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16. Abstract

The opioid epidemic is a pressing public health issue in the United States and globally, and disparities in access to treatment for opioid use disorder (OUD) persist across the US. One of the key challenges identified in treatment is access to treatment facilities; thus, transportation is a critical component to improving the situation. In this project, we investigated the current needs and limitations with regard to treatment accessibility across the state of Tennessee given current transportation mechanisms in place and performed a case study evaluation of three communities to demonstrate travel for treatment for individuals across urban, suburban and rural areas. Based upon the needs assessment for the state and the case study analysis, options to improve accessibility for residents in Tennessee are presented. Additionally, a small set of interviews of staff at treatment facilities was conducted to provide additional context on the issues at hand. The methodology utilized publicly available data for transferability to other locations that are attempting to mitigate the opioid epidemic.

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Executive Summary

The purpose of the research study "Opioid Crisis and Transportation Investments in Tennessee" was to investigate and evaluate the current situation related to treatment accessibility in Tennessee and consider options that may help mitigate the opioid epidemic across the state. To accomplish this, the project team performed a review of literature related to treatment and transportation considerations; a baseline evaluation of current treatment and transportation options or lack thereof in Tennessee; and evaluation of three counties representing urban, rural, and suburban areas as a case study analysis of the "costs" of transportation for community members to access treatment. As part of the study, efforts were made to both gather perspectives from treatment facility staff for additional context on the issues under consideration and gain access to key data sources that offer additional opportunities for evaluation and analysis. While these efforts were not completely successful, they did provide great insight into some of the challenges that both researchers and practitioners face when trying to mitigate the situation of OUD.

From the study, several key findings were identified as described below. Additional research including potential for interviews of patients on individual challenges, transportation options, and preferences would be beneficial. Future work in this area would benefit from development of collaborative data sharing agreements between state agencies to further enable robust evaluation of the needs, transportation costs (financial or otherwise) to patients, and shared support in developing solutions. Regardless, some initial recommendations are provided below based upon the findings in the current study that have potential for implementation without significant financial burden.

Ultimately, TDOT and other state DOTs have an opportunity to positively impact the outcomes of substance abuse treatment by lessening the burden that individuals face in simply gaining access to treatment. Additional research would be beneficial to pilot test any policy, service, or infrastructure changes to truly quantify the impacts of such changes.

Key Findings

Using statistical analysis and publicly available data, the needs assessment took into consideration transportation access, individual household vulnerabilities, locations of treatment facilities across the state. Key findings include the following:

- Transportation access is one of the greatest barriers to successful treatment outcomes due to the need for regular visits to clinics.
- In the state of Tennessee, high-need predominantly exists in rural counties with high poverty rates, limited transportation resources, and limited treatment facilities in-county.
- The challenges are diverse and multi-faceted and require localized solutions
- Individuals in Tennessee may drive as far as 100 miles to access treatment centers and the costs can be over $40 per one-way trip
- In more urban areas, the costs of rideshare goes up, but more options for transportation exist such as transit and even walking to obtain treatment.
- In rural areas, the most prevalent and cost-effective option to access treatment is use of a personal vehicle.

- Counties in West Tennessee have higher prevalence of need for improved access to treatment facilities than the rest of the state

Key Recommendations

Based upon the research using available data and input from practitioners, several recommendations have been identified that would potentially improve the situation regarding access to treatment for patients across Tennessee.

- In areas where transit exists, evaluate the connectivity to treatment facilities and whether service times align with facility hours.
- In areas where ridesharing exists and provides reliable service, consider subsidizing the ridesharing for individuals through working with treatment facilities to offer vouchers or other options to minimize the cost of transportation.
- In rural areas, one transportation service that has potential to be utilized by individuals is the paratransit service, which at present has limitations that would prevent OUD patients from utilizing the service. However, paratransit exists in all 95 counties.
- The western portion of the state has the majority of the counties in highest need based upon the current analysis; and therefore, efforts should be made to prioritize additional, local analysis toward optimal transportation options in those areas.
- One of the largest challenges as determined by the data is the lack of facilities in rural areas. While dedicated treatment facilities may not be feasible in many of these areas of high need, working with the Tennessee Department of Health to develop treatment services at County Health Departments may be an approach that is not transportation-centric, but reduces the need for individuals to travel long distances for treatment. Each county has a public health department.

Additionally, while the focus of this study was on opioid use disorder and treatment, it should be noted that any investment and improved access to treatment for patients has potential additional benefits in improving access for other types of medical treatment and services as well as positive impacts to individuals and their families.

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Glossary of Key Terms and Acronyms

CDC	Centers for Disease Control
MOUD	Medication for opioid use disorder
OUD	Opioid use disorder
SAMHSA	Substance Abuse and Mental Health Services Administration

Chapter 1 Introduction

The opioid epidemic in the United States was the cause of nearly 841,000 deaths from 1999 to 2019 (Centers for Disease Control and Prevention (CDC), 2021a). From April 2020, drug overdose deaths accelerated in the US, with a 28.5 percent increase compared to the prior twelve month (CDC, 2021b). Fatalities are not the only harm experienced due to misuse of opioids: nonfatal overdoses can be impactful to individual's wellbeing and those around them. Furthermore, opioid use disorder (OUD) may reduce quality of life, harm relationships, and impair the ability to maintain employment (Strang et al., 2020). According to the Tennessee Department of Health's Annual Overdose Report prepared by the Office of Informatics and Analytics, overdose deaths related to opioid use has shown a steady increase in the state since 2013 regardless of age or race. Couple this with the fact that nearly 93% of the state is rural according to the 2010 US Census leading to potential for health disparities across the state, especially when considering the challenges with providing access to treatment.

Lack of access to treatment prevents individuals from utilizing resources to treat and cope with OUD. One of the key challenges identified in treatment is access to treatment facilities; thus, transportation, but not just the extent of roadway coverage, is a critical component to improving the situation. The objective of this project was to investigate and evaluate the current situation related to treatment accessibility in Tennessee and consider options that may help mitigate the opioid epidemic across the state. Key questions to be addressed include the following:

- What areas are in greatest need of assistance related to helping patients have improved access to treatment facilities?
- What transportation options exist for patients to utilize across the state that could be leveraged to mitigate transportation and accessibility barriers?
- What are the "costs" to patients that are trying to gain access to treatment in different types of communities?

In the sections that follow, we present a review of literature related to treatment and transportation considerations; a baseline evaluation of current treatment and transportation options culminating in a needs assessment for the state; and evaluation of select counties representing a range of urban to rural communities as a case study analysis of the "costs" of transportation to access treatment. Furthermore, we provide a discussion on data considerations and limitations related to accessibility of data for the study and additional context at a localized level. We conclude with a summary of our findings and some initial recommendations toward potential improvements that may help overcome the accessibility challenges for residents in the state seeking treatment.

Chapter 2 Literature Review

Prior to the COVID-19 pandemic, most treatment options for OUD required frequent in-person visits to clinics or other medical facilities for both medicated and non-medicated treatments and services such as group therapy. Rollbacks on federal policies and the pressure to provide care during the pandemic broadened the options for OUD treatment. Despite a significant shift towards the use of telemedicine to treat OUD (Uscher-Pines et al., 2023), its relatively novel applications in OUD treatment means research about its effectiveness, although promising (Cales et al., 2022; Hailu et al., 2023), is still emerging. Furthermore, though online options are increasingly being seen as acceptable (Tauscher et al., 2023) there are still those that may prefer in person services (Berle et al., 2015; Predmore et al., 2021), particularly for those with limited access to technology. In rural areas, the distances driven traveled for treatment can be significant with the only viable transportation options being a personal vehicle. Therefore, mobility and access to transportation resources can become a barrier to successful treatment. In the following sections, we provide an overview of treatment options, the role of transportation or lack thereof in treatment, and potential alternative solutions that may be utilized to mitigate the challenges related to transportation accessibility in treatment success.

2.1 Treatment Options

Treatment for OUD may include either pharmacotherapy, including the use of a class of evidence-based approaches referred to as medication for opioid use disorder (MOUD) and non-pharmacologic therapy, involving behavioral & exercise therapies. In terms of treatment options, MOUD, a pharmacotherapy, has stood out as an effective way to reduce opioid use and improve treatment program retention (National Academies of Science, 2019; NIDA, 2016). MOUD treatments involve using prescribed medication such as an agonist or antagonist to facilitate the substitution of a compound that binds to the opioid receptors, acting as a placeholder for the abused substance. There are a few medications that are frequently used for MOUD treatment: methadone, buprenorphine, naltrexone, and naloxone. Methadone, the most consistent treatment up to this point, is a Schedule 2 agonist used to reduce cravings and withdrawal symptoms. Schedule 2 substances are classified as having a high potential for misuse but can be approved for medical use. Methadone is taken at a treatment facility and may be prescribed for at home dosages between visits as needed (SAMHSA, 2022b). Methadone is generally taken for a minimum of 12 months, with longer treatment plans reaching a few years. Buprenorphine is a partial agonist that can be used to limit the effects of withdrawal (C. P. Thomas et al., 2014). It can be dispensed in other facilities outside of opioid treatment facilities, thus it's easier to access (SAMHSA, 2022a). Naloxone and naltrexone are antagonists, meaning they bind to the opioid receptors without activating the receptors, removing the euphoric effects typically associated with opioids. Naloxone is used to counteract an opioid overdose by reversing the resultant depression of the nervous and respiratory system. It can be administered intravenously or nasally during an overdose incident and has no potential for abuse (ASHP, 2022; NIDA, 2022), so it is frequently included in emergency response kits to treat acute opioid overdoses. Naltrexone is also used in an extended-release formulation, but its effectiveness is limited without an extensive detox period (Lee et al., 2018), and it has comparatively low treatment retention rates (Minozzi et al., 2011). There are treatments that combine these medications to increase efficacy, such as a buprenorphine and naltrexone treatment. A mix of buprenorphine and naloxone helps to reduce cravings (McAnulty et al., 2022) and limit misuse (Wesson & Smith, 2010). Methadone, Buprenorphine, and Naltrexone require an approved physician to sign off on the prescribed dosage at minimum, but naloxone can be purchased over the counter in most states.

Non-pharmacologic treatments that have been shown to be effective for treating substance misuse include cognitive behavioral therapy (KM et al., 1996; J. E. Thomas et al., 1984), group therapy, acceptance and commitment therapy, holistic therapies, and educational based methods (Louw et al., 2011) which center attention on addressing root causes of addictive behaviors. A broader description of these types of therapy can be referenced elsewhere (López et al., 2021). Group therapy typically involves discussions that will be held 2-5 times per week and typically last 90 to 120 minutes (Hoffman et al., 1996; Lo Coco et al., 2019). The West Virginia Comprehensive Opioid Addiction Treatment (COAT) employed a new group-based treatment method, providing group medication of buprenorphine with weekly support groups. They've successfully retained 50% of their patients for 5+ years and it has helped to offset staffing shortages (Lander et al., 2020) . Educational methods have also been used to help patients reconceptualize their understanding of pain and medication in a variety of applications (Louw et al., 2011). Non-pharmacologic methods have not been subjected to many comparative studies to examine the effectiveness as a sole intervention, so there is some ambiguity about the effectiveness relative to pharmacological treatments (Nadeau et al., 2021; Skelly et al., 2018). However, when used in tandem with medicated treatment, a combination of the two has been shown to be more effective than pharmacological therapy alone (López et al., 2021). Ultimately, success for each of these therapies is contingent on consistent participation and attendance (i.e., access).

