polygon). The population characteristics of the circle would then be the sum of the four portions it covers of the other polygons.



Calculating proportion of individuals below poverty using apportionment for CSA in fig 3.2

Proportion of CSA for each segment	Proportion of polygon in poverty	Proportion of segment in poverty
S1 = .10	P1 = .15	.10 * .15 = .015
S2 = .20	P2 = .05	.20 * .05 = .01
S3 = .30	P3 = .06	.30 * .06 = .018
S4 = .40	P4 = .02	.40 * .02 = .008

CSA proportion under poverty:
(.015 + .01 + .018 + .008) = **.051**

Figure 3.2. *Example of apportionment.*

For this study, the overlaid shape was the clinic service areas (CSA), and the underlying shapes were the census block group polygons with their associated community-level census data. The center of a CSA was a clinic, so the author aggregated the agency/provider variables (client/therapist language match, and proportion of service settings outside the office) from the claims level to the CSA level. The resultant product from the apportionment process was a dataset where the observations were the CSAs and the predictors were the agency/provider and community variables aggregated to the CSA. The following example demonstrates how the author aggregated the variables using apportionment.

For example, to calculate the proportion of individuals living below the poverty line for the hypothetical CSA in figure 3.2, the author executed the following steps using ArcMap 10.6. First, the author calculated the area of the CSA, the circle in figure 3.2. Second, he calculated the area of the segments within the CSA (i.e. pie slices within the circle). Third, he ascertained the proportion of the service area covered by each segment by dividing the segments’ area by the CSA area. In the figure above, the number within each segment represents the proportion of the

CSA covered by the segment (e.g. the blue segment is .40 of the service area). After calculating the segment area proportion, the author then multiplied each segments' proportion by the proportion of individuals who lived below poverty for the segment's polygon. The proportion of individuals living below poverty line is listed in each polygon in figure 3.2 (e.g. blue polygon p4 = .02). The calculation for the blue segment would be .40 * .02 (segment proportion * segment's home polygon proportion of individuals below poverty). The resultant weighted proportion for the segment would be .008. The author used this calculation for each segment to get their weighted proportion and then summed the segments to get the aggregated variable for each CSA. The author lists the steps for this example in the call-out box in figure 3.2. The author also outlines the final list of variables in table 3.5. The author initially calculated the variables using the method outlined in the "calculation" column. He then aggregated the values using the apportionment procedures described in the previous paragraph.

Table 3.5 *Description of variables that author apportioned for final regression analysis*

DV/IV	Description	Data source	Calculation of variable prior to apportionment
DV	CSA coverage score.	Claims and ACS	Number of distinct clients served by clinic divided by number of target PEI population
IV	Proportion of claims with a language match between client and therapist	Claims	Number of claims where therapist language matched clients' language divided by the clinic's total number of claims.[a]
IV	Proportion of claims provided in a setting outside the clinic	Claims	Number of claims executed outside of the office divided by the clinic's total number of claims
IV	Proportion of population who identify as an ethnic minority	ACS	1 – proportion of non-Hispanic whites
IV	Proportion of population who were born outside the U.S.	ACS	Number of individuals born outside the U.S. divided by the number of individuals
IV	Proportion of the population below the poverty line	ACS	Number of individuals below the poverty line divided by the number of individuals
IV	Proportion of households without access to a vehicle	ACS	Number of households without a vehicle divided by the number of households
IV	Proportion of adults (≥25) with at least a college degree	ACS	Number of adults (≥25) divided with at least a college degree by the number of adults (≥25)
IV	Proportion of households designated as having limited English	ACS	Number of households designated as limited-English speaking divided by the number of households
IV	Population density of 0 to 24y/o	ACS	Divide the number of individuals between 0 and 24 by the area

[a] all English-speaking clients were considered match regardless of therapists' listed primary language.

3.3 Aim 1 data analysis

This descriptive aim used geospatial methods and small-area variation analysis (SAVA) to calculate a coverage score for LA county, its eight serving planning areas, and the clinic service areas buffers for all eligible PEI clinics. These coverage scores were compared to each other at the SPA level using descriptive statistics and data visualization.

The small-area variation analysis (SAVA) method guided this aim.[159–161] Small-area variations refer to "differences in the rates of use of medical services between geographic regions."[159] This study used adapted procedures outlined by the Health Services Research Group.[159] Their method includes five steps (1) determine the numerator, (2) determine the denominator/specify geographic region, (3) consider rate stability, (4) make adjustments for sex and gender, and (5) apply statistical tests.[159]

SAVA is a fitting method for this aim. John Wennberg, referred to as one of the developers of SAVA, enumerated distinguishing characteristics of a SAVA study:[161]

> "First, it provides population-based rates. Second, it focuses on local provider communities…with the intent of measuring variability among providers. Third, it can provide a comprehensive description of the health care delivery system…Fourth, it seeks answers to policy-relevant questions."

The current study measured population-based coverage (contact coverage), these scores were connected to provider communities (i.e. clinic-service-areas), and the study sought to answer policy relevant questions. These characteristics of the current study match well with Wennberg's SAVA characteristics.[161]

The first step in the Health Services Research Group's SAVA method is to identify the numerator, which is the number of individuals who received the service under examination.[159] The index of individuals who have received a service is one of the most important to calculate.[151] As explicated in section 3.2, the author calculated the numerator for the county, SPA and CSA levels by identifying distinct children and youth in the claims data who received one of the approved EBTs during FY 2013-2014. This study counted a child as having received services if they had at least one session. The literature on dose-effects in child/youth mental health treatment have yielded inconclusive findings, suggesting that number of sessions is not associated with improvement.[162–164] Furthermore, previous PEI service penetration studies used one session as their inclusion rule.[16] Table 3.6 provides examples of the variation in numerators and denominators researchers have used to calculate coverage.

Table 3.6 *Examples of contact coverage operationalization variation.*

Author (year)	Numerator	Denominator
DOH (2012)[165]	# of clients treated by IAPT program based on client database.	Adult population multiplied by epidemiologic prevalence rate from the Adult Psychiatric Morbidity Survey, then multiplied by 15% (the percentage of adults they estimate will seek treatment, receive diagnosis, and enroll in services)
Bruns (2016)[1]	# of clients who received one of the selected EBTs	# of adults and youth considered to have a SMI based on general estimates from state mental health department
Graaf (2018)[166]	# of youth who received care	Total youth population
Brown (2014)[97]	# of families who received intervention	Did not calculate
Pirkis (2011)[167]	# of clients receiving services captured in claims and admin data	Prevalence of psychiatric disorders from 2007 national Survey of Mental Health and Wellbeing
Araya (2018)[8,168]	National cross-sectional survey asking respondents whether they had received services in connection with a depressive episode over the past 12 mths.	CIDI-SF diagnostic tool used to establish 12-month prevalence of depression in cross-sectional survey
Aagaard (2004)[169]	# of inactive patients based on their activity in the national psychiatric registry	Prevalence of SMI based on national registry (diagnosis + high service utilization)
Lin (2010)[92]	# of service users taken from clinical records	# of opiate addicts registered with local police department

Martini (1985)[170]	Clients registered as being in contact with a case manager	Prevalence rates multiplied by population
Marinoni (1983)[171]	Clients who receive services per admin data	Total population

The second SAVA step is to identify the denominator which also requires specifying the geographic area.[159] As noted in section 3.2, the geographic units are the county, SPA and CSA. The denominator can be calculated in several different ways (see Table 3.6).[8] The most blunt measure is multiplying the geographic unit's population of children/youth by the epidemiologic prevalence rates for any mental illness.[8] The population data for this type of calculation would come from the ACS and the prevalence rates would come from the mental health literature.[172,173] Other researchers, however, have advocated the importance of modifying the denominator such that it more closely reflects the realities of actual service utilization.[8,17,165,174]

In-line with those recommendations, this study reduced the denominator following a process similar to the one used by the Improving Access to Psychological Therapies program[165] and others.[17] The author used a five-step process to specify the denominator (see Table 3.7). Step one, obtain the child/youth population estimate for each census block group based on data from the 5-yr ACS 2014 dataset. As previously reported in the section 3.1, the 2014 5-year estimates average the population characteristics in LA county from January 2010 to December 2014. This window of time overlaps with FY 2013-2014 LACDMH claims data, and the 5-year estimates provide the most accurate population estimates.[149] Step two, multiply the child/youth population estimate by the percentage of the population in the census block group who were enrolled in Medi-Cal[175] given that PEI services are intended for that population. Step three, multiply the Medi-Cal eligible child/youth population by the epidemiologic prevalence rate for any PEIqualifying mental disorder.[172,173] Step four, multiply the population of children/youth with any qualified mental disorder with the prevalence rate for non-serious disorders[176] because PEI is a prevention/early intervention initiative.[13,14] Step five, multiply the non-severe prevalence population by the percentage of youth likely to seek services.[44,99] Given that the prevalence rates of child/youth mental disorders has been relatively stable, the same prevalence percentages will be used to cover full fiscal year FY 2013-2014.[177,178] The author created a denominator for each census block group and used apportionment (see section 3.2) to calculate the denominator for each CSA. The reduction step proportions, sources of data, and their confidence intervals are in Table 3.8.

Table 3.7 *Contact coverage denominator reduction steps using zip code 90011 as an example*

Step	Description					
1	Initial denominator (children/youth population)	35,247				
2	Medi-Cal eligible	35,247	x	45.3%	=	15,967
3	Any mental disorder prevalence	15,967	x	32.8%	=	5,237
4	Non-serious disorders	5,237	x	92%	=	4,818
5	Likely to seek services	4,818	x	50.6%	=	2,438
	Specified denominator	2,438				

Table 3.8 *Source, percentage and confidence intervals for denominator reduction steps.*

Step	Description	%	CI[a]	Source
1	Initial denominator (children/youth population)			Apportioned block group to the CSA from 2014 5yr ACS
2	Medi-Cal eligible	45.3%	45.4% - 45.2%	California Dept. of Health[175]*
3	Any mental disorder prevalence	32.8%	31.9% - 33.7%	NCS-A[173]**
4	Non-serious disorders	8%	7.5% - 8.5%	NCS-A[173]**
5	Likely to seek services	50.6%	48.8% - 52.4%	NHANES[44]

[a] the confidence intervals were calculated using p + Z * square root ([p * q] / n).[179]
*They didn't report the denominator for youth population, but the author retrieved it from the 2011 ACS 5yr estimate data. The report gave the raw number of 0-18, and ACS had up to 17, so the estimate is slightly too high. The author divided the ACS 15 to 17 y/o category. Those age groups would add around 147,400. Adding that to the denominator the 0-18 estimated enrollment rate is 45.3%
**NCS-A has an any disorder prevalence estimate of 40.3%, PEI doesn't cover certain diagnoses included that estimate (e.g. bipolar), so the prevalence for those disorders was removed, bringing the prevalence down to 32.8%.

The third SAVA step is to consider the stability of the data.[159] To assess stability, the author examined trends in the data from a published report that assessed the penetration of EBTs within the PEI over the first five years of the initiative.[16] Penetration rates climbed steeply when PEI began but soon leveled off and appear to have remained stable.

The fourth SAVA step is to make adjustments for age and sex.[159] Rather than providing expected estimates of service utilization,[174] the author reduced the target denominator to make the proportion more precise. Green argued to create a denominator that reflects the "fraction of the people who assumes the patient role", which the denominator reduction steps aimed to do.[174]

The fifth SAVA step is to apply statistical methods for comparison. The author used descriptive statistics and data visualization to explore the coverage scores at the county and SPA level. The author created a heat map based on the SPA coverage scores to facilitate comparison.[180,181] Heat maps are effective tools for communicating health related information to the public[181] because they quickly and intuitively depict variation in the intensity of a phenomenon within a particular geographic area. The darker the geographic unit on the map, the larger their contact coverage score.

Researchers have deployed a number of statistics to facilitate comparisons between small-areas.[182–185] These descriptive statistics include: extremal quotient, unweighted and weighted coefficients of variation, systematic component of variation, chi-squared, and empirical Bayes.[182–184] The type of statistic to deploy depends largely on the characteristics of the data.[182] For example, the extremal quotient[186] is fitting if the sampled geographic units are large and of similar size, readmission does not occur, and the expected values are sufficiently large.[183] In their simulation comparison of several SAVA statistics, Ibanez found the empirical Bayes approach to be the best among several alternatives (depending the nature of the data).[182] These approaches are beyond the expertise of the author, so between-SPA comparison will be limited to descriptive statistics and data visualization. The author used OLS regression to examine predictors at the CSA level.

3.3 Aim 2 data analysis

This aim used LACDMH claims data and ACS data to examine the influence of local system and community factors on clinic service area coverage using OLS regression. The results were the identification of factors that influence coverage and estimates of their contribution to variance explained.

The unit of analysis for this aim was the clinic-service-area (CSA) as mentioned previously. This aim used all qualified claims, even those for the small percentage of clients who received services from more than one clinic because the coverage score for this geographic level assumes the perspective of the clinic, and removing the clients who received services from more than one clinic would not accurately represent all of the clinics' coverage scores. Initially there were 261 CSAs in the dataset. One of the CSAs was outside LA county, and six additional CSAs had buffers which crossed the county line. The census block group data was specific to LA county, so those buffers who crossed LA county lacked estimates for the census blocks outside the county. The predictors and the coverage denominators for those buffers would be underreporting the characteristics of the buffer, as such, the author dropped them from the analysis which resulted in a final analytic sample of n=254.

The author used multivariate OLS regression for this aim's analysis.[20] Other SAVA studies have used multivariate regression models with varying sample sizes (e.g. 68,[187] 13,[160] 10,[188]). The dependent variable for the analysis was the contact coverage score for each CSA created in Aim 1. While there is empirical guidance on the selection of predictors and correlates in the mental health service access literature, as outlined in chapter 2, these predictors have not been analyzed in relation to contact coverage. Given the exploratory nature of this study, the author will use an iterative regression approach to fit a final regression model.[189] An iterative approach in conjunction with guidance from the literature is fitting for this study given its exploratory natue.[190] The predictor variables are outlined in Table 3.9.

Table 3.9 *Predictor variables for the Aim 2 analysis. Each predictor was aggregated to the clinic service area using apportionment*

Level	Predictor Variables	Data source
Clinic	Proportion of claims with a language match between client and therapist	Claims
	Proportion of claims provided in a setting outside the clinic	Claims
Community	Proportion of population who identify as an ethnic minority	ACS
	Proportion of population who were born outside the U.S.	ACS
	Proportion of the population below the poverty line	ACS
	Proportion of households without access to a vehicle	ACS
	Proportion of adults (≥25) with at least a college degree	ACS
	Proportion of households designated as having limited English	ACS
	Population density of 0 to 24y/o	ACS

The current list of predictors was based on the mental health service literature as reported in section 2.2.3. The influence that community and neighborhoods play in mental health and mental health service use have been noted by others.[93–96] Ethnic minorities status,[99–102] immigrant status, [103–107] socioeconomic status,[95,96,108–115] access to transportation,[116–118] education level,[119–122] and English proficiency[123–125] have been associated with mental health service utilization. Others have used similar census-based, community-level predictors in mental health service access research[93] The author selected the clinic service setting because service location can have an impact on access and subsequent coverage.[112,126,127] In addition, matching client and provider language has yielded improved mental health service outcomes (utilization, satisfaction, positive perception of therapist, etc.).[129–131] The population density variable is the number of 0 to 24-year-olds within the CSA per square mile. The author included this variable as a control.

Six of the predictors are dichotomized proportions (e.g. proportion of population who identify as an ethnic minority, proportion below poverty, etc.). Researchers have tested multivariate models in SAVA studies and used a similar approach to construct their variables.[174,188] For example, one SAVA study used the percentage of unemployed and the percentage of college-educated per unit of analysis rather than all of the employment and education categories because using all of the categories did not add any predictive value.[174]

The first model used CSA contact coverage score as the dependent variable and the predictors listed in Table 9. The author assessed OLS assumptions for the model.[191] Visual inspection and results from the Shapiro-Wilks W test suggested that the distribution of the residuals was skewed. Cook's D test identified a number of influential observations. The Breusch-Pagan / Cook-Weisberg test for heteroskedasticity indicated that the model was not homoscedastic. The predictor with a variance inflation factor above 10 was the proportion of the households identified has having limited English.[20] This predictor was highly correlated (.894) with the proportion of the community who were born outside the U.S. Other predictors were also highly correlated (e.g. poverty and having no vehicle, minority status and college education). The author assumes some degree of spatial autocorrelation given the close geographic proximity and overlap of buffers in certain regions of the county. Visually inspecting the linearity between the outcome and predictor variables revealed some departure from linearity. Geospatial regression methods to address these concerns are beyond the author's scope, so he utilized a number of remedial measures to improve the model.

The author used a series of corrections due to departures from OLS assumptions. The author used a log transformation to correct for the skewed distribution of the dependent variable. The author retained influential observations after determining that there were no data errors.[20] There are some CSAs who had coverage scores above 1.0. Examining those CSAs, it appeared that they were located in geographic regions where it is likely that clients from outside the buffer came to receive services because there were few alternatives. The author dropped the limited English variable from the model given its inflated VIF and high correlation with the immigrant variable. The author retained the other variables because they reflect important social determinants of mental health service access. The author applied the robust variance estimator to minimize the influence of auto correlation in the data and correct for any issues with heteroskedasticity.[192–194] Furthermore, the author added a weighting variable based on the number of clients each clinic served in the FY.[192] The CSA coverage score would largely depend on the size and capacity of the clinic. The claims data did not have information sufficient to create an accurate agency-size variable. The weight variable attempts to account for that influence.

The author executed a series of models making iterative adjustments to correct for assumption violations. The final model reflects the most conservative analytic approach given the nature of the data. The final OLS model included a log transformed dependent variable, all the predictors in table 3.9 with the exception of household limited-English, with a robust variance estimator correction and a weighting variable. These corrections improved the assumptions outcome for the model. The residuals appeared much more normal, though still slightly skewed. There were no predictors with a VIF above 10 and no issues with heteroskedasticity. There remain influential observations, some issues with linearity, and the author assumes that a degree of spatial auto correlation persists even with the correction. The author used Stata v. 14.2 (Stata Corp., College Station, TX) for all OLS data management and analysis.

3.5 Protection of human subjects

The data were considered a limited dataset because they contained service dates.[195,196] The author received IRB approval for this study from Washington University (#201903099).

Chapter 4: Results

4.1 Aim 1 results

Aim 1 addresses the first two research questions, the extent to which PEI has reached its target audience and if there were differences between geographic locales in coverage. To answer these questions, the author examined the data at two geographic levels, the county and the service planning area (SPA).

4.1.1 County level coverage

The county level assumed the perspective of the LACDMH and the coverage of PEI services over the entire county (n=1). The numerator of the county coverage score is the number of distinct children served by any of the 261 clinics who submitted PEI-related psychotherapy claims in FY 2013-2014. The denominator for the county was 236,312 (after the denominator reduction steps). The county coverage score for FY 2013-2014 was 17.0%. As a point of comparison, the coverage score for FY 2010-2011 at the county level was 9.7%.

Figure 4.1 shows a map of LA County and the 261 clinics who submitted PEI-related claims in FY 2013-2014. The spaces in the map without any clinics are largely occupied by state parks and national forests shown in Figure 4.2. The clinics cluster in the more urban areas in the southern part of the county. Appendix 1 maps clinics in LA County and present population density of the census block groups.