2.2 The Role of Transportation in Treatment

The success of MOUD programs is typically measured by patient retention and the frequency of visits, which inherently is a function of patient mobility and accessibility. As discussed earlier, treatment is often provided via periodic visits to receive prescriptions and may include individual or group therapy sessions. Despite this, transportation to meetings remains a factor in retention success. Consistent medication is also vital to patient retention and successful treatment (Magura & Rosenblum, 2001). Furthermore, methadone treatment is exclusively distributed at opioid treatment program (OTP) sites. The factors described above create a requirement for reliable and accessible means of transportation. Patients often come from a variety of backgrounds, with variable socioeconomic statuses and access to personal transportation options. Patients experience longer drive or commute time for OTP than other medical facilities requiring frequent engagement due to sparser distribution of facities, with a 21% increase in drive time for patients in rural areas as compared to urban areas (Joudrey et al., 2019). Patients from rural areas also tend to spend more on transportation (Sigmon, 2014) and are more likely to use cars as compared to public and private transport (U.S. Census Bureau, 2021), but overall, counties with high rates (>10%) of zero-car households are majority rural (Bellis, 2020; US Census Bureau, 2020) in the United States.

There are certainly other reasons that the overwhelming majority of people that suffer from substance use disorders like OUD do not participate in treatment programs (Ahrnsbrak et al., 2017). In 2020, only 6.5% of those with substance abuse disorders (alcohol, opioid, stimulant, etc.) sought treatment (Center for Behavioral Health Statistics, 2021), with most of those who didn't seek treatment indicating that they did not see a need for treatment. A few qualitative studies have suggested this may be in part the result of negative stigma associated with receiving treatment, both from healthcare providers (Garpenhag & Dahlman, 2021) and the community at large (Corrigan et al., 2009; Newman & Crowell, 2021). Overcoming this stigma associated with opioid treatment will be a key factor in quelling the epidemic, but any attempt at intervening must include transportation.

2.3 Transportation Disparities

Several studies have detailed the disparities in transportation access across ethnicity, age, and socioeconomic status (Guerrero et al., 2013; Guerrero & Kao, 2013; Wendt et al., 2021). A 2017 study showed almost 6 million Americans indicated they delayed medical care due to transportation, with those below the poverty level and ethnic minorities being more likely to indicate this was the case (Wolfe et al., 2020). Other studies suggest distance from treatment facilities is inversely proportional to treatment completion in urban and rural areas (Alibrahim et al., 2022; Beardsley et al., 2003). Rural areas are particularly plagued by non-prescription opioid use amongst their younger population (Havens et al., 2011), which have been attributed to changes in social structures (Dew et al., 2007). Syed et.al. did a review of nine studies that showed there was not necessarily consensus in the degree to which participants' general healthcare utilization were affected by distance, but most identified distance from facilities as a barrier to healthcare (Syed et al., 2013). A study done in Baltimore, Maryland, US, identified a one-mile threshold as a barrier for treatment, where comparisons between distances above one mile and below one mile showed a 50% reduction in treatment completion for the latter, but comparisons between distances exceeding one mile showed no significant differences (Beardsley et al., 2003). Other studies defined opioid treatment deserts as areas greater than one mile driving distance and 30 minutes using public transit (Hyder et al., 2021)

There are documented disparities between urban and rural access to healthcare transportation that vary in severity. As of 2015, 82% of counties without a buprenorphine prescriber were rural (Rosenblatt et al., 2015). Rural regions typically face a relative dearth of available medical treatment facilities (Rosenblum et al., 2011). Car ownership does play a role, as a study in rural Appalachia found that those with access to a car and/or driver's license had greater healthcare utilization, independent of other factors (Arcury et al., 2005). Yet distance is not strictly an issue for rural Americans. Even in urban settings, transportation options that were restricted to walking and/or public transport increased likelihood of missed visits (Rask et al., 1994). Rural areas present a set of challenges that are distinct from urban areas (Sigmon, 2014) but also have characteristics (e.g., social connectedness) embedded in the environment that may provide opportunities for successful local interventions (Young et al., 2018).

2.4 Vulnerability and Equity

To determine where need may be highest for relevant resources, including transportation and economic, there are a number of ways to characterize economic and social vulnerability. The most recent version of the social vulnerability index (SoVI) developed by Cutter et al., a measure used to indicate social vulnerability to environmental hazards, combines data across demographic and socioeconomic categories, including racial composition, income and poverty levels, health insurance availability, educational attainment, employment information, housing indicators, and vehicle availability (Cutter et al., 2003; University of South Carolina, n.d.). Similarly, the U.S. Agency for Toxic Substances and Disease Registry (ATSDR) with the Centers for Disease Control and Prevention (CDC) created a social vulnerability index (SVI) to help emergency response planners predict high need areas in the event of a public health emergency, combining socioeconomic status indicators, household composition and disability status, minority status and language, and housing type and transportation resources (Agency for Toxic Substances and Disease Control, 2021). It is important to be thoughtful on which features to include and the limits of the information they convey, a concept explored in more depth by scholars who have cautioned against the use of categories such as race as explanatory features without a clear reason for their inclusion, meaning, and larger societal context (Helms et al., 2005; Boyd et al., 2020).

Furthermore, William Lucy described five conceptions of equity for planning purposes: equality, need, demand, preference, and willingness to pay (1981). Lucy recommended that while it may not be possible to satisfy all five dimensions in any one scenario, at least two should be used in any decision-making context. Martens described how distributional justice could be applied in a transportation equity planning context, suggesting three potential guiding principles for the distribution of a transport good: equality, where goods are equally distributed over all people; merit, where a burden, past actions, and a moral judgment determines the reward (e.g., our income system for employment determines income levels based on a judgment on the merit of work completed); and need, where transport goods availability would be determined on a needs-based system (2012).

2.4 Current Interventions and Solutions

Any potential set of solutions for addressing medical transportation access will have to consider regional and national trends. Globally, trends indicate urbanization and increasing wealth inequality are directly contributing to changes in transportation access in general. As such, any consideration of interventions must address concerns relevant to the populations being served. Areas with urban sprawl are likely to have higher private vehicle ownership, whereas compact, dense regions have more residents within an area that don't rely upon private vehicles. Historic trends have associated increasing gross domestic product (GDP), an indicator of wealth of a community, region, or nation, with increasing car ownership in several countries (Dargay & Gately, 1999), and another suggests that the increases in car ownership are more prominent in wealthier nations.

2.5 Metropolitan Public Transport Systems: Light Rail & Buses

Public transportation systems have expanded access for those in city centers but still may be neglecting those with the greatest access needs. Dense city centers with industrialized economies have invested in light rail systems to counter congested roadways, an approach suited for those near metropolitan areas but one that may neglect rural regions. Likewise, public buses tend to be less efficient for rural areas where destinations may be more diffuse. This is issue of access is amplified when considering the costs to upgrade public transportation services. Rail systems are either inter-city or urban-focused (Burgueño Salas, 2022), with the average U.S. rail project costing around $172 million per mile of track (Lewis, 2021). Despite billions of dollars in investments, rail & bus transit ridership has declined (Erhardt et al., 2022), likely due to increased access to ride hailing services, demographic turnover (Berrebi & Watkins, n.d.) and more recently public health crises like the COVID-19 pandemic, which will be discussed later. This is a departure from international trends, which have mostly seen transit ridership increase in response to investments in climate-friendly transportation. There has been discussion about the purpose and impact of such expensive transportation systems, mainly between it being a method for improving access to transport or substituting existing transport options for another (Grengs, 2004). Suburban and rural areas have begun to experience somewhat of a "demographic inversion" as lower income residents are priced out of cities, limiting their transport options. This is sure to affect the accessibility needs of those seeking treatment for OUD, many of whom fall within the demographics likely to experience this phenomenon (Lippold et al., 2019). High investment costs for construction and the limited reach of many urban-focused transport systems means that for regions that have a high proportion of rural residents, these options simply cannot meet the needs quickly enough.

2.6 Paratransit

Paratransit stands out as an immediate option to bridge the widening transportation access gap for residents in non-metro areas. Paratransit are those transportation services that supplement mass-transit routes by providing rides to individuals and groups at adjustable hours and locations. Examples of paratransit include on-call van services & specialized buses for elderly and disabled patients. Operators typically have a medical background and are equipped to work with patients with a wide spectrum of disabilities. Paratransit is primarily a service organized by the state and is provided through methods like fee for service, Medicare-managed care, or through third party brokers. A report showed that around 3.2 million people used NEMT IN 2018, with patients that undergoing OUD using around 25 rides annually (~ bi-weekly) (Buderi & Pervin, 2021). Federal funding has been made available in the past to support access to healthcare for eligible patients via Medicare and Medicaid (Consolidated Appropriations Act, 2021), with many of the projects focused on increasing access to substance use disorder treatment. Companies have designed software to provide patients, caregivers, and volunteers to schedule micro-transit services (Fishman & Grela, 2021). A pilot program has been tested in Washington D.C. using funding from a State Opioid Response grant from SAMHSA. Non-Medicaid expansion states use funds from this grant to supplement existing modes of transport through gas cards, bus passes, and rideshare (Marcovitz et al., 2022). Paratransit and other services have been shown in the past to improve treatment retention relative to individual vouchers (Friedmann et al., 2001)

Paratransit may be restrictive at times when it comes to OTP patients. Transit providers are required to follow the eligibility rules outlined in the Americans with Disabilities Act (ADA)(49 CFR Part 37, 2023), but not all services readily accept new patients, and wait times can exceed 60 minutes (US Government Accountability Office, 2016). Due the flexibility of the Medicaid funding program, some operators have restrictions on their capacity and patient profile, as well as expectations for preauthorization that vary state to state (Heath, 2018; Kaiser Family Foundation, 2018). In the same report by Buderi and Pervin, NEMT users indicated that while the services greatly improved their independence, mobility, and mental health, they desired more flexibility in the qualification policies and provider accountability (e.g., background checks, commitment to punctuality) (Buderi & Pervin, 2021). There has been concern in the past that legislation changes that govern the funding that states are required to provide for transportation via Medicaid could be redirected (Dickson, 2018), but the 2021 Consolidated Appropriations Act codified the requirements for state provision as a statute in the Social Security Act(State Plans for Medical Assistance, 2021) . State policy will play a large role in determining the level of access that OTP patients have to paratransit services.

2.7 Ridesharing

Ride sourcing companies like Uber and Lyft have also been explored as a viable option for filling in transportation gaps that public transit and traditional paratransit cannot cover. Lyft's Concierge and Uber's collaboration with Circulation in 2016 have already established themselves as conduits for increasing options for non-emergency medical transportation (NEMT) (B. Powers et al., 2016). NEMT is an estimated $5 billion industry, and most funding is provided by state and federal Medicaid/Medicare funding, providing a relatively reliable source of income for ride-share providers. Recent partnerships have expanded the capabilities to give doctors the ability to schedule rides through patient medical records (Pifer, 2020).

Several benefits have emerged from the integration of ride-sharing services into the NEMT portfolio. Early results showed a 30% decrease in wait time and a similar decrease in cost (B. W. Powers et al., 2016) as compared to previous NEMT options. Using Lyft for inter-facility transport decreases the length of stay by around 20 minutes (Blome et al., 2020) . A study done in Massachusetts estimated that the majority of patients are aware of ridesharing services as an option for medical transport (Pearlmutter et al., 2017) and there is general support for such methods from the patient perspective (Ledingham et al., 2022), despite the fact that there is a preference for family or friends to provide transport (Tomar et al., 2019) A cost benefit analysis for NEMT used for chronic diseases showed these interventions to be cost effective, with some producing net savings when examined using health economics metrics like Quality Adjusted Life-Year (Transit Cooperative Research Program, 2006).