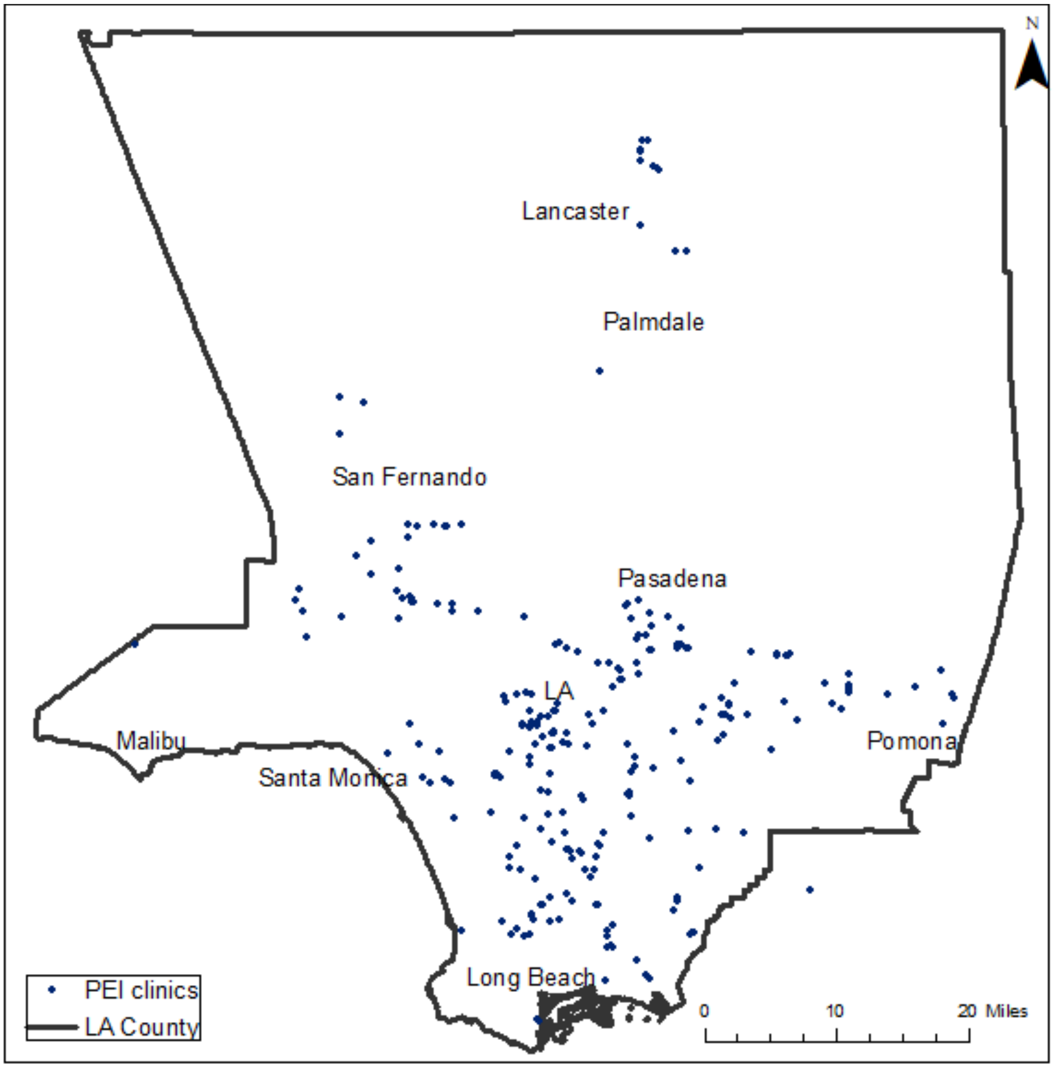


Figure 4.1 *Map of LA county with clinics who received reimbursement for providing PEI services in FY 2013-2014 (city locations are only approximations and not to scale)*

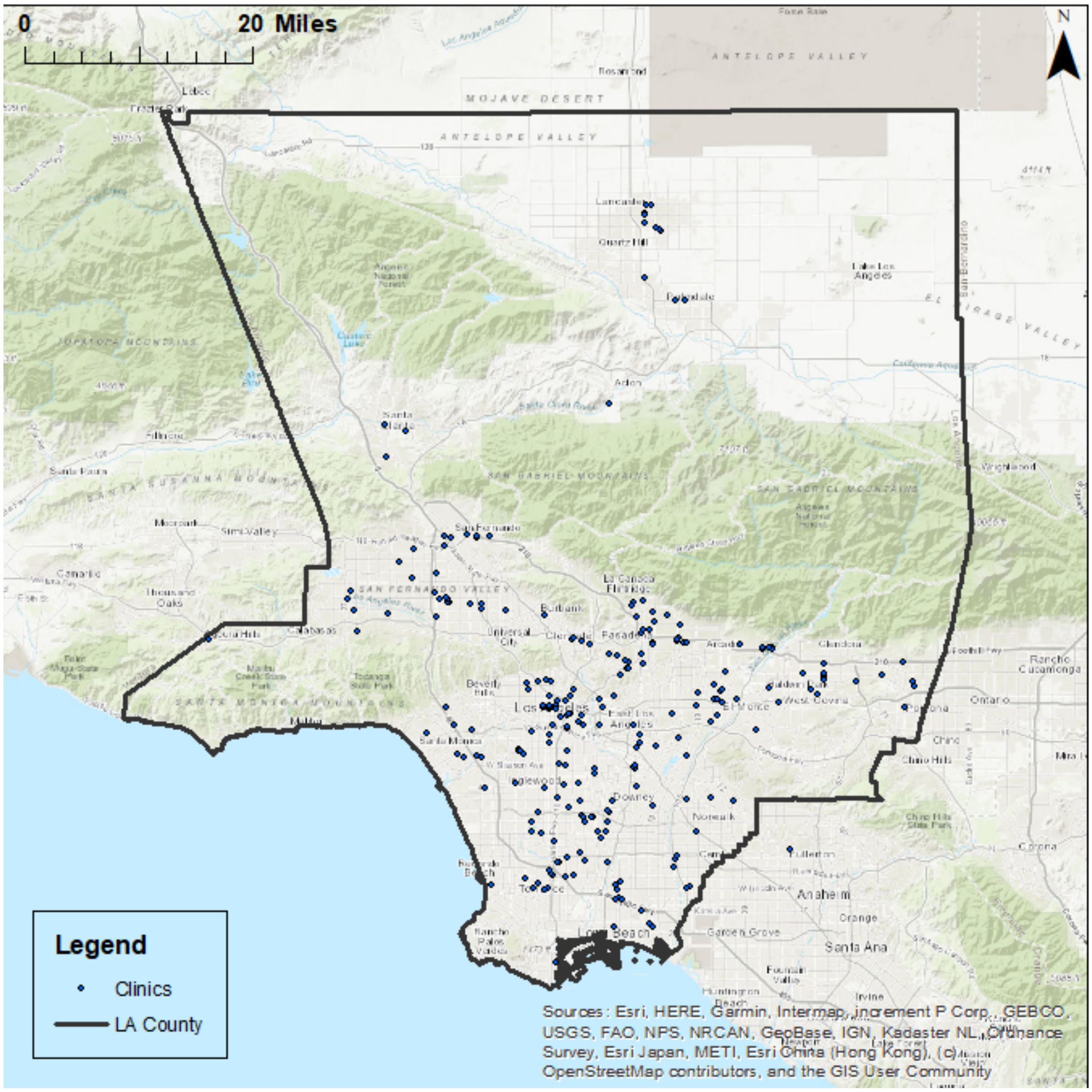


Figure 4.2 *Map of LA county with clinics who received reimbursement for providing PEI services in FY 2013-2014 with LA county topography*

Overall, 40,132 distinct children and transitional age youth received psychotherapy services (see table 10 for client descriptive statistics). There were more males (55%) than females (45%), most clients identified as Latino/a (71%) followed by African American (15%), and the majority listed English as their primary language (72%) followed by Spanish (27%). Prevalence of admission diagnoses varied. The most prevalent were mood disorders (30%), followed by disruptive behavior disorders (23%), adjustment disorders (12%), anxiety disorders

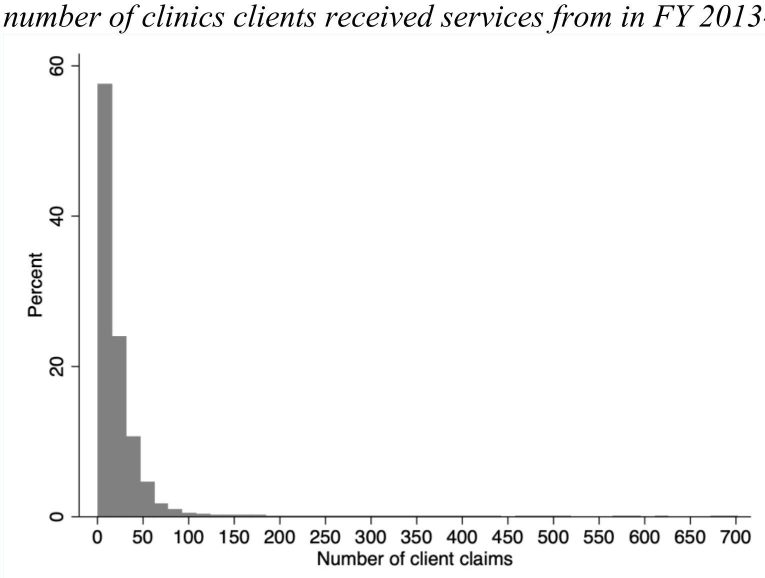
(11%), hyperactive/attention disorders (10%) and trauma (8%). Client average age was 11-years-old with a range from 0 to 25 (SD= 4.68).