Despite this there are some aspects of ride-sharing services that may limit its use. In contrast to the aforementioned reports, Chalyachati et.al ran a study that displayed little to no improvement in reducing missed primary care appointments via free rideshare services (Chaiyachati et al., 2018). There are challenges with incorporating ride-sharing services, including driver medical training and logistics related to failed pickups (Eisenberg et al., 2020; B. W. Powers et al., 2016). Interestingly enough, the Eisenburg et.al study found that increasing the proportion of rideshare NEMT led to an increase in failed or late pickups(Eisenberg et al., 2020). There are concerns that drivers would be ill-equipped to handle a medical emergency without relevant medical background information and training, neither of which are formally provided by Lyft or Uber (Wetsman, 2022).There are also issues related to accessibility for patients with disabilities that have resulted in legal proceedings (Lien, 2018). Any public -private partnerships for rideshare-based NEMT will need to establish protocol for training, clarify funding mechanisms, and ensure the offerings are compliant with ADA and HIPPA. Future research should consider whether there is a more effective way to measure the impact of transportation barrier interventions and policies, as the studies have indicated there are more factors to consider than just scheduling rides.

2.8 Telehealth & COVID-19

Telehealth is not a direct transportation intervention, but its increased deployment is rapidly changing how people access OUD treatment and highlighting potential benefits and drawbacks for its use. A study in Philadelphia (Aronowitz et al., 2021) interviewed 22 OUD treatment prescribers at low barrier facilities, which are treatment hubs purposed to minimize barriers that may limit access such as cost, location, stigma, or rigid attendance requirements (mobile units and harm reduction centers are two examples of this). The general consensus was that telehealth makes access easier and helped to adjust to the additional barriers imposed by the COVID-19 pandemic. It has also been shown that telehealth was just as successful in retaining patients in MOUD programs as the in-person treatments (Chan et al., 2021).

However, despite the rapid adaptation of telehealth and generally positive feedback, there are challenges to overcome. Many patients lack access to phones/computers that can support telehealth, and there is "substantial variability" between groups in terms of being accustomed to the technology and associating the telehealth visit with actual medical care (Aronowitz et al., 2021). Studies have suggested that broadband availability may prove to be a challenge to implementing telehealth in rural areas, where there is a lower saturation of Wi-Fi towers (Drake et al., 2019). The American Community Survey estimated that around 80% of households have a broadband subscription as compared to 62% of rural counties with high rates of zero-car households (ACS, (Bellis, 2020)). Nearly a quarter of rural America lacks coverage from 25/3 Mbps broadband, a minimum standard the FCC uses to determine broadband access [(FCC, 2020). The same challenges for access may extend to rural health clinics and small physician offices (< 4 physicians), 70% of which are in rural areas (FCC, 2010). The FCC recommends a minimum of 10 Mbps for rural health clinics (FCC, 2010). There are criticisms in how the FCC determined rural access beyond the census tract level. Namely, they've likely overestimated the percentage of those with internet access by counting census blocks as having coverage when there is at least one individual residence covered, allowing for others without coverage in the census block to be overlooked (BroadbandNow, 2021). Despite this, there are several evidence-based models for successful telehealth with just a small percentage of the threshold bandwidth set by the FCC (Chan et al., 2021; Hudson, 2005; Struminger & Arora, 2019).

There are also legal challenges to overcome. In 2019, the effects from a global shutdown shifted the landscape of public healthcare in a way that may have permanence. There was a 13.2% increase in fatal overdoses during the pandemic (Ahmad et al., 2021) . In response to this, government agencies sought to lessen restrictions on medical treatment options for OUD, temporarily suspending policies like the Ryan Haight Act, which requires that initial visit evaluations for medical opioid treatment must be done in person. The emergency policies that loosened this requirement to make treatment more accessible have allowed for telehealth and more remote options to be used ubiquitously. In June 2021, mobile narcotic treatment units were approved by the DEA to dispense methadone via mobile units to streamline registration and improve registrants' ability to provide services to patients in remote or underserved areas (DEA, 2021). As of the time of writing, the DEA is considering new policies for prescribing MOUD after the COVID-19 public health emergency expires (DEA, 2023), but these have been described by many industry stakeholders as "overly restrictive" (American Telemedicine Association, 2023). Overall, the prospect of a policy proposal still represents an improvement in access over the last decade, with potential for greater improvement moving forward being spurred by the forced adaptations in response to the COVID-19 pandemic.

2.9 Summary

A continual rise in opioid misuse and the complexity associated with treatment requires reliable methods of transportation to limit what can be characterized as a fourth wave of the opioid epidemic. Rural and urban centers face challenges associated with distance from treatment centers, although the challenges may differ in complexity and severity. Vulnerability and equity are key factors for consideration when trying to prioritize services to mitigate access because there is no one-size fits all solution and these factors play significant roles in accessibility. Federal and state programs have sought partnerships with ridesharing companies and paratransit to fill in access gaps, but there are challenges associated with driver training and logistics that may prevent these solutions from fully addressing the problem. The shift to telehealth, accelerated by the COVID-19 pandemic, may serve as a reliable supplement to in-person visits, but will require the persistence of remote-friendly policies, improvements in access to broadband in more remote areas, and accommodations for sub-populations who will continue to require in person services for various reasons.

Chapter 3 Needs Assessment

For this portion of the study, efforts were made to characterize the current situation across Tennessee in terms of access to treatment facilities and potential challenges for patients in accessing the facilities. Specifically, the focus was on how transportation need and economic vulnerability influences access to care. Publicly available data was collected from multiple sources at different geographic scales to create county-level scores to indicate potential need for investment or mitigation. Statistical analysis was performed to compare how various factors may impact results using different modeling choices. Of note is the importance for consideration of the ethical implications of using limited data to guide funding allocation decisions and how these findings could be used moving forward.

3.2 Methodology

To assess need across the state, multi-criteria decision making (MCDM) was utilized because it offers insight on quantitative strategies for evaluating alternatives based on varied, and potentially conflicting criteria (Triantaphyllou, 2000). MCDM allows for a large degree of control by the modeler and for relatively easy modifications to be made if new data becomes available or if preferences or priorities shift (Yannis et al., 2020). For problems with a discrete and known set of options, approaches include simple additive weighting (SAW), multi-attribute utility/value theory (MAUT/MAVT), elimination and choice translating reality (ELECTRE), preference ranking organization method for enrichment evaluations (PROMETHEE), and analytic hierarchy process (AHP) (Yannis et al., 2020). One of the oldest and most common forms of MCDM is the simple additive weighting or the weighted-sum model, where attributes are scaled and summed based on relative importance weights to determine a single measure that combines multiple attributes (Triantaphyllou, 2000). SoVI and SVI are two examples of this approach, where demographic and socioeconomic data are combined to develop one vulnerability indicator within a geographic area. We used the weighted sum model because of its simplicity and interpretability.

Other MCDM considerations beyond model type include data normalization and feature weighting. Data normalization allows you to compare and aggregate data across multiple units, scales, and directions of benefit (Vafei et al., 2016). There are a number of approaches to normalize data, and some are considered to be more suitable for specific decision methods than others (Vafei et al., 2016; Milani et al., 2005). For the current study, we compared two normalization approaches, detailed in the following. Some researchers have developed specific approaches for determining appropriate feature weights based on individual feature influence and decision-maker preferences (Wang et al., 2010), while another study evaluating the impact of changes to weights found their solution rankings were relatively robust to reasonable deviations in weights (Guhnemann et al., 2011). In this work, we compared our results across varied feature weights and normalization types to investigate how our county-level rankings change based on changes to our index or scoring model configuration. In addition, we will compare different subsets of our features to evaluate the importance of careful feature selection in our county prioritization efforts. These efforts allow for testing the sensitivity of the model to specific variables/features.The approach taken involved collecting publicly available data from multiple sources, described in the Data section below. The data used includes estimated travel times to treatment facilities, potential prevalence of OUD, potential indicators of vulnerability, and existing transportation resources.

We utilized data normalization, weighted sums, and feature choice to create various indices to combine and compare these data indicators across the state of Tennessee at the county level toward arrival at key counties that may be in greatest need of assistance to mitigate the opioid epidemic.

3.3 Data

Four primary data categories were identified to perform the needs assessment: treatment need, treatment supply, transportation need, and transportation supply to evaluate differences between counties. Each are discussed in detail below.

3.3.1 Treatment need

Treatment need was estimated based on potential OUD prevalence indicators within each county: nonfatal overdose rates, fatal overdose rates, and prescription opioid dispensing rates per capita. County-level fatal and nonfatal overdose rates are reported by the Tennessee Department of Health (TN.gov, n.d.-b), and county-level prescription dispensing rates are provided by the CDC (CDC, National Center for Injury Prevention and Control, 2019). While this is not an exact measure of OUD treatment need, it is the lowest granularity for this data obtainable from publicly available sources. Individual-level health records could help with spatial granularity but would still not capture OUD that has gone untreated or undiagnosed and has not resulted in an overdose.

3.3.2 Treatment supply

To estimate available treatment services, the Substance Abuse and Mental Health Services Administration's (SAMHSA) Behavioral Treatment Services Locator was used, which uses treatment facility data collected from SAMHSA's Center for Behavioral Health Statistics and Quality's (CBHSQ) annual surveys: the National Survey of Substance Abuse Treatment Services and the National Mental Health Services Survey (SAMHSA, n.d.-b). The Locator dataset is also regularly maintained, with verified changes to facilities updated weekly and new facilities updated monthly if requested by facilities. (SAMHSA, n.d.-a). The four facility types included in the SAMHSA data are: Substance Abuse, Buprenorphine Practitioners, Mental Health Facilities, and Health Care Centers run by the Health Resources and Services Administration (HRSA). For this study, both Substance Abuse facilities and HRSA Health Care Centers were used to represent facilities. Substance Abuse treatment centers listed by SAMHSA's Locator must meet certain criteria including state or national licensure or accreditation to provide substance use treatment but does not include facilities who provide treatment exclusively to persons who are incarcerated. The HRSA is a federally-funded agency whose primary role is to improve access to health care for individuals who are geographically isolated, economically or medically vulnerable (U.S. Health Resources & Services Administration, 2021). Buprenorphine practitioners (BPs) are any healthcare practitioner that have applied for and received a waiver to prescribe buprenorphine in any medical setting as described in the Controlled Substances Act and self-reported their status to SAMHSA (SAMHSA, 2021; SAMHSA, 2022). Mental health facilities can provide valuable resources to overcoming OUD, but in the SAMHSA dataset, there is no requirement that they provide any OUD-specific treatment, medication, or resources, so we did not include this data. For the remainder of this study, we include only substance abuse and HRSA facilities that have no restrictions on genders served. Single-gendered facilities were not used in this analysis to allow for inclusion of facilities where ALL potential patients can be served. This avoiding having to approximate or estimate gender as an additional factor for consideration in the statistical analysis and modeling efforts.

3.2.3 Transportation need

Potential indicators of economic vulnerability from the American Community Surveys (ACS) were used to represent need for transportation investment, including the percentage of the population aged 18 to 64 for whom poverty status is determined who are living in poverty, the percentage of the civilian noninstitutionalized population with no health insurance coverage, and the percentage of occupied housing units reporting no vehicles available (ACS 2015-2019, 5-year estimates). Other features considered included the unemployment rate for the civilian population over 16 years of age, educational attainment for the population aged 25-years and older, percentage of households receiving social security benefits, and racial composition. Ultimately, these additional features were not included in the indices presented in this study either because of their high correlation rates with other included features or because they were not direct indicators of need.