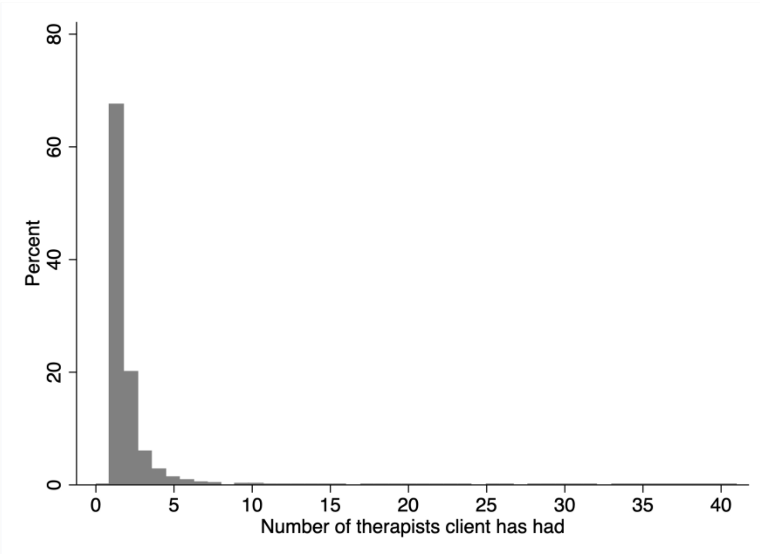
Table 4.1: *County-level PEI client demographic and service statistics for FY 2013-2014 (n=40,132)*

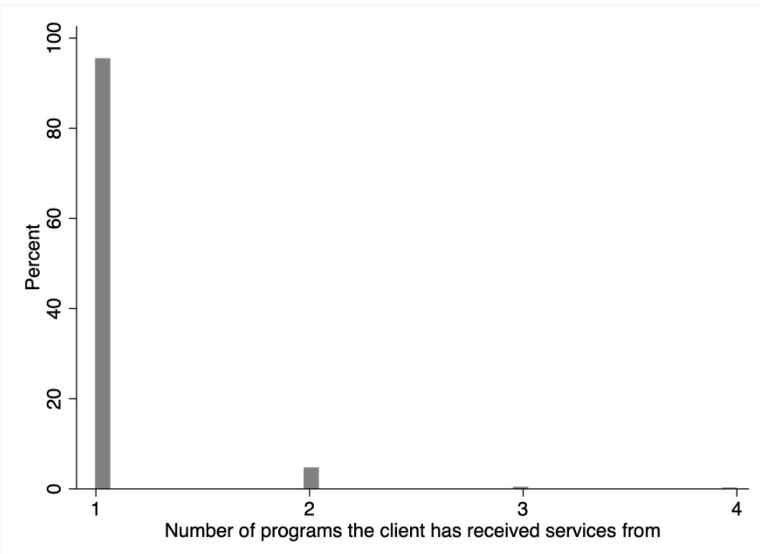
	N(%) / Median(SD)
Gender	
Male	22506 (54.9)
Female	18068 (45.0)
Missing	8 (.02)
Ethnicity	
Latino/a	28298 (70.5)
African American	6122 (15.3)
White	3056 (7.6)
Not reported	972 (2.4)
Other	761 (1.9)
Asian	669 (1.7)
American Indian	193 (.5)
Pacific Islander	61 (.2)
Primary Language	
English	28898 (72.0)
Spanish	10666 (26.6)
Other	430 (1.1)
Not reported	138 (.3)
Admission Diagnosis	
Mood	12133 (30.2)
Disruptive behavior	9224 (23.0)
Adjustment disorder	4625 (11.5)
Anxiety	4522 (11.3)
Attention/Hyperactive	3946 (9.8)
Trauma	3034 (7.6)
Other	2452 (6.1)
Autism/PPD	185 (.5)
Substance use	11 (.03)
Age (years)	11 (4.7)
Number of sessions	13 (25.8)
Number of therapists	1 (1.8)
Number of clinics	1 (.23)

There was a range in the number of sessions clients received and a range in the number of therapists they had and clinics they attended. Number of sessions per client ranged from 1 to 703, 50% of the clients received 13 sessions or less, 75% received 26 sessions or less (see figure 4.2 for distribution of sessions). The mean number of sessions was 19.8 (SD=25.8) and the median was 13. It was not possible to accurately determine the number of therapists each client had because there were missing therapist identification numbers from the claims data. There were 21 clients who did not have a therapist ID associated with any of their claims. If those clients were removed, the range of therapists was 1 to 41, 50% of clients had one therapist, the mean was 1.7 and the median was 1 (see figure 4.2). Clients received services from one to four different clinics. The mean was 1.7 (SD=1.8) and the median was 1, 50% of clients received care from one clinic and 75% received treatment from three or less (see Figure 4.3).

Figure 4.3: *Distributions of the number of clients' sessions, number of clients' therapists, and number of clinics clients received services from in FY 2013-2014.*







Determining the number of distinct therapists was not possible because 1,398 claims did not have a therapist identifier. There were 4,798 distinct therapists, which would make the range of possible therapists 4,798 to 6,196, assuming that each missing therapist identifier represented a distinct therapist. It is unlikely that the missing values all represented a distinct therapist, but it is not possible to tell from the claims. Beyond therapist identifiers, there was little information about the characteristics of the therapists.

Therapist characteristics which could be ascertained from the claims data included therapists' discipline, the therapists' primary language, number of clinics they worked in during the fiscal year, how many clients they served, and how many sessions, overall, they provided (see table 11 for therapist characteristics). The five most frequent disciplines among therapists was Marriage and Family Therapy (28%), Rehabilitation (22%), Counseling (22%), Social Work (10%), and Student Trainees (8%). Over half of therapists listed English as their primary language (54%), followed by Spanish (37%) and Other (8%). There was a small number of therapists who had two languages listed among their respective claims (n=20, .4%). The number of clinics these therapists worked in ranged from 1 to 5, with 75% of therapists working in 1 clinic. The mean number of clinics the therapists worked in was 1.2 (SD=.51) and median was 1. Therapists provided care for 1 to 279 different clients, with 50% of therapists with 10 or less clients and 75% of therapists with 20 or less clients. The mean number of clients was 13.9(SD=14.8) and the median was 10. The range of sessions the therapists provided their clients ranged from 1 to 2362. The mean number of sessions was 165.1 (SD=192.7) and the mean was 93. These figures combined with the client characteristics provided a high-level snapshot of the PEI claims.

Table 4.2: *Therapist characteristics for FY 2013-2014 (n=4,798)*

	N (%) / Median(SD)
Discipline	
Marriage and Family Therapist	1344 (28.0)
Rehabilitation Professional	1052 (21.9)
Counselor	1048 (21.8)
Social Worker	476 (9.9)
Student Trainee	375 (7.8)
Case Manager	257 (5.4)
Psychologist	148 (3.8)
Other	47 (1.0)
Psychiatrist	37 (.8)
Nurse	14 (.3)
Primary language	
English	2591 (54.0)
Spanish	1784 (37.2)
Other	402 (8.4)
More than one listed	20 (.4)
Number of clinics	1 (.5)
Number of clients	10 (14.8)
Number of sessions	93 (192.7)

The author examined coverage by service planning area in addition to county area to assess geographic variation in the degree of coverage. The next section reports PEI claims at the SPA level.

4.1.2 Service planning area level coverage

LA county is divided into eight service planning areas (SPA), [150] and the coverage scores between these SPAs varied (see table 4.3). The contact coverage scores for this geographic level reflect the perspective of the LACDMH. The numerator of the SPAs' coverage score is the number of distinct clients within the county who received at least one psychotherapy session from a clinic within the boundaries of the SPA (see table 4.3). There were 1.7% of the clients who received services in more than one service area. The figures in this section are based on clients and their subsequent claims being assigned to the service area where they received most of their care. There was also one clinic outside all of the SPAs which was not included in the numerator calculation. The denominators were based on the target population for each SPA using the denominator reduction process described in chapter 3. Figure 4.4 shows a heat map of the SPAs with their coverage scores.

Table 4.3 *LA county service planning area (SPA) PEI psychotherapy coverage scores for FY 2013-2014*

#	Service planning area name	Numerator	Denominator	Coverage score
1	Antelope Valley	2604	10799.95	24.1%
2	San Fernando Valley	6731	48975.4	13.7%
3	San Gabriel Valley	7561	40803.38	18.5%
4	Metro	5157	22828.41	22.6%
5	West	1198	12421.48	9.6%
6	South	5681	29922.43	19.0%
7	East	4101	34166.63	12.0%
8	South Bay (includes Catalina Island)	6950	36394.63	19.1%

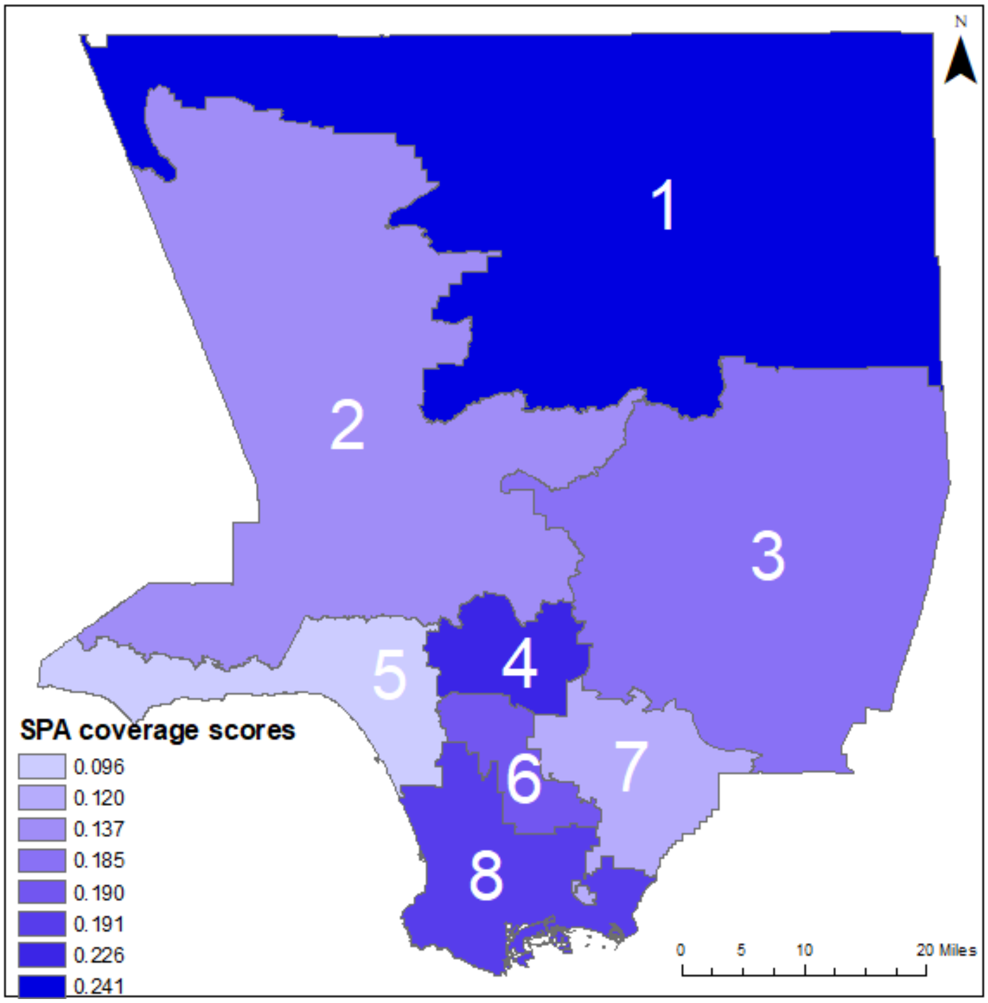


Figure 4.4 *Coverage scores for the LA county mental health service planning areas for FY 2013-2014*