Another factor used to determine transportation need was a proximity-based accessibility measure of estimated travel time to the nearest treatment facility using the SAMHSA dataset with the criteria described above. Travel time was estimated using the Google Distance Matrix API for the method of driving. Each census tract in Tennessee was queried using its centroid as the origin, a method that is useful for estimation, though it may yield underestimated driving times in rural areas with larger and less densely populated tracts (Nobles et al., 2014). For each census tract, we ran a query of the four closest facilities of each type in our data subset (substance use, HRSA health care centers) by Euclidean distance. The query returned an estimated travel time and distance using the actual road network, and we proceeded with the shortest available travel time from each census tract centroid. Because the remainder of our data was primarily available at the county level, we aggregated census tract-level access to the county-level using a population-weighted mean of census tract values weighted by census tract population relative to the county population. The dataset created at the census tract level is shown in Figure 1, where darker shading indicates longer estimated driving times to the nearest treatment option.

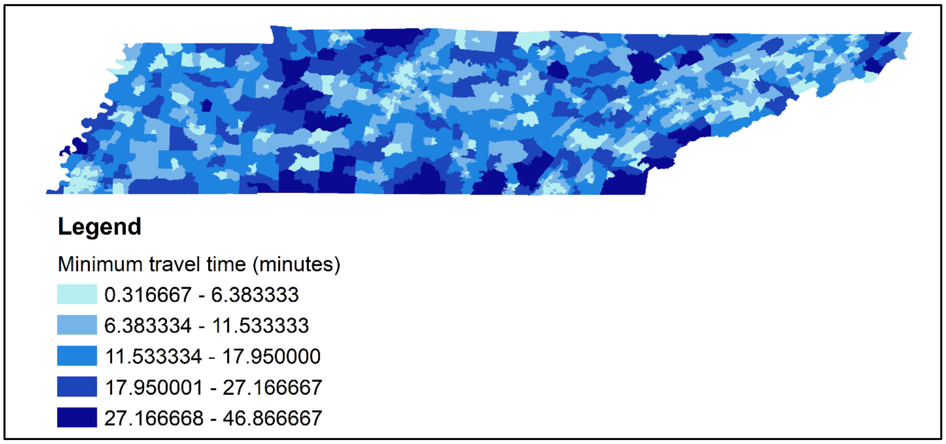


Figure 1: Minimum driving time from census tract centroids to nearest treatment facility.

3.2.4 Transportation supply

To understand existing public transportation supply, we gathered data from the Tennessee State Government resource pages on public transit services (TN.gov, n.d.-c; TN.gov, nd.d-d; TN.gov, n.d. -e). The source included transportation options listed at the county level, so all options were assigned to their county of operation. This data collection included type of service (fixed route or on-demand), service restrictions (i.e., age restrictions, wheelchair accessibility, disability status), area of operation (i.e., within city limits, within county limits, unknown), and indicators of hours of operation (i.e., operates in the evenings after 5 pm, operates on weekends).

A summary of all of the data sources used, including their reason for inclusion, source, and spatial scale, is shown in Table 3-1.

3.3 Data analysis using a weighted sum model

The weighted sum model was used to combine our collected data and generate index or score values for each county in Tennessee. The variations of how these data sources are combined (i.e., normalization and weighting) was evaluated to understand the impacts of such changes on the overall index because of the potential use of findings to inform policy and investment decisions. Transportation supply data was analyzed separately utilizing the indexing results.

3.3.1 Normalization

Data normalization allows for the transformation of data across different scales and units into comparable and combinable numerical data (Vafaei et al., 2016). Raw data values with min-max normalization and Z-score normalization were compared with the min-max normalization producing a scale that is consistent across all features. The equation used for min-max normalization is found in Table 3-2. Z-score normalization represents outliers better than min-max normalization, but it produces values centered around zero and with an inconsistent range across features. The equation for Z-score normalization is also found in Table 3-2, and it functions by subtracting the mean value of each feature I(μ_i), from each data point and dividing by the feature's standard deviation (σ_i). In this first iteration, features were only considered representing economically-based transport need: percentage of households with no vehicles available, percentage of adults living in poverty, and percentage of the non-institutionalized population with no health insurance. The index value was found using equal weighting of each of the three features with the following normalization schemes: Index 1 uses no normalization; Index 2 uses Z-score normalization; and Index 3 uses min-max normalization.

Table 3-1: Summary of publicly available data considered

Category	Relevant data	Source	Spatial scale
Treatment need	Fatal and non-fatal overdose rates (per capita)	Tennessee Drug Overdose Data Dashboard (TN.gov, n.d.-b)	County
Treatment need	Opioid prescribing rates (per capita)	Centers for Disease Control and Prevention, National Center for Injury Prevention and Control, 2019	County
Treatment supply	Treatment providers, facility types, service restrictions	Substance Abuse and Mental Health Services Administration (SAMHSA) Behavioral Treatment Services Locator (n.d.-b)	Point Address
Transportation need: Economic vulnerability	Car ownership rate, Adult poverty rate, Health insurance rate	American Community Survey 2015 – 2019, 5-year estimates (U.S. Census Bureau, 2020)	County
Transportation need: Direct need	Travel times to closest treatment facility	Google Maps Distance Matrix API	Tract → County
Transportation supply	Public transportation resources	Tennessee State Government (TN.gov, n.d.-c; TN.gov, nd.d-d; TN.gov, n.d. -e)	County

Table 3-2: Indices 1-3, using vulnerability data only and comparing normalization approaches

Index #	Index components:	Index equation for each county's values
1	**No normalization** Features: • % no vehicles (VH), • % adult poverty (AP), • % uninsured (U) Equal weights	$\frac{VH_i + AP_i + U_i}{3}$
2	**Z-score normalization** Features: • % no vehicles (VH), • % adult poverty (AP), • % uninsured (U) Equal weights	$\left(\frac{VH_i - \mu_{VH}}{\sigma_{VH}} + \frac{AP_i - \mu_{AP}}{\sigma_{AP}} + \frac{U_i - \mu_U}{\sigma_U}\right)/3$
3	**Min-max normalization** Features: • % no vehicles (VH), • % adult poverty (AP), • % uninsured (U) Equal weights	$\left(\frac{VH_i - \min VH}{\max VH - \min VH} + \frac{AP_i - \min AP}{\max AP - \min AP} + \frac{U_i - \min U}{\max U - \min U}\right)/3$

3.3.2 Weighting

Additional indices were developed included the features relevant to treatment supply and treatment need: fatal and nonfatal overdose rates, prescription opioid dispensing rates, and travel time to nearest treatment facility. We used min-max normalization and tested varying the weights assigned to each of the features, shown in the equations in Appendix A. Additional information on indices 4-8 is also provided in Appendix A.

3.4 Evaluating existing transportation supply within counties

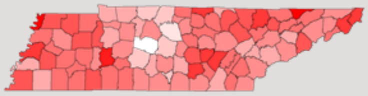
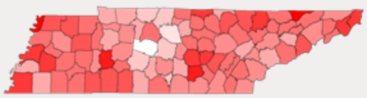
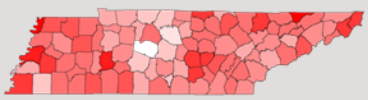
Following our analysis of potential overall county-level treatment need, we evaluated existing public transportation options for potentially high-need counties. Because we are evaluating county-level access with the goal of allocating funding to improve this access, it is important to understand both where there are no existing resources and how potential investments could integrate with existing transportation infrastructure. We evaluated transit options using four criteria levels with increasing service requirements, detailed in Table 3-3. The minimum criteria (Criteria 1) for a service to be considered usable for the general public is that it has no age restrictions, is not limited to seniors, is not limited to adults with disabilities, and is wheelchair accessible. Criteria 2 adds the restriction that the service area not be limited to within city limits or listed as “unknown” on the data source for broader geographic usage. Criteria 3 includes services that operate after 5 pm (allowing for later appointments). Finally, Criteria 4 requires that the service also operate on weekends.

Table 3-3: Criteria for evaluating existing public transit services

Requirement	Criteria 1	Criteria 2	Criteria 3	Criteria 4
No age restriction	✓	✓	✓	✓
Not limited to senior activities	✓	✓	✓	✓
Not limited to adults with disabilities	✓	✓	✓	✓
Is wheelchair accessible	✓	✓	✓	✓
Operates in county (not just in city limits or unknown)		✓	✓	✓
Operates after 5 pm			✓	✓
Operates on weekends				✓

3.5 Results

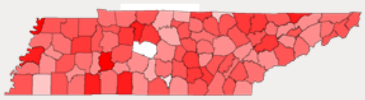
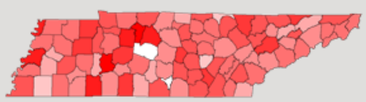
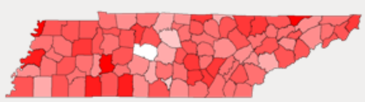
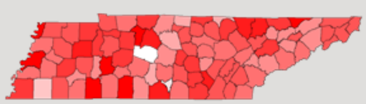
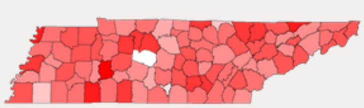
The results from Indices 1 through 3 are shown in Figure 2, including a shaded map to illustrate geographic distribution of index values, as well as the top five counties by index value for each of the six indices. Figure 3 contains the results for indices 4 through 8. From these results, we can observe some consistencies across indices. Lake and Perry County were identified in the top 5 counties across all 8 indices. Hancock was identified in all but one; Hardin was identified in indices 4, 5, 6, and 8; Cheatham in 4, 5, 7, and 8; Lauderdale in 2, 3, 7; and Grundy in 2, 3. The remaining counties were only identified in one index.

Index	Notes	Top 5 counties, index values	
1 	Equal weights **No normalization** VH + AP + U	Lake	0.175
		Hancock	0.169
		Perry	0.155
		Clay	0.147
		Johnson	0.145
2 	Equal weights **Z-score normalization** VH + AP + U	Lake	2.258
		Hancock	1.895
		Perry	1.589
		Grundy	1.415
		Lauderdale	1.321
3 	Equal weights **Min-max normalization** VH + AP + U	Lake	0.854
		Hancock	0.784
		Perry	0.702
		Lauderdale	0.695
		Grundy	0.683

Map key: Min index value — Max index value

Text formatting used to highlight consistent county appearances

Figure 2: Index results for Indices 1-3, including the top five ranked counties for each

Index	Notes	Top 5 counties, index values	
4 	Min-max normalization **Equal weights** OD_F + OD_NF + OP + TT + VH + AP + U	Perry	0.566
		Lake	0.527
		Hancock	0.511
		Cheatham	0.511
		Hardin	0.504
5 	Min-max normalization **Varied weights:** OD rates + prescribing > travel info > economic info	Cheatham	0.554
		Perry	0.533
		Hardin	0.501
		Lake	0.487
		Davidson	0.483
6 	Min-max normalization **Varied weights:** Economic info > travel info > OD rates + prescribing	Perry	0.612
		Lake	0.577
		Hancock	0.565
		Lawrence	0.514
		Hardin	0.512
7 	Min-max normalization **Varied weights:** Travel info > OD rates + prescribing > economic info	Perry	0.517
		Cheatham	0.506
		Lake	0.504
		Lauderdale	0.497
		Hancock	0.490
8 	Min-max normalization **Varied weights:** Economic info > OD rates + prescribing > travel info	Perry	0.617
		Lake	0.555
		Hancock	0.537
		Hardin	0.529
		Cheatham	0.510

Map key: Min index value — Max index value

Text formatting used to highlight consistent county appearances

Figure 3: Index results for Indices 4 through 8, including the top five ranked counties for each

Table 3-4 shows actual feature data for each of the counties identified as top five counties by index values across the six indices. This table allows us to return to the original data and visualize which components of the indices contributed most strongly to the rankings for each county. For example, Lake and Lauderdale Counties, both rural areas, have the highest rates of households with no vehicles across the state, which is a clear indicator of need. Similarly, Perry, Lake, and Hancock Counties all have high adult poverty rates. Conversely, Cheatham County has relatively lower rates of our economic vulnerability measures but contains the maximum values for fatal and non-fatal overdose rates. Of note is that Cheatham County is adjacent to the large, urban Metropolitan-Nashville Davidson County area. This table provides context that can be considered in concert with the indexing as part of the needs analysis. It can also serve in considerations of the benefits of potential investment strategies.