The SPAs differed across the variables of interest outlined in chapter 3 (see table 4.4). The average coverage score was 17.3% (SD=.051) where SPA 1 had the highest coverage score (24.1%) and SPA 5 had the lowest (9.6%). Across SPAs the average percentage of the community who identified as an ethnic minority was 72% (SD=17.8%), SPA 6 had the highest percentage (97.4%) and SPA 5 had the lowest (39.9%). The average percentage of being born outside the use was 33.0% (SD=8.2%) where SPA 4 had the highest (44.6%) and SPA 1 had the lowest (18.6%). The average percentage living below the poverty line was 19.3% (SD=6.7%), SPA 6 had the highest poverty rate (32.4%) and SPA 5 had the lowest (12.3%). Most households in the SPAs had access to a vehicle, the average percentage without a vehicle was 10% (SD=5.5%), SPA 4 had the highest percentage of households without a vehicle (20.2%) and SPA 1 had the lowest (6.0&). The average percentage of limited-English speaking households was 13.4% (SD=5.8%), SPA 4 had the highest percentage (23.7%) and SPA 1 had the lowest (7.2%). On average, 29% of adults across SPAs had a college degree (SD=16.1%). The highest was SPA 5 (61.4%) and the lowest was SPA 6 (9.6%). On average, 47.7% of the sessions occurred outside of the clinic, SPA 8 had the highest percentage of sessions conducted outside the clinic (63.6%) and SPA 5 had the lowest percentage (33.6%). The average match between client and therapist language was high (89.6%, SD=2.6)% with SPA 1 having the highest proportion (91.9%) and SPA 4 having the lowest (83.6%). The client characteristics also differed between SPAs.

Table 4.4 *Coverage scores with clinic and community predictors aggregated to the SPA level, all values are percentages (n=8)*

SPA	Coverage	Ethnic minority	Born outside US	Below poverty	No vehicle	Limited-English	College degree	Sessions outside clinic	Sessions with language match
1	24.1	67.3	18.6	21.3	6.0	7.2	15.6	47.6	91.9
2	13.7	57.1	37.1	15.0	7.3	13.0	33.7	46.8	88.8
3	18.5	79.5	38.0	14.0	6.2	14.6	30.7	46.3	90.3
4	22.6	75.4	44.6	25.1	20.2	23.7	33.1	41.5	83.6
5	9.6	39.9	26.0	12.3	7.2	6.2	61.4	33.6	91.2
6	19.0	97.4	35.9	32.4	17.0	17.0	9.6	51.7	90.1
7	12.0	86.8	35.2	17.4	7.7	16.0	16.6	50.9	91.1
8	19.1	72.6	28.3	16.9	8.2	9.6	31.7	63.6	89.7
Mean	17.3	72.0	33.0	19.3	10.0	13.4	29.0	47.7	89.6
Median	18.8	74.0	35.6	17.1	7.5	13.8	31.2	47.2	90.2
SD	5.1	17.8	8.2	6.7	5.5	5.8	16.1	8.6	2.6

Note: All values are percentages.

While the characteristics of the clients differed across SPAs, the demographic patterns were very similar (see table 4.5). Across all SPAs, males received more services than females with SPA 2 having the highest percentage of males (57.5%). The most predominant ethnic group among SPAs was Hispanic. SPA 7 had the highest percentage of Hispanic clients (87.5%) and SPA 1 had the lowest (45.9%). English was the dominant primary language of clients for all SPAs. SPA 1 had the highest percentage (89.0%) and SPA 4 had the lowest (62.7%). Admission diagnosis profiles varied among the SPAs. Mood disorders had the highest percentage followed by disruptive behavior disorders. Admission diagnosis patterns varied after that. For example, the third most common admission diagnosis in SPA 1 and SPA 2 was anxiety, for SPA 4, 5, 7, & 8 it was adjustment disorder, and for SPA 3 and SPA 6 it was hyperactive/attention disorder. Average age ranged from 10.5 to 11.7. The median number of sessions ranged from 10 sessions (SPA 6) to 15 (SPA 4). The median number of therapists and clinics was one.

Table 4.5 *Client characteristics by service planning area for FY 2013-2014*

	N (%) / Mean (SD)							
	SPA 1	SPA 2	SPA 3	SPA 4	SPA 5	SPA 6	SPA 7	SPA 8
Gender								
Female	1190 (45.7)	2870 (42.5)	3372 (44.2)	2248 (44.0)	573 (47.8)	2514 (44.3)	1963 (48.7)	3189 (45.8)
Male	1414 (54.3)	3889 (57.5)	4254 (55.8)	2864 (56.0)	625 (52.2)	3166 (55.7)	2072 (51.3)	3772 (54.2)
Missing	0 (0)	1 (.01)	1 (.01)	2 (.04)	0 (0)	1 (.02)	0 (0)	3 (.04)
Ethnicity								
Latino/a	1195 (45.9)	4829 (71.4)	5552 (72.8)	4123 (80.6)	704 (58.8)	3770 (66.4)	3529 (87.5)	4520 (64.9)
American Indian	20 (.8)	13 (.2)	21 (.3)	75 (1.5)	1 (.1)	7 (.12)	47 (1.2)	8 (.1)
Asian	19 (.7)	75 (1.1)	287 (3.8)	104 (2.0)	19 (1.6)	21 (.4)	32 (.8)	112 (1.6)
Pacific Islander	2 (.1)	5 (.1)	7 (.1)	5 (.1)	2 (.2)	7 (.1)	0 (0)	32 (.5)
African American	827 (31.8)	587 (8.7)	744 (9.8)	355 (6.9)	224 (18.7)	1698 (29.9)	112 (2.8)	1522 (21.9)
White	430 (16.5)	903 (13.4)	566 (7.4)	161 (3.1)	178 (14.9)	84 (1.5)	188 (4.7)	534 (7.7)
Not reported	61 (2.3)	132 (2.0)	285 (3.7)	226 (4.4)	17 (1.4)	56 (1.0)	82 (2.0)	111 (1.6)
Other	50 (1.9)	216 (3.2)	165 (2.2)	65 (1.3)	53 (4.4)	38 (.7)	45 (1.1)	125 (1.8)
Primary Language								
English	2318 (89.0)	4902 (72.5)	5654 (74.1)	3205 (62.7)	951 (79.4)	3924 (69.1)	2952 (73.2)	4853 (69.7)
Spanish	275 (10.6)	1702 (25.2)	1786 (23.4)	1831 (35.8)	226 (18.9)	1721 (30.3)	1061 (26.3)	2054 (29.5)
Other	6 (.2)	127 (1.9)	168 (2.2)	41 (.8)	16 (1.3)	18 (.3)	17 (.4)	37 (.5)
Not reported	5 (.2)	29 (.4)	19 (.3)	37 (.7)	5 (.4)	18 (.3)	5 (.1)	20 (.3)
Admission Diagnosis								
Anxiety	360 (13.8)	866 (12.8)	793 (10.4)	638 (12.5)	214 (17.9)	399 (7.0)	449 (11.13)	803 (11.5)
Attention/Hyperactive	304 (11.7)	517 (7.7)	896 (11.8)	353 (7.0)	102 (8.5)	810 (14.3)	303 (7.5)	656 (9.4)
Mood	748 (28.7)	2241 (33.2)	2636 (34.6)	1347 (26.3)	283 (23.6)	1605 (28.3)	1343 (33.3)	1867 (26.8)
Trauma	325 (12.5)	439 (6.5)	504 (6.6)	458 (9.0)	54 (4.5)	527 (9.3)	255 (6.30	464 (6.7)

Disruptive behavior	521 (20.0)	1628 (24.1)	1772 (23.2)	1169 (22.9)	261 (21.8)	1253 (22.1)	880 (21.8)	1669 (24.0)
Substance use	0 (0)	0 (0)	4 (.05)	1 (.02)	0 (0)	1 (.02)	3 (.1)	0 (0)
Other	119 (4.6)	591 (8.7)	226 (3.0)	402 (7.9)	49 (4.1)	379 (6.7)	168 (4.2)	518 (7.4)
Adjustment Disorder	221 (8.5)	456 (6.8)	752 (9.9)	715 (14.0)	231 (19.3)	656 (11.6)	617 (15.3)	975 (14.0)
Autism/PPD	6 (.2)	20 (.3)	44 (.6)	31 (.6)	4 (.3)	51 (.9)	17 (.4)	12 (.2)
Age (years)	10.7 (4.8)	11.6 (4.6)	11.7 (4.5)	10.7 (4.9)	10.7 (4.5)	10.5 (4.5)	11.5 (4.7)	10.7 (4.8)
Age (years) median	11	12	12	11	11	11	12	11
Number of sessions	17.6 (17.5)	21.1 (20.4)	25.5 (45.1)	20.4 (19.2)	16.3 (14.5)	15.7 (17.0)	15.1 (13.9)	18.3 (16.3)
Number of sessions median	14	15	14	15	12.5	10	11	14
Number of therapists	1.6 (1.2)	1.8 (1.4)	2.0 (2.9)	1.8 (1.5)	1.3 (.7)	1.5 (.9)	1.3 (.7)	1.4 (1.0)
Number of therapists median	1	1	1	1	1	1	1	1

Describing the coverage score of the PEI psychotherapy interventions at the county and SPA level answered the question about the extent to which the PEI initiative reached its target population and if there were differences between locales (i.e. SPAs). However, the sample size of these geographic levels precluded comparing the locales using inferential statistics. Nor did the sample size allow an examination of possible factors associated with the range in coverage scores. The second aim used the clinic service area (CSA) level to answer the third research question about factors associated with coverage score.