Table 3-4: Comparison of absolute values for counties identified in top 5 most vulnerable across the 8 indices.

County Name	County pop	No vehicles (%)	Adult poverty (%)	No insurance (%)	Travel time (min)	Fatal OD per 10,000	Nonfatal OD per 1,000	Opioid dispensing per 100
Perry	7,962	4.9	25.3	16.1	17.5	1.3	3.8	100.6
Lake	7,401	11.5	29.6	11.3	6.6	2.7	4.1	10.4
Hancock	6,587	9.7	30.3	10.8	12.8	0.0	3.2	79.2
Hardin	25,715	5.8	20.9	11.4	14.3	2.7	3.2	108.7
Cheatham	40,181	3.2	11.2	9.4	21.8	6.7	5.5	36.2
Lauderdale	25,989	11.7	20.1	9.8	11.0	2.7	2.7	63.5
Grundy[1]	13,529	6.9	21.7	14.6	*10.7*	*3.0*	*2.8*	*22.9*
Value range across the entire state:								
Min	5,001	2.0	4.4	4.0	5.8	0.0	1.0	7.0
Median	32,043	5.0	16.5	9.6	11.4	2.6	2.4	56.7
Max	929,744	11.7	30.3	16.1	34.9	6.7	5.5	150.2

Table Notes: Grundy, was only identified in Indices 2-3 only, which did not include the italicized features in the index calculation. Shading used to illustrate value magnitude; County name text color carried over from Figures 2 and 3.

3.6 Existing transportation resources

For the counties reoccurring among the top five using the indices, public transportation resources that met our inclusion criteria were also considered. Unfortunately, as demonstrated in Table 3-5, none of the seven counties under consideration have any fixed route services that met even our least restrictive criteria. Five of the seven have on demand services that meet Criteria 1 and 2, but these services are not operational after 5 pm or on weekends, which may limit their usability for individuals who are not able to attempt to access treatment centers during weekday business hours.

Table 3-5: Evaluation of existing public transportation resources in top index identified counties

	Criteria 1		Criteria 2		Criteria 3		Criteria 4		County Info	
County Name	**Fixed route services**	**On demand services**	**Fixed route services**	**On demand services**	**Fixed route services**	**On demand services**	**Fixed route services**	**On demand services**	**County population**	**Households with no vehicles (%)**
Perry	0	1	0	1	0	0	0	0	7,962	4.9
Lake	0	1	0	1	0	0	0	0	7,401	11.5
Hancock	0	0	0	0	0	0	0	0	6,587	9.7
Hardin	0	1	0	1	0	0	0	0	25,715	5.8
Cheatham	0	1	0	1	0	0	0	0	40,181	3.2
Lauderdale	0	0	0	0	0	0	0	0	25,989	11.7
Grundy	0	1	0	1	0	0	0	0	13,529	6.9

Table notes: Gray shading used to highlight any available resources; red shading carried over from Table 5 to demonstrate relative magnitude of values; County name formatting carried over from Figures 2 and 3.

3.2 Additional considerations for preliminary identification of counties

In an effort to interpret the results, geographic distribution across the state was also considered. In Figure 6, we can observe that the identified potential high-need counties are more concentrated in the central and western regions of the state, while the potentially low need counties are more centrally located. This indicates that our indices may be measuring something that skews our results away from the eastern region of the state, and we may be missing a feature that would help identify counties across the state with similar levels of need. It may also be illustrating an existing phenomenon in the state, where resources and need may not be evenly distributed. Additional research is needed to evaluate what other factors may be contributing to these trends.

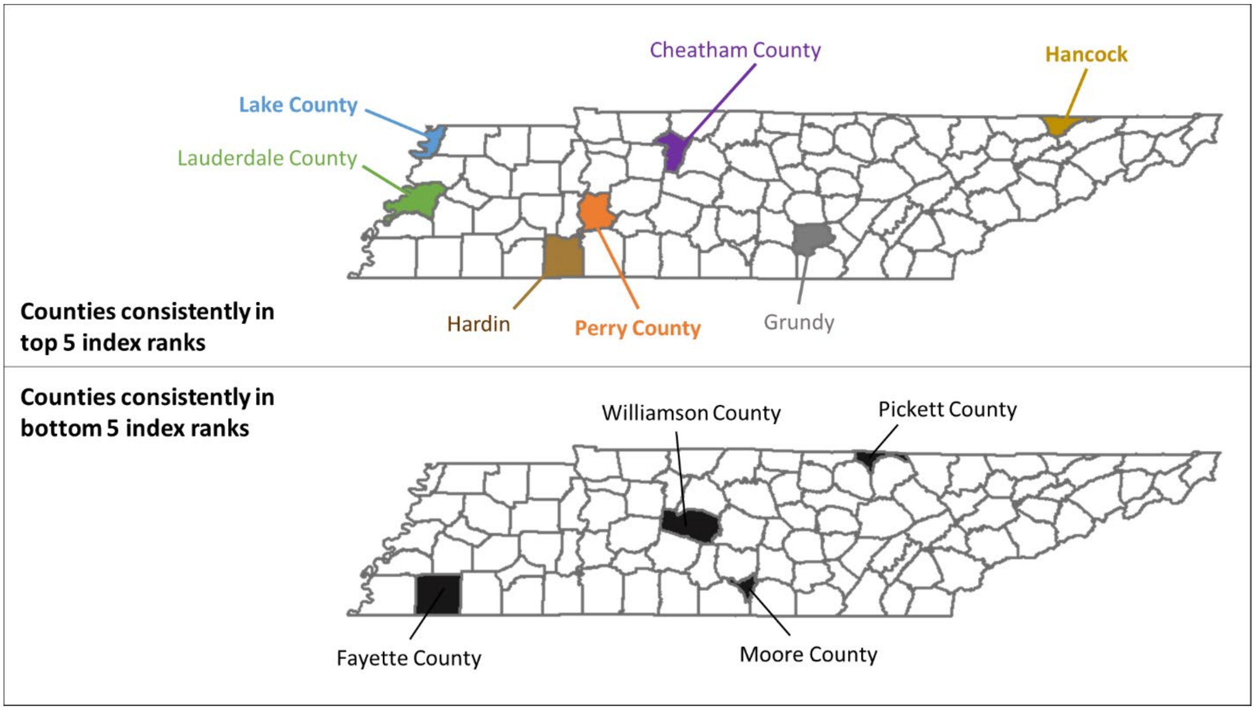


Figure 4: Geographic distribution of recurring counties identified as potentially high need (top) and potentially low need (bottom). Text color for high need counties carried over from previous figures.

All of our analysis to this point has been conducted at the county level, which is helpful for identifying potential areas for system level investment into public transport resources, which are often distributed at the city and county levels. However, further analysis into how investments should be spent within those counties will need to evaluate the distribution of need within the county at a finer spatial scale. In the next Chapter, a case study evaluation does just that.

4. Summary

In our analysis mixed methods and sum weighting were used to create and compare indices to evaluate need for possible transportation investment across the state of Tennessee to mitigate accessibility to treatment for opioid use disorder patients. It is important to be clear with potential decision makers and stakeholders what information was used in drawing conclusions and how it was combined. In this work, we are capturing imperfect information about four questions at a county level and displaying the counties where need and lack of supply overlap: 1) What are the existing needs for OUD treatment? 2) What are the existing resources available for OUD treatment? 3) What are the existing financial, transportation, and non-OUD resource-based needs, including proximity-based access levels to treatment facilities? 4) What are the existing publicly available transportation resources? Based on these four questions, we have a basis for determining which counties across the state may have the highest need for investment, but determining how to invest will require more localized analysis and further investigation.

Identifying distribution of need is a challenging problem across many contexts, due to limited ability to validate and verify the information while maintaining the privacy of individuals and efficient use of resources. In the state of Tennessee, high-need predominantly exists in rural counties with high poverty rates, limited transportation resources, and limited treatment facilities in-county. Variation in need was identified within more urban counties.

Chapter 4 Transportation Cost Case Study

Using the needs assessment results from Chapter 3 and in partnership with TDOT project managers, a subset of counties identified as representing urban, rural, and suburban high-needs areas (i.e., Shelby, Davidson, and Lake County). Davidson County represents an urban area. Shelby County is also urban but has a high low-income population and different transportation accessibility issues and is used to represent a somewhat suburban area. Lake County represents a rural county with high need. These counties were used for demonstration and analysis of potential transportation "costs" across diverse communities using different modes of transportation that are available. For the analysis, the ability to model some transportation options was limited due to consistency across the three counties. Therefore, mobility to treatment that was simulated for cost analysis included walking, driving, and use of rideshare (i.e., Uber).

4.1 Methodology

To assess hypothetical transportation costs in a way that protects individual patients and is transferable to other areas, a model simulation approach was used. To create the model, appropriate data or surrogate data was needed as described below. The process involved obtaining and processing the data, performing routing analysis using simulation techniques, and mapping the analysis using ArcGIS software. Details of the approach are provided below.

4.1.1. Data

The required data sets identified for use in the case study analysis of transportation costs include the following: treatment facility locations, census data, information on residential buildings, coordinates of county boundaries, and access to transportation related Application Programming Interfaces (APIs).

As in Chapter 3, the locations of the treatment facilities were derived from the Substance Abuse and Mental Health Services Administration (SAMHSA) website (Substance Abuse and Mental Health Services Administration, n.d.). Facilities under the categories of "Substance Use" and "Health Care Centers" were selected as suitable treatment facilities (Chapter 3). The raw data omits county information for most of the facilities. Therefore, we reversed the coordinates using Nominatim to assign county information for each facility (Nominatim, n.d.). The list of county boundary coordinates was obtained from OpenDataSoft (HIFLD, 2017).

The number of people being treated for substance use disorders at the county level was obtained from the Tennessee Department of Health website (Tennessee Department of Health, n.d.). The Tennessee Drug Overdose Dashboard, which can be found on the website, provides data for both fatal and nonfatal drug overdose. The value for "Outpatient Stays Involving All Drug Overdose (excluding heroin)" of nonfatal drug overdose was selected to represent the number of patients within a county that may need treatment. This is only an estimate because as mentioned before there are likely several more individuals that have OUD that are not accounted for that need treatment. The data from 2020 was used as the dashboard was not updated to a more recent year at the time of the analysis. The nonfatal drug overdose counts under this category were 835 for Shelby County, 701 for Davidson County, and 3 for Lake County in 2020.

The information on residential buildings in Tennessee was provided by CoreLogic (through a connection to one of our project team members). CoreLogic is a leading provider of consumer, financial and property information with 98.7% of U.S. residential real estate property records. The data set from 2017 was used as it was the most recent version that access was made available to.

4.1.2 Patient Locations

In the simulation model, to estimate the travel times for individuals seeking treatment, we created hypothetical patients. A number of hypothetical patients were generated representing the number of individuals with substance use disorders in a county as identified from the Tennessee Dashboard and then placed randomly throughout the respective county of interest. A uniform random distribution was used to place patients throughout a county. Minimum and maximum values for both latitude and longitude from the county boundary coordinates were used to create the bounds for the distribution. Coordinates are assigned using a random generator to the hypothetical patient and then it is checked to ensure the patient is within the county boundaries. If the hypothetical patient is withing the county boundaries, then a point is placed to mark the patient's location. If the coordinates fall outside the county boundaries, a new set of coordinates is generated and tested. This process was continued until the number of patients within the county (according to the Dashboard) was satisfied. Other types of distribution could also be used including representing population density to strategically place hypothetical patients, but the project team wanted an approach that is easily replicated.