4.2 Aim 2 results

Examining the coverage scores at the CSA level assumed the perspective of the clinic and the coverage of PEI services over the clinic's service area buffer (n=254). The numerator of the CSA coverage score is the number of distinct children who received a PEI approved psychotherapy EBT during FY 2013-2014 for each clinic. 4.7% of the clients received services from more than one clinic (n=1885). Because this coverage calculation was from the perspective of the clinic, clients was counted towards the numerator for every clinic they received care. The apportionment process described in chapter 3 yielded the denominator for each CSA.

The coverage scores as well as the values of the predictor variables varied across the CSAs (see table 4.6 for descriptive statistics). The average coverage score for CSAs was 14%. Some CSAs had very large coverage scores (max 306%), the CSAs with higher coverage values increased the average. The median CSA coverage score was 6%. The average percentage of individuals within the CSAs who identified as an ethnic minority was 77%. The average percentage of individuals within the CSA born outside of the US was 34%. The average percentage of individuals below the poverty line was 20%. Most households across the CSAs had access to at least one vehicle, the average percentage of households without a vehicle was 11%. On average, 26% of the adult population (25 years and older) within the CSAs had a college degree. The average percentage of sessions conducted outside of the clinic in CSAs was 45%. The language match between therapist and client (assuming all English clients received services in English regardless of therapist's primary language) was high, the average was 91%. The density of children/youth 0 to 24-years-old ranged from 28 per square mile to 11481 per square mile among the CSAs, the average density was 4059 youth/sq. mile. Four of the aggregated community and clinic variables were statistically significant in the regression model.

***Table 4.6** Descriptive statistics* for the clinic service areas FY 2013-2014 (n=254).*

	Mean	SD	Median	Min	Max
Coverage score	14.0	30.0	5.8	0.0	305.9
Ethnic minority	76.8	17.8	78.9	24.2	99.3
Born outside US	34.3	11.2	32.9	13.0	59.6
Below poverty	19.8	9.5	17.0	5.0	44.7
No vehicle	11.1	8.0	8.4	2.1	39.5
College degree	25.6	14.6	23.5	4.2	66.2
Sessions outside office	44.9	33.2	43.3	0.0	100.0
Language match	90.9	9.2	92.6	47.4	100.0
Population density (per sq mile)	4058.65	2462.44	3390.33	27.58	11480.87

*All values are percentages except for population density.

The final regression model included a log transformed coverage score as the dependent variable and the predictors listed in table 4.7. The results of the multivariate regression suggested that the predictors explain 36.9% of the variance (R^2=.37, F(8, 245)=12, p<.001). Specifically, the proportion of ethnic minorities in the CSA (ß=-2.68, p<.001), the proportion of immigrants (ß=-2.08, p<.013), the proportion of the adult population with a college degree (ß=-3.22, p<.001), and the population density of individuals 0 to 24-years-old (ß=-.00, p=.039) predicted CSA coverage score (see table 4.7). The author used guidance from Yang (2012) to interpret the significant predictors of the model with its log transformed dependent variable.[197] The higher the proportion of ethnic minorities in a CSA, the lower the coverage score. Holding all other variables constant, every unit increase in the proportion of ethnic minorities in the community resulted in 93% decrease in the coverage score. The higher the proportion of individuals born outside the US, the lower the coverage score. The CSA coverage score decreased by 88% for every unit increase in the proportion of individuals born outside the US in the community, holding all other variables constant. The higher the proportion of individuals with a college degree, the lower the CSA coverage score. The coverage score decreased by 96% for every unit increase in the proportion of the adult population who have a college degree, holding all other variables constant. The more densely populated a CSA, specifically for 0 to 24-year-olds, the lower the coverage. The coverage score decreased by .01% for every unit increase in the population density of 0 to 24-year-olds in the CSA. In sum, the model suggests that there is an association between a CSA's coverage score and its ethnic composition, immigrant composition, level of education, and population density.

Table 4.7 *Regression coefficients of community and clinic predictors on clinic service area coverage score (log transformed) for PEI claims FY 2013-2014*

	Coef.	95% CI		Est. change	Est. change 95% CI	
Ethnic minority	-2.68*	-3.88	-1.48	-.93	-1.01	-.85
Born outside US	-2.08*	-3.72	-0.45	-.88	-1.08	-.67
Below poverty	-0.76	-4.56	3.04	-.53	-2.30	-1.23
No vehicle	0.29	-3.80	4.37	.33	-5.08	5.74
College degree	-3.22*	-4.81	-1.63	-.96	-1.02	-.90
Sessions outside office	0.23	-0.23	0.69	.26	-.31	.83
Language match	-1.73	-3.53	0.08	-.82	-1.14	-.50
Population density (per sq mile)	0.00*	0.00	0.00	-.0001	-.00	-.00
R^2 = .37						
N = 254						

* p<.05

Chapter 5: Discussion

5.1 Study discussion, implications, and limitations

Child and youth mental illnesses are prevalent, debilitating, and costly.[42–44,49,172,198] Fortunately, there are effective interventions to treat these disorders.[66] Systems of mental health care across the United States have engaged in various initiatives to implement these effective treatments.[2] The extent to which these initiatives have reached their target populations and the identification of any factors associated with their respective degrees of population coverage are largely unknown.[1,8] An adapted framework based on ExpandNet and the Health Services Coverage frameworks (see figure 2.1) informed the selection of outcome and predictors.[4,11] The present study sought to address these gaps in the literature by assessing the scale-up of EBTs for child and youth mental illnesses in LA county through their PEI initiative. The LACDMH PEI initiative is a herculean effort to provide needed mental health services to children and youth.[13,14] The study yielded coverage scores of the PEI initiative at various geographic levels and identified community-level factors associated with those scores.

5.1.1 Coverage rate at the county and SPA levels

The key outcome in this study per the conceptual model is coverage. The first coverage score is at the county-level. The LACDMH provided evidence-based, psychotherapy services to 40,132 children/youth during FY 2013-2014 with each of these clients receiving a median of 13 sessions. The PEI initiative reached approximately 17% of the target population. It is difficult to discern how this coverage score compares to other such initiatives given the dearth of coverage score reporting in the mental health services literature.[8] One national study found that child/youth mental health EBTs in the US had a coverage score of 1% to 3%.[1] That study's denominator was number of youth identified by the state as having serious emotional disturbance.[1] The coverage score for PEI used a more refined denominator following methods suggested by others.[8,17,165] The difference between these denominators made the two coverage scores difficult to compare. A country-wide effort to increase psychological care for depression and anxiety in the UK has reached 16% of the target population which was based on the prevalence rate of depression and anxiety in the adult population.[18] US-based efforts in the Veterans Administration to scale-up trauma care has yielded a range of coverage rates. One estimate suggests that of all veterans with a PTSD diagnosis 3%-4% received Cognitive Processing Therapy or Prolonged Exposure.[199] Others in the Veterans Administration have found coverage rates of 6%[200,201] and 12%.[202] When researchers used veterans with a PTSD diagnosis who received psychotherapy as the denominator, instead of veterans with a PTSD diagnosis, the coverage rate was 14%-59% (mean 36%).[203] These rates, however, are largely informed by a computer algorithm that researchers used to detect which intervention the therapists used during the session.[200,203] EBP note templates became available in 2015, but not all therapists used them.[203] As a self-comparison, the LA county coverage score during 2010-2011, the year when the county rolled out training and implementation support for a suite of EBTs, was approximately 10%. Calculating the coverage scores for each of the county service planning areas (SPAs) allowed for further descriptive comparisons.

PEI coverage varied across the county's SPAs. For example, Antelope Valley (24.1%) and the Metro (22.6%) SPAs had the highest coverage scores and the West SPA had the lowest coverage score (9.6%). Demographically, communities in the West SPA had the lowest proportion of ethnic minorities, the lowest percentage of individuals living below poverty, the lowest proportion of households designated as limited-English speaking, and the highest percentage of college graduates among adults compared to the other SPAs. These community demographics would typically suggest that this SPA should have had a higher coverage score. Researchers have noted that ethnic minorities, immigrants, those living in poverty, and those with lower education experience lower mental health service access.[93,99,108,121,100–107] The nature of PEI services could explain the discrepancy between the West's coverage score and the literature on mental health treatment access/utilization. LACDMH intended PEI services to reach impoverished individuals and communities. Medi-Cal was essentially the only insurance provider for PEI clients. It is no surprise that a highly affluent SPA, like the West, would have a lower coverage score. This conclusion is only anecdotal because it was not possible to use inferential statistics at the SPA-level to assess factors that might have influenced the coverage score. Examining the data at the clinic service area (CSA) level did allow for this assessment and yielded four factors associated with CSA coverage score. These factors largely aligned with the descriptive findings at the SPA level. These factors fit with in the "environment construct in the conceptual model for the study (fig 2.1).

5.1.2 Factors associated with coverage

The first factor associated with CSA coverage was CSA ethnicity composition. The higher the proportion of ethnic minorities in the CSA, the lower the coverage score. This pattern fits with the larger mental health service literature. Ethnic minority children and youth have lower mental health service utilization rates[99–102], and more broadly, communities with higher concentrations of ethnic minorities have lower mental health service access even when individual-level and other socioeconomic factors are accounted for.[93] A lower coverage score was also associated with the proportion of immigrants in the CSA.

The second factor associated with coverage, was the percentage of individuals in the CSA born outside the US. The higher the percentage of individuals born outside the U.S. in the CSA, the lower the coverage score. This pattern is supported by the mental health services literature. Immigrants in the US have lower mental health service utilization than non-immigrants.[103–107] There are structural barriers (e.g. cost, insurance, language), cultural norms and attitudinal preferences (e.g. stigma, group norms), and systemic discrimination that inform service selection and participation by the immigrant community.[106] For example, some immigrants prefer to seek services from family members, friends, and/or religious leaders rather than formal mental health services.[106] Others are more willing to seek services from a medical professional and view the issue somatically rather than emotionally.[106]

The third factor associated with CSA coverage was education. The higher the percentage of college educated adults in the CSA the lower the coverage score. This finding, initially, appeared counter to the mental health services literature. Mental health service utilization researchers have found that lower education typically is associated with lower service utilization.[93,119–122] Initial research also suggests that children with parents who have higher education have higher utilization rates.[121] Given this precedent, it was surprising to see education negatively associated with coverage. It is possible this phenomenon occurred because PEI services were almost exclusively provided to Medi-Cal eligible recipients, and poverty is associated with lower college enrollment.[204] This suggests that the target population for PEI is less likely to have a college education. The negative association with percentage of college graduates in the CSA and coverage score could be interpreted as the more college graduates in the CSA, the less likely they are to be eligible for Medi-Cal and the less likely they would qualify for services which would decrease the overall coverage score.

The negative association between the number of adults with a college degree in a CSA and coverage rates could be a signal that PEI is reaching its intended population. PEI aimed to serve those enrolled in Medi-Cal and those with a college education are less likely to have Medi-Cal insurance. This suggests that the LACDMH's approach has an elevated degree of specificity, which is to say that their scale-up approach is reaching its intended target.

The final factor associated with PEI coverage at the CSA level was population density, specifically, the density of children and transitional age youth (0 to 24) per square mile. The population density of this age group aligns with the ages served by the PEI program. In this study, the higher the population density the lower the coverage score. The CSA buffers were the same size (i.e. 2 miles) so clinics in densely populated portions of the county would have higher denominators than less-densely populated CSAs in the county, And, to reach the increased number of potential clients, the clinics in highly populated areas would need increased capacity (e.g. more therapists) and the data do not provide that information. The negative association between population density and coverage may also be related to clinic clustering. The clinics are closer to each other in the southern part of the county. It is possible that a client had multiple options within similar distances. Furthermore, others have found a negative association between health service access and population density.[205,206]

5.1.3 Implications of the current study on practice and policy

The findings from this study suggest a few service and policy implications. First, the study demonstrates that meaningful geographic coverage can be calculated with existing administrative claims and census data. Though the literature may not provide clear coverage comparisons, the LACDMH can use the county coverage score as a benchmark for subsequent planning efforts and goals. For example, the UK monitors their coverage, currently 16% of the targeted adult population, with a goal of reaching 25%.[18] The differing coverage scores between SPAs could lead to subsequent analyses to determine organizational sources of the variation.

A second service implication is the need to consider ways of improving coverage equity. Notwithstanding the explicit focus of PEI reaching historically marginalized groups,[13] service inequities among ethnic minorities and immigrants persisted. Others have recommended increasing the diversity of the mental health workforce to reduce service access disparities.[207] Unfortunately, due to the unreliability of the therapist's ethnicity variable in the claims data, it was not possible to assess whether therapist ethnicity influenced coverage. Improving claims data-entry processes to ensure data accuracy would improve the county's ability to assess and improve inequities. Monitoring the composition of those who receive services in relation to the composition of the community will allow the LACDMH to make adjustments when inequities arise.

Next, coverage scores would be much more precise if they were based on client geography. Understandably, client geographic identifiers were not included in the dataset for privacy reasons. To retain client privacy and to improve geographic accuracy, the LACDMD might consider releasing aggregated geographic data at various geographic-levels (e.g. census block group, tract, service planning area). This would preserve client privacy and allow service analysts to examine coverage in more geographically precise ways.

A final service/policy implication relates to cost. The LACDMH has provided thousands of children and youth with evidence-based mental health services, which represent a coverage percentage similar to other large-scale initiatives.[18] There was large variation in the number of claims submitted by clinics for PEI services. Current audit reports indicate that LACDMH has a large surplus of funding.[208,209] The variation in coverage scores and the variation in the number of claims could identify areas which could benefit from additional support to provide PEI services.

5.1.4 Implications of the current study on scale-up research

The study also provides implications for scale-up of mental health services research. First, SAVA and geospatial methods are underutilized in scale-up mental health research and can yield helpful insights,[152,188,210–213] and these methods can be used with existing administrative and census data for both surveillance and research purposes. The distinction between surveillance and research is largely determined by its purpose.[214–216] Research has been described as, "A systematic investigation, including research development, testing and evaluation, designed to develop or contribute to generalizable knowledge."[216] Whereas surveillance has been described as, "The ongoing systematic collection, analysis and interpretation of health data, essential to the planning, implementation and evaluation of public health practice, closely integrated to the dissemination of these data to those who need to know and linked to prevention and control."[216] Both approaches may utilize the same methods and approaches. The present research study highlighted a need for ongoing mental health service surveillance. The LACDMH claims system allows the tracking of intervention, service type, service location, provider characteristics and client characteristics. These data could be mapped geographically to inform the service provision decisions.

Second, the study identifies a set of initial predictors that could inform subsequent scale-up research projects. The constructs from ExpandNet provided a good starting place for predictor selection but lacked enough specificity to operationalize the necessary variables.[11] The framework might benefit from separating client-specific determinants from the larger environment construct and identifying client related characteristics associated with successful scale-up. The empirical literature offered a number of candidate predictors, but many of them were extrapolated from research on individual-level service utilization. Had this study been testing hypotheses based on this existing literature, minority and impoverished communities would most likely be those with lower coverage rates.

Third, the study underscores the importance of explicitly stating the perspective (e.g. county vs. clinic), the unit of analysis, and the specification of the numerator and denominator when constructing coverage. For example, the coverage score would have been much lower without the denominator reduction steps. The coverage score also would have changed if the author retained a county perspective rather than a clinic perspective for the CSAs. The clinic perspective counted all the distinct clients the clinic served; a county perspective would have only counted distinct clients within the county (i.e. clients who received services from more than one clinic would be assigned to one clinic). Making and explicitly reporting decisions about perspective, unit of analysis, and numerator/denominator construction will support better cross-project comparison and better fitting interpretations of the data. The Health Services Coverage framework clearly identified a meaningful outcome variable for this study (i.e. coverage) and provided meaningful guidance for its calculation.[4] The present study expands the utility of that framework by suggesting researchers specify what perspective they are using when they calculate the coverage score, and by offering an example of denominator tailoring steps to more closely approximate the target population.

5.1.4 Strengths and limitations of the current study

The present study has a number of strengths. This is the first study, known to the author, which calculated a coverage score for a mental health scale-up initiative in the U.S. outside the Veterans Administration.[8] The author was able to make these calculations using available census and claims data which exerted minimal burden to LACDMH staff and no burden on service providers or clients. In addition, this study created meaningful geography without access to client geographic identifiers using GIS methods. This approach facilitated the construction of predictors fitting with the extant mental health service literature. The author was able to explore possible factors associated with coverage using those predictors. In the most recent review on mental health service coverage research, only one study examined predictors of scale-up.[8] Notwithstanding these strengths, the study also has a number of limitations.

The findings from this study should be viewed within the context of its constraints and limitations. This study used administrative data which was not designed for research. However, there has been a call to use administrative data to assess the impact of state mental health initiatives,[217] and multiple states have used administrative data to inform their service and policy decisions.[218] The data and methods do not allow for a cause/effect determination of the PEI initiative on scale-up. A pre/post design would be a possible way to determine the direct effects of the LACDMH initiative; however, before the initiative began, there was no formal tracking of interventions so it would not be possible to discern the reach of specific EBIs prior to the initiative.

This study used a GIS approach to approximate the coverage of a mental health service initiative. The coverage scores would have been more precise if client geographic identifiers, like zip code, would have been available. Notwithstanding this constraint, the author used geographic data from LA county-based studies to create meaningful clinic catchment areas.[142,143,157] The apportionment procedures the author used to create the regression dataset assumed that the characteristics of the population within the geographic unit (e.g. census block group, CSA) were evenly distributed. This is largely not the case in the real-world. Future research could add land-use characteristics as a layer in the GIS data to account for where people within the geographic unit live. This approach assumed that clients resided in the CSA, which may not have been the case. Also, due to the uniform size of the CSAs there may have been portions of the county not covered by a CSA. For example, some CSAs had coverage scores over 100%. It appeared that several of these clinics were surrounded by areas without another clinic nearby, so it is likely that individuals drove to the clinic from outside the catchment area. Though, retaining the 2-mile buffer coincided with previous research, approximated the average distance between a large sample of the clinics, and prevented total geographic overlap for clinics in highly dense areas. The GIS method also did not account for difference in clinic service capacity. The OLS model attempted to account for clinic capacity by using a weight variable based on clinic volume.

The proximity of CSAs to each other introduced spatial autocorrelation. Autocorrelation without corrections can lead to errors in significance testing, mean squared error (MSE) underestimates, and standard deviation underestimates.[20] The model used robust variance estimators to correct for autocorrelation but would likely need additional geospatial corrections. While the corrections improved the model fit, the geospatial nature of the data warrants using a comparison geospatial regression model (e.g. spatial autoregressive model) for sensitivity testing. The spatial regression would account for the possibility that CSA characteristics and coverage score are related to nearby CSAs due to some geographic proximity effect.

And though the author based the denominator reduction steps on the most fitting available literature, additional sensitivity testing could also be done with various rates in the denominator reduction steps. Notwithstanding these limitations and constraints, this study provided one of the very few coverage scores in the mental health literature, offered methods to calculate meaningful predictors using census data in relation to the coverage scores, and posited initial factors to explore in subsequent scale-up studies.[1,8]

5.1.5 Next steps

The findings from the study prompt a number of next steps. The author will apply this study's method to other fiscal years of LACDMH data and compare the coverage scores over time. The present study was unable to ascribe causality between the LACDMH's efforts and the resultant coverage score. Comparing coverage over time could show patterns of growth and change. Next, the author will apply additional geospatial-specific regression techniques to the data for sensitivity analysis. The author will also apply other SAVA statistics to coverage scores at the SPA level to see if there are statistically significant differences. SPAs represent a meaningful geographic unit for the LACDMH. Moving beyond descriptive statistics and being able to indicate if the present differences are significant could inform subsequent planning efforts.