The generated patient locations may not correspond to an actual residential building location as they were simply generated by sampling from a spatially uniform random distribution. The locations may include uninhabitable areas, restricted areas, waterways or wetlands, and many other instances where an individual would not be residing. To solve this issue and to prevent possible routing errors in the following steps, each generated patient location was projected/shifted to the nearest residential building. CoreLogic's 2017 building data was used for this process. Properties only marked "Y" on a "Residential Model Indicator," indicating whehter property is residential or not, and those with valid latitude and longitude information were accepted as valid residential buildings. The Haversine formula was used in finding the nearest residential building for each patient, and the generated patient was then allocated to that building rather than its randomly generated coordinates.

The number of properties included for the patient placement efforts were 1,049,664 in Shelby County, 770,847 in Davidson County, and 4,575 in Lake County. To expedite the computation time of this process, we converted the Python codes into machine codes by using Numba package, an open source just-in-time compiler that translates a subset of Python and NumPy code into fast machine code (*Numba*, n.d.).

4.1.3 Locating nearest treatment facility

The next step in the process was to identify the nearest treatment facility from the hypothetical patient's projected residential building. The list of treatment facilities were removed that did not coincide with the specified three counties of focus.

To find the closest facility, transportation APIs were used to estimate the travel distance or time from the patient's location to every treatment facility in the county. However, due to limitations on the number of allowed calls to the APIs and the prohibitively long simulation run times, the closest facility was determined using the Haversine formula. An alternative would be to narrow the list down to the nearest three facilities rather than the single closest by the Haversine formula and then compare the actual travel distance per transportation mode. In this research, we found the nearest facility by Haversine formula and used the results for both driving and walking to keep run times feasible. Note that in Logan et al. (2019) and Williams et al. (2020), a similar approach was used except that they found the nearest 10 facilities of interest for each household by straight-line distance and then used a routing algorithm to find the travel distance and time to each of these. In our case, even using 10 was computationally prohibitive due the large number of simulation replications we are conducting relative to the single run done by Logan et al. (2019) and Williams et al. (2020).

4.1.3 Model simulations

Using the processes described above resulted in valid origin and destination points for each hypothetical patient within the counties of interest. Because the goal is to estimate the travel distance and time from patient location to treatment facility for different travel modes, a simulation approach was used. In this project, we focused on accessibility by driving, walking and Uber and simulated the network analysis and origin-destination logistics of each using the Open Source Routing Machine (OSRM, n.d.) and Uber website for Uber cost estimation (Uber Technologies Inc., n.d.). Multiple replications of the simulation have been completed. A total of 340 replications have been performed for Shelby County, 220 replications for Davidson County, and 130 replications for Lake County, all of which we identified as more than necessary in meeting stochastic convergence.

4.1.4 Travel cost estimations

OSRM was used to estimate travel time and distance by driving and walking. OSRM is an open-source routing engine for shortest paths in road networks. OSRM returns the shortest path network along with the corresponding travel time and distance for the given travel mode. Driving cost was calculated based on mileage rates for businesses set by the IRS. The IRS has set the business standard mileage rate for the remainder of 2022 as $0.625 per mile. Thus, the driving cost is $0.625 times the number of miles returned from OSRM.

The Uber website was used to estimate Uber prices. The website takes pickup and destination locations as addresses and shows a list of recommendations that best seem to match. We selected the first recommendation for all instances. The addresses for pickup locations were generated by reversing the coordinates of the residential buildings using ArcGIS. For destination locations, the addresses on the treatment facility information from SAMHSA were used. If the addresses were missing, we reversed the treatment facility coordinates by ArcGIS to get the addresses. However, there are times when addresses are not accurate enough to pinpoint an exact location. This may be due to the original data or the results from reversing coordinates with ArcGIS being incorrect, imprecise, or inaccurate. Using these addresses as inputs for the Uber website poses a problem as the website recommends different locations. This led to Uber prices being invalid, from being in different currencies, to being unusually high, or even being unavailable. For these cases, we included an additional step to do the search once more. If the results were still invalid, the cases were excluded from the final results.

4.2 Results

The simulation outputs across multiple replications for each county were merged into contour plots. A total of six plots have been created for each county of interest representing driving time, driving distance, driving cost, walking time, walking distance, and Uber price estimate. The red dots on the figures presented represent the treatment facilities, the blue lines and areas represent hydrography, and the yellow lines are the interstates.

4.2.1 Shelby County

With respect to Shelby County and driving considerations alone (Figure 5), it can be seen that patients on the western side of Shelby County have the longest and most expensive driving access to treatment facilities. However, Uber price estimates do not follow this pattern. Instead, the middle part of the county shows the highest in price range. This may indicate that there are other reasons that affect Uber prices, such as places where drivers would be less willing to pick up a passenger from.

Figure 5 presents results for walking distance and walking time. For this study, potentially walkable was defined as up to 5 kilometers (3.1 miles) of distance and 60 minutes of walk to the nearest treatment facility. The areas that are not colored and left white are areas that are above this threshold implying unwalkable regions in the county. It can easily be seen that much of the county is not walkable to the nearest treatment facility.

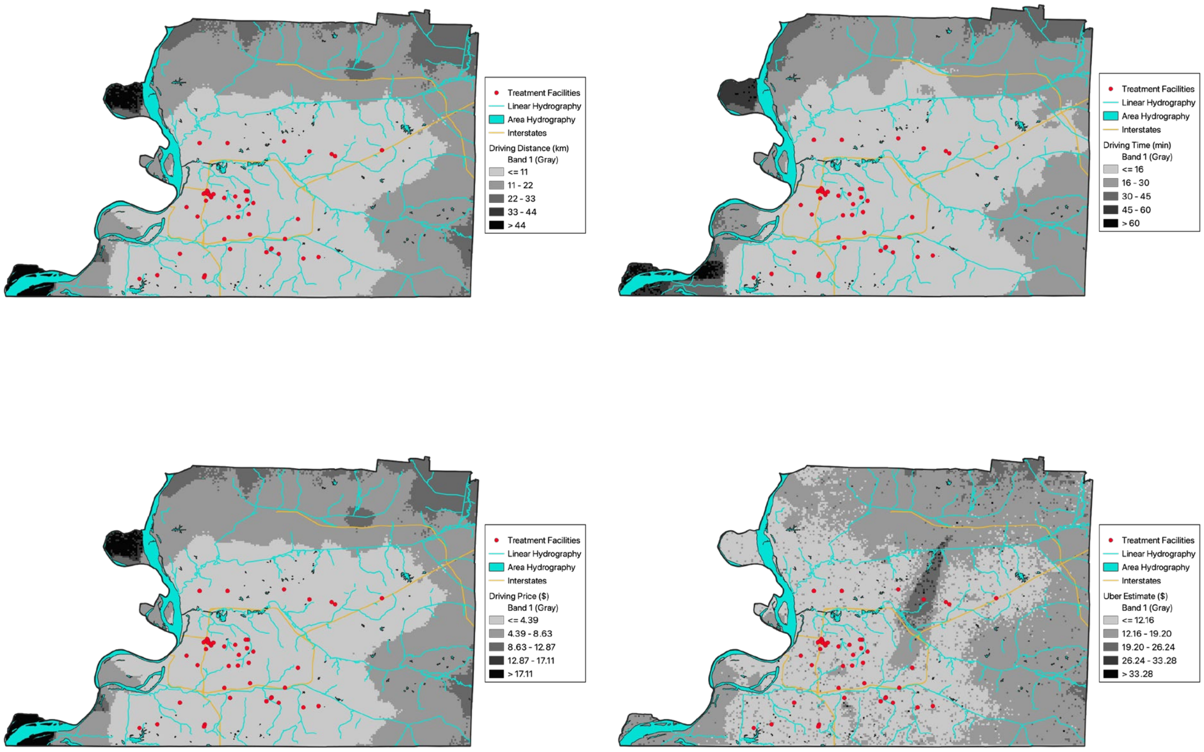


Figure 5: Clockwise - (upper left) Estimated driving distance to treatment facilities for Shelby County, estimated driving time (upper right), estimated Uber price (lower right), and estimated driving cost (lower left) calculated as $0.625 times the driving distance.

Figure 6 provides the simulation results for walking distance and walking time. Potentially walkable was defined as being up to five kilometers of distance and 60 minutes of walking time to the nearest treatment facility. The areas that are left white are areas that are beyond this threshold implying unwalkable regions in the county. For a large county with limited treatment facility options, it is expected that much of the county would not be within walkable ranges to treatment facilities.

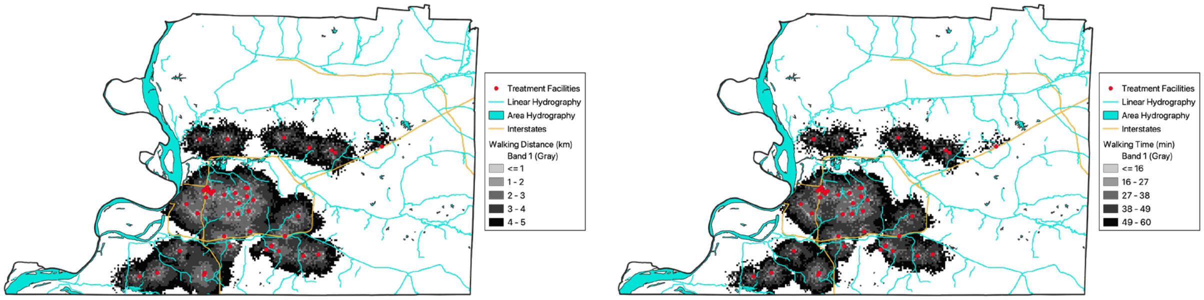


Figure 6: Walking distance (left) and walking time (right) to treatment facilities in Shelby County. Note that the white areas are beyond the defined "reasonable" distance/time to walk for treatment.

Figure 7 shows the locations of the invalid Uber price estimates. Out of the 283,900 patients generated from 340 replications, 255 instances showed unavailable Uber options. This means the search results showed no Uber options available or the only available options were "Black Hourly," which was also decided to be deemed as unavailable as it requires a reservation for at least two hours rather than to a specific destination (Uber Technologies Inc., n.d.). The plot shows that there are two places the points are clustered, North and South of Memphis. The southern location is close to Memphis International Airport. It is unclear why these two areas have a larger, though still low in comparison to overall totals, proportion of invalid price estimates from Uber.

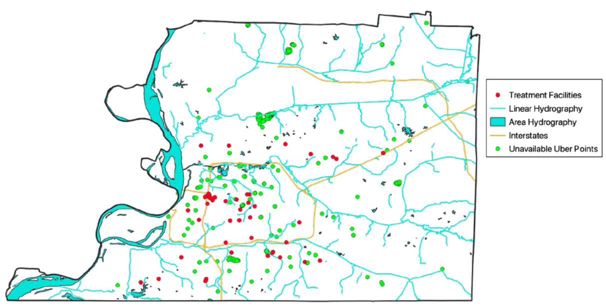


Figure 7: Locations of invalid Uber price estimates for Shelby County.

4.2.2 Davidson County

The contour plots from Davidson County shows that the west side of the county, especially the northwest and southwest areas, have the longest drive times and highest driving costs to the nearest facility. There are also a few darker areas in the middle surrounded by the Cumberland River and to the east of Percy Priest Lake. However, the plotting of Uber price estimates shows that there is no significant difference in accessibility by Uber from these areas likely due to the urban characteristics and population density across the county.