5.2 Conclusion

This study ascertained the coverage of a public mental health early intervention initiative in LA County. Overall, the initiative reached 17% of the target population. This rate tracks with other large-scale efforts[18] and provides an initial benchmark for subsequent efforts to improve the reach of evidence-based mental health services for children and youth. There were regional differences in coverage rate. Community-level factors such as the proportion of ethnic minorities, immigrants, and individuals with a college degree were negatively associated with coverage scores. Fortifying data collection processes would permit a more refined assessment of factors related to coverage. This study represents one of the first to examine factors associated with the scale-up of evidence-based mental health care and offers methods to calculate meaningful coverage scores and predictors based on administrative and publicly available data.

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Appendix 1

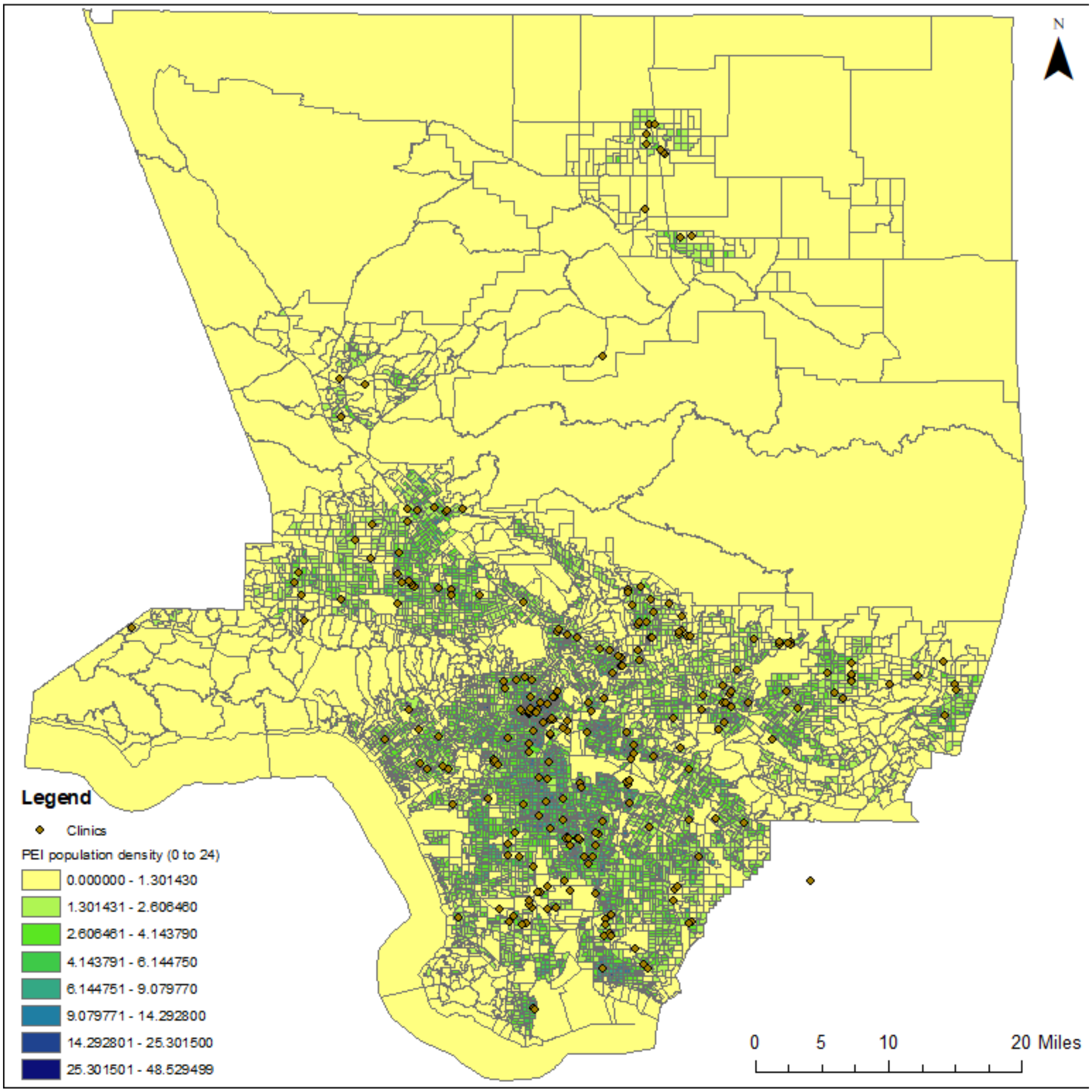

Figure A1. *PEI reimbursed clinics with the population density of 0 to 24-year-olds (PEI target age group) by block group.*

Appendix 2

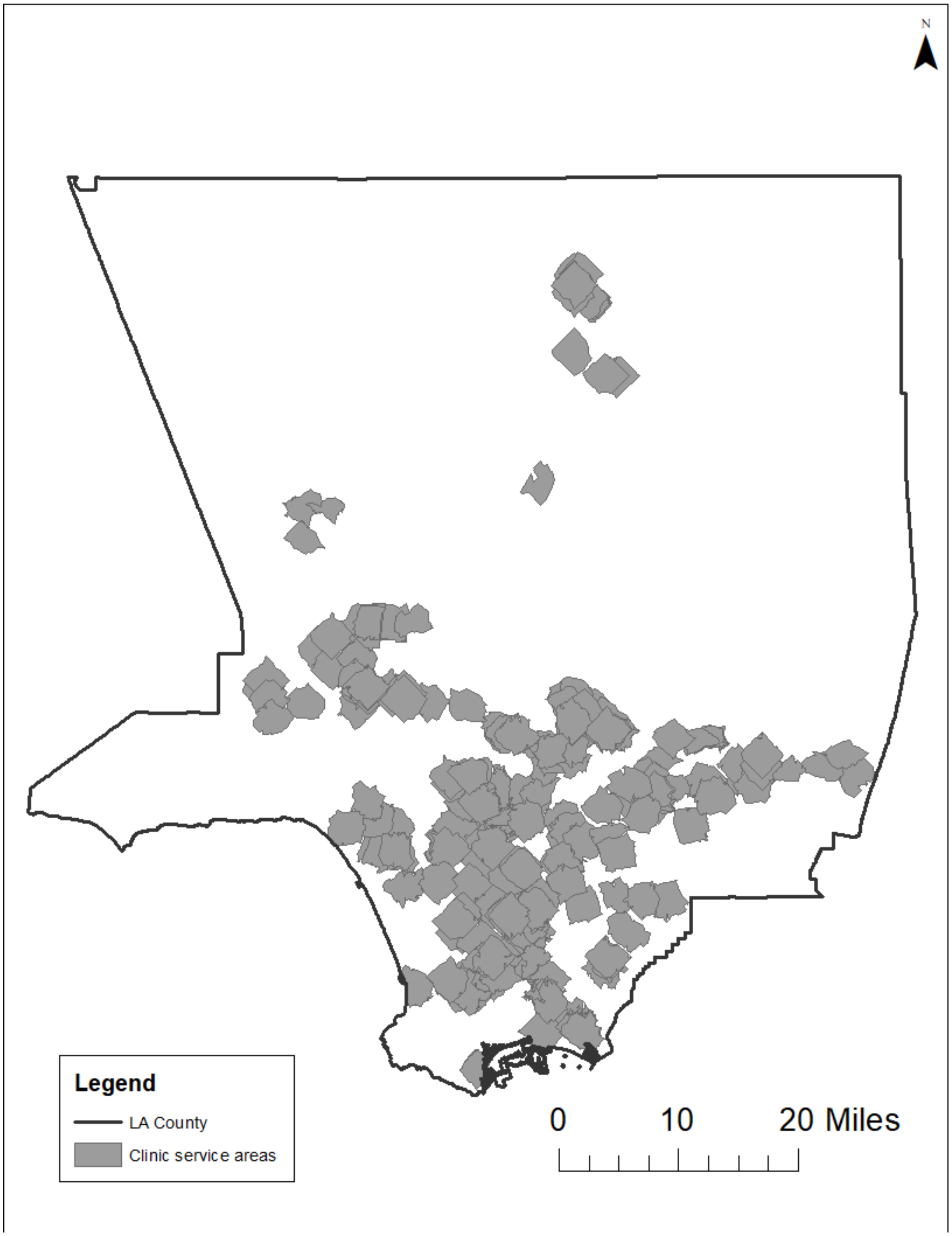

Figure A2. *LA County and the clinic service areas used for analysis, FY 2013-2014 (n=254)*

Appendix 3

Table A3.1. *Correlation matrix of coverage score and community characteristics at the service-planning-are (SPA) level, FY 2013-2014 (n=8).*

	1	2	3	4	5	6	7	8	9
1. SPA coverage	1.00								
2. Ethnic minority	0.41	1.00							
3. Born outside US	-0.02	0.41	1.00						
4. Below poverty	0.57	0.68	0.23	1.00					
5. No vehicle	0.38	0.44	0.61	0.80	1.00				
6. Limited-English	0.27	0.61	0.90	0.54	0.79	1.00			
7. College degree	-0.51	-0.85	-0.06	-0.66	-0.21	-0.34	1.00		
8. Sessions outside clinic	-0.31	-0.55	0.08	-0.20	0.07	0.01	0.58	1.00	
9. Sessions with language match	-0.34	-0.09	-0.73	-0.31	-0.76	-0.77	-0.12	-0.15	1.00

Table A3.2. *Comparison of regression models for analysis*

	Model 1	Model 2	Model 3	Model 4
Ethnic minority	*-0.96	-1.71	-1.67	*-2.68
Born outside US	*-1.25	0.06	-1.81	*-2.08
Below poverty	*-1.27	-3.07	-3.40	-0.76
No vehicle	0.88	4.81	3.68	0.29
College degree	*-1.21	-2.52	-2.29	*-3.22
Sessions outside office	*0.15	*0.90	*0.89	0.23
Language match	-0.27	*-4.59	*-4.67	-1.73
Population density (per sq mile)	-0.00002	*-0.0002	*-0.0002	*-0.0001
Limited-English	*1.209366	-3.259825		
R^2	0.27	0.23	0.23	0.37

Model 1 = base model
Model 2 = log transform DV, robust estimators
Model 3 = removed limited-English var
Model 4 = final model add number of clients served weight
*= p<.05