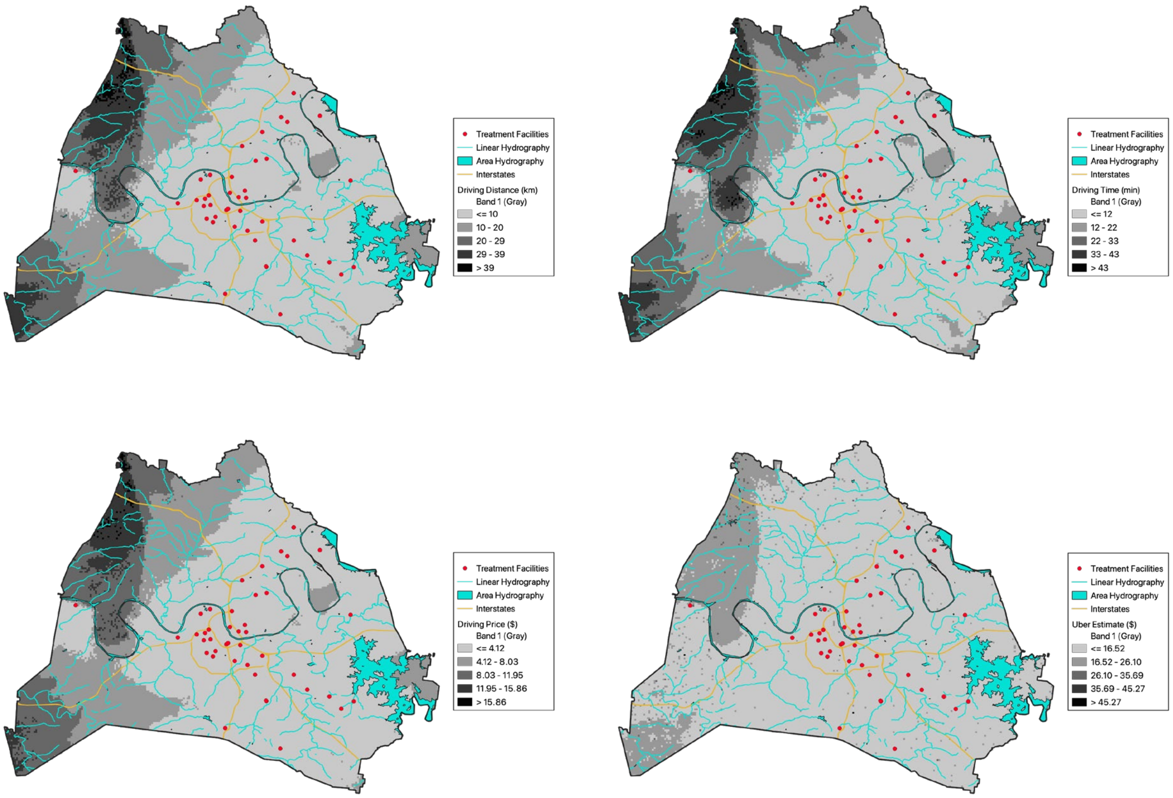


Figure 8: Clockwise - Estimated driving distance to treatment facilities for Davidson County (upper left), the estimated driving time (upper right), estimated Uber price (lower right), and estimated driving cost, calculated as $0.625 times the driving distance (lower left).

Figure 9 shows the estimated walking distance and time to treatment facilities. As with Davidson County, the white areas are those that are above a five km or 60-minute threshold of potential walkability. Compared to Shelby more parts of the county are potentially walkable, but there remain large areas, particularly western Davidson County, that do not have walkable access to treatment facilities. Western Davidson County is predominantly greenspace and less connected to the more urban commercial and industrial areas where facilities would exist.

In total, 220 replications of the model simulation with 701 patients each were completed for Davidson County. Only 208 instances returned unavailable Uber options out of the 154,220 cases. The green dots in Figure 10 represent these cases. It was more difficult to identify a pattern than it was for Shelby County, but some points are clustered in the southeast regions of the county. The clusters on the eastern side of Nashville may be caused by proximity to the Nashville International Airport. However, it is surprising to see clusters that are very near the treatment facilities. This may indicate that Uber may be unavailable when routes are too short, which could become a problem for those who have limited ability to walk on their own.

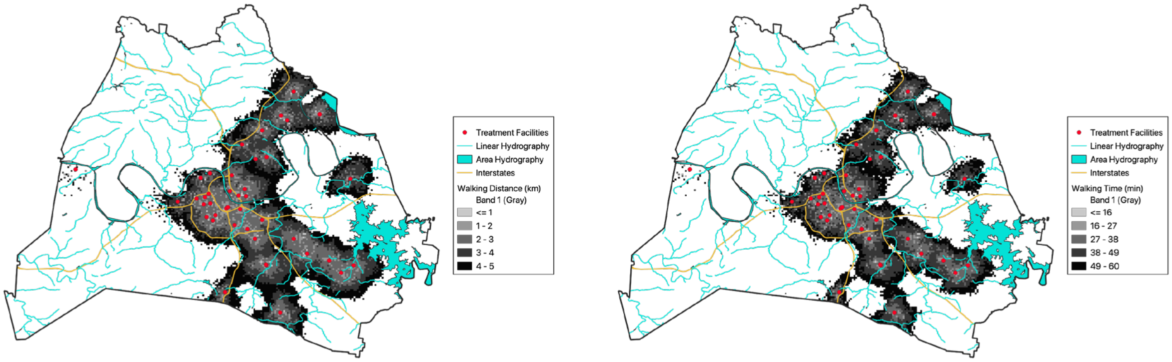


Figure 9: Walking distance (left) and walking time (right) to treatment facilities in Davidson County. The uncolored areas indicate those that are beyond a five km or 60-minute threshold.

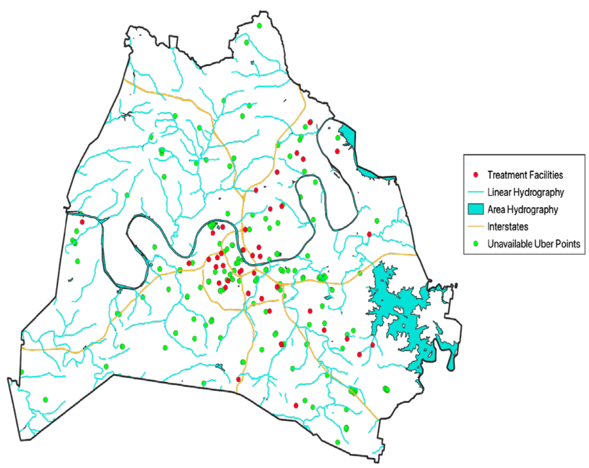


Figure 10: Spatial locations of invalid Uber price estimates for Davidson County.

4.2.3 Lake County

Lake County is a predominantly rural county and has only two treatment facilities. Figure 11 shows the estimated driving distance, time, and cost and Uber price estimates for access to these two treatment facilities. Relative to the two more urban counties above, Lake County has reduced access to treatment via driving, though Uber prices are not substantially different. The northeast and southwest regions of Lake County, furthest away from the treatment facilities, have the least access. However, it is surprising to find that the Uber price estimates from the southwest region are in the lower range despite the longer driving distances.

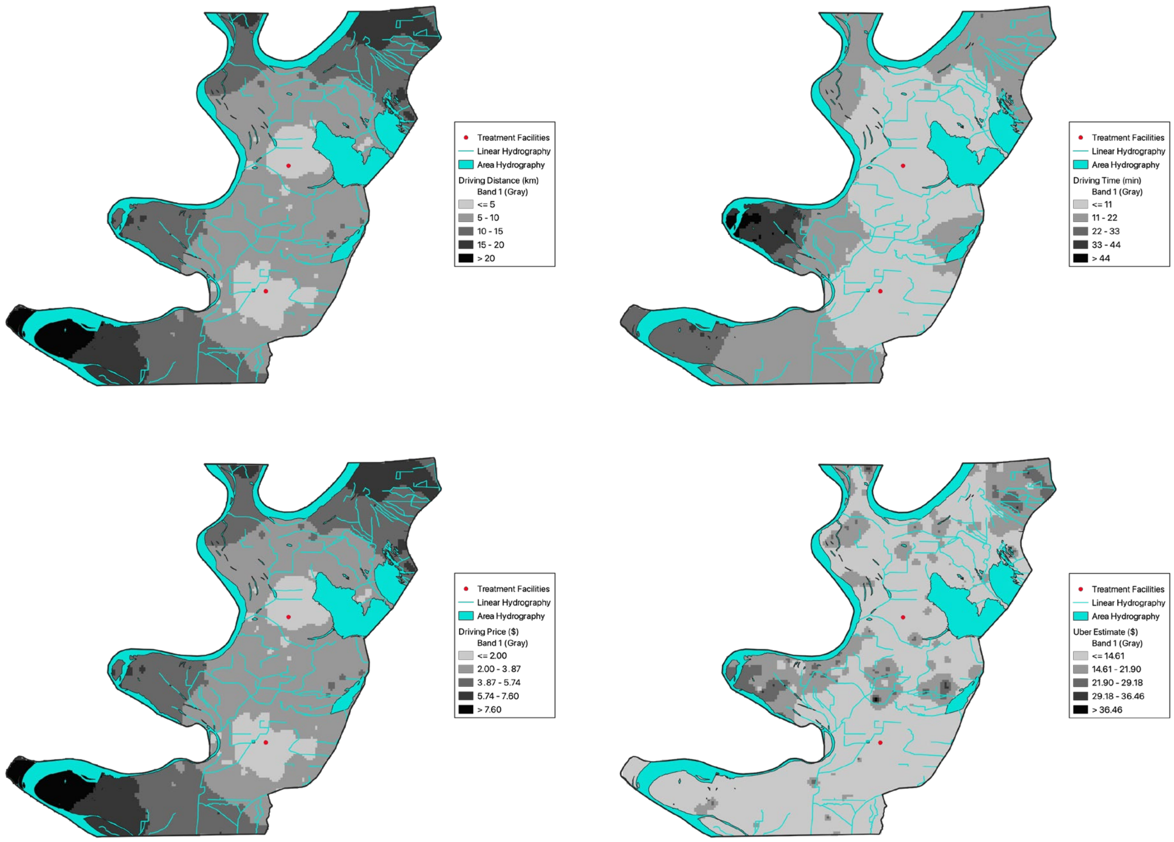


Figure 11: Clockwise - Estimated driving distance to treatment facilities for Lake County (upper left), estimated driving time (upper right), estimated Uber price (lower right), and estimated driving cost, calculated as $0.625 times the driving distance.

When considering walking distance, the lack of facilities becomes readily apparent in Lake County as illustrated by the contour plots (Figure 12). A total of 130 replications with three patients each were completed for Lake County. Due to the comparably smaller sample size of 390 patients, there were no instances where Uber was unavailable in Lake County.

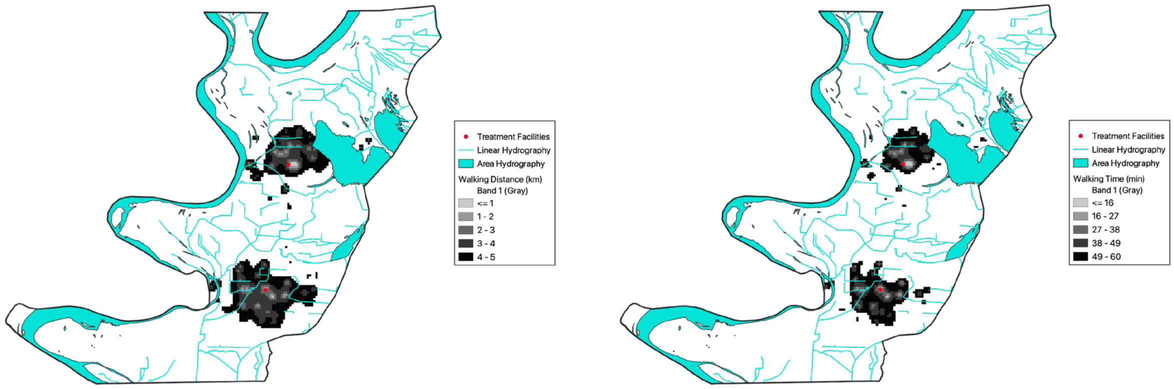


Figure 12: Walking distance (left) and walking time (right) to treatment facilities in Lake County. The same limits of 5 kilometers and 60 minutes of walking time were set for Lake County as well. The uncolored areas indicate those that are beyond a five km or 60-minute threshold.

4.3 Summary

Simulation using ODLE were performed for three counties as a case study to evaluate potential transportation costs to hypothetical patients seeking treatment. These costs were estimated in terms of distance and time, and monetary costs for three options: walking, driving, and use of rideshares (i.e., Uber). Hypothetical patients were placed using randomization techniques across the counties of Davidson, Shelby, and Lake in Tennessee to reflect potential patients using quantities obtained from the Tennessee Department of Health for overdose statistics. Across both Davison and Shelby Counties with urban cores, more transportation access exists and walkability to treatment seemed to be more feasible than in Lake County which has only two treatment facilities and is predominantly rural. The maximum costs for individual transportation (assumed to be personal vehicle using US federal mileage reimbursement rates) ranged from approximately $7.60 in Lake County, to $17.11 in Shelby County, to $15.86 in Davidson County. The estimated costs for an Uber ride increased with increasing urbanism with the maximum being $36.46 (Uber) for Lake County, $33.28 for Shelby County, and $45.27 for Davison County. However, what was not evaluated was the availability of services in each county and hours of operation. Based upon general knowledge, Uber and other ridesharing services are less prevalent in rural areas.

Additionally, transit was not easily evaluated as part of this study and is non-existent in Lake County, but options exist in some areas of both Shelby and Davidson Counties. Additional research would be needed to evaluate transit options for the hypothetical patients in the counties where it exists. For the purposes of this study, we focused on transportation options that existed in all of the counties under consideration to demonstrate the approach. It is recommended that similar analysis be done for all of the counties of need and include transit where it exists for a more complete picture of the options available for patients.

Chapter 5 Additional Context and Considerations

Over the course of the project, it became apparent that reliance upon publicly accessible data alone for analysis limits the ability to perform a robust analysis and truly evaluate the granular, individualized challenges and opportunities for mitigation of the opioid epidemic in Tennessee through transportation services. Therefore, the project team sought out additional information through various sources. These included working closely with a private treatment facility, a clinician involved in treatment of diverse individuals, coordination with multiple state agencies, and phone conversations with staff at treatment facilities.

5.1 Additional Data Considerations

Through prior connections, the research team was able to develop a partnership with a private treatment facility that shared information about treatment types and also a snapshot of de-identified data about patient timelines in various treatments. While this was helpful and provided a foundation for the research team's considerations of the approaches to use in analysis, the treatments used at the facility were limited to non-medicated treatments, data was limited and not representative of Tennessee residents who would likely face accessibility issues. The patients from this facility represented 39 states including Tennessee. Therefore, this data was not useful for a study focused on treatment accessibility in Tennessee and consideration of options that may help mitigate the opioid epidemic across the state.

Due to the uniqueness of the study (i.e., a state transportation agency supporting research related to challenging health issues), media interest led to both an article through Vanderbilt News being developed, a press release, and local television stations running short segments about the project. This opened up interest from both a clinician at Vanderbilt Medical Center and outreach from various other groups. The clinician met with the project leads and helped to educate the team about terminology changes, medically assisted treatment (MAT) types, and about current efforts in Tennessee to mitigate the opioid epidemic. Through these conversations, the project team learned more about the various efforts related to opioid treatment in the state established and managed by the Tennessee Department of Mental Health and Substance Abuse Services (TDMHSAS) and the Division of Substance Abuse Services (DSAS).

In recent years, Tennessee has adopted a Hub and Spoke system that links treatment facilities to a centralized Hub to improve treatment outcomes and provide support to regions across the state. Additionally, TDMHSAS utilizes the Tennessee Web-based Information Technology System (TN-WITS) to track enrollment in services, type of services received and outcomes based on demographics (including race, gender, ethnicity, preferred language and sexual orientation). Through multiple efforts, the project team worked closely with TDOT staff to gain access to the data in this system unsuccessfully. Additional data exists through some treatment programs in the state which provide transportation subsidies to help mitigate the accessibility issue for patients to receive treatment. Gaining access to de-identified trip data would allow for improved modeling and understanding of the true "costs" for transportation access for individuals and programs to mitigate the opioid epidemic. Despite multiple attempts, the project team was not able to gain access to this data for the current study, but a follow-on study in partnership with

TDMHSAS would be highly beneficial toward understanding true needs for the state and options for improvements.

5.2 Facility-level Perspectives

As a result of the data limitations and with desire for additional context at the patient and facility level, the project team had identified use of surveys of treatment facility staff as one approach to fill gaps and arrive at specific recommendations for transportation investment and improvements. Upon further consideration and limitations on facility contact information, phone conversations with facility staff was determined to be the best approach and minimize potential risks to patients, staff, etc.

In the needs assessment portion of this study, treatment facilities across the state were identified. Using that list, facilities were called and when an individual answered or returned the call, a conversation was held discussing treatment options offered, general patient population demographics, transportation observations, and general thoughts on patient needs and challenges.

5.2.1 Characterization of Facilities

Out of the full population of treatment facilities in the state, only five facilities participated in conversations with representation from both urban and rural communities. All facilities offered outpatient care through medication assisted therapy (MAT), all but one offered telehealth options. Three were private and two were public facilties. Medicare/TennCare was accepted at three out of five locations and typical self-pay options (HMO, PPO, EPO, POS) were available at three of the five as well. Group therapy was available at three out of the five facilities and none offered inpatient care. The three private facilities do not receive any state or federal funding.

Interviewees included program managers, counselors, and care coordinators with about 3-5 years of experience working at their current facility. Four out of five interviewees had experience prior to the COVID-19 pandemic in their current role, which gave them the opportunity to highlight the unique challenges that the pandemic created. One interviewee was a recent hire during the pandemic.

5.2.2 Patient Populations

The variation amongst the demographics of patients highlights the unique needs of patients across the state. Only one facility mentioned providing services to adolescents. Four out of five have regularly served patients that speak English as a second language. Average distance traveled is estimated to be around 20 miles, but three of the facilities indicated that patients have commuted as far as 100 miles one way for treatment. Patients attending the public and private facilities in an urban county used personal vehicles for transportation, followed by public transport. This is compared to the other counties which indicated that drop-offs from family and friends were more prevalent.

5.2.3 Transportation and Other Needs

Personal vehicles, rides from friends, and paratransit are the most used transportation methods. The number of visits at one facility were reported to be around 95 patients per day on average, with the lowest being around 80 patients per day. Another facility receives up to 400 patients annually.

When asked about challenges facing patients, one respondent stated that treatment facilities are "few and far between". This was a theme for all conversations, with the respondents sharing that patients will travel significant distances for treatment. Another facility coordinator noted that the methods of transportation that were used were affected by the variability in gas prices, further highlighting the difficulties associated with travelling long distance to facilities. All respondents agreed with the statement "Transportation is a barrier to successful treatment outcomes". One facility identified ridesharing services as the third-most used transportation type, the other facilities indicated that ridesharing was less common than other modes of transportation.

Insurance and other social determinants played a role in treatment consistency as well. Out-of-pocket-insurance costs or insurance lapses limit patient consistency. One even remarked that "some are not yet ready for help", referring to the fact that the challenges patients face is multifaceted and require diverse and curated solutions.

5.2 Summary

Data exists that could and should be utilized to further advance the understanding of challenges and opportunities for improved outcomes to treatment successes in Tennessee including mitigating the accessibility challenges where individuals may travel extended distances to obtain treatment. While multiple programs and efforts are underway to help patients across the state, the issues at hand are complex. Local context coupled with access to granular data could prove beneficial in further advancing the ability of the state to meet the needs of patients. Interagency collaboration in partnership with researchers could further improve the outcomes for patients in Tennessee. Expanding access to transportation to opioid treatment is a promising step forward in the fight against the opioid epidemic by helping to provide regular and stable access to care especially for rural areas like much of our state.

Chapter 6 Conclusions

The Tennessee Department of Transportation's interest in better understanding ways that expanding access to transportation could help mitigate the opioid epidemic in the state is a promising step forward in the fight against the OUD. This study was a first step in that effort through considering the literature related to treatment options and accessibility, performing a needs assessment that accounted for vulnerabilities such as low income and also locations of treatment facilities, and estimated the travel "costs" for individuals to access treatment in a set of select counties as a case study. Additional context was obtained from conversations with practitioners on the front lines of the treatment of patients seeking treatment.

From the analysis, several, predominantly rural counties appeared in multiple applications of indices developed as part of this project to assess need. The indices included factors or variables such as the percent of households with no car, percentage of adults in poverty, and percent uninsured within a county. Overdose rates from the Tennessee Department of Health were used as surrogates or indicators of the number of individuals in need of treatment within a county.

A case study analysis was performed for three counties (Davison, Shelby, and Lake) to simulate travel times and distances and estimate costs in terms of distance, time, and monetary costs. From the simulation for randomly placed hypothetical patients, the maximum travel cost for an individual to access treatment for one trip, one-way ranged from less than $10 (using a personal vehicle) to over $40 (using Uber) in Davison County. It is recommended that the analysis be repeated for other counties of high need and transit options be evaluated. For the purposes of this study, where we were establishing the approach and seeking to understand the scope of the problem, transit was not included because Lake County has no transit options.

It should be noted that this is a first step and additional research is needed. Furthermore, the dimensions of access not measured in this study include acceptability, affordability, and awareness. Any investment decisions will need to consider these dimensions, including soliciting input from potential end users to understand their perspectives on what solutions are acceptable and affordable. In addition, any investment will need an accompanying awareness campaign to ensure the target population is aware of the resource and how to use it. Solution usability is very important to determining the ultimate success of an investment, as solutions implemented without consulting and gaining buy-in of key stakeholders (end users) are often unsuccessful.

The research team has several recommendations for both future research and for TDOT to move forward in efforts to mitigate the opioid epidemic through investment.

The first set of recommendations are focused on data. One of the largest limitations of this study was the availability of data for robust, in-depth analysis. Specifically, individualized private health data such as that managed through the Hubs in Tennessee may allow for more individualized insight when compared to aggregated public data, particularly when evaluating proximity to subpopulations rather than at the census tract centroid level. When analyzing potential treatment facilities, SAMHSA has stated that almost all healthcare settings could be used to screen for OUD and offer medication either onsite or by referral (SAMHSA, 2021). Our study focuses only on healthcare sites tailored specifically for substance use or federally funded HRSA health care centers. As options and locations for treatment expand, our understanding of access and what should be considered accessible will also need to adapt. When studying existing transportation resources, more rideshare service data may improve our understanding of existing transportation resources. Currently Uber and Lyft both claim full geographic coverage of the state, but this does not indicate actual user experience or wait times in more rural areas with potentially fewer available drivers. Some of these data improvements could be achieved for future research if TDOT partners with the Tennessee Department of Health with a data sharing agreement and potentially also with Uber or Lyft to obtain better data about their service availability, wait times, and costs.

When thinking about overall mobility and accessibility for OUD patients, this work has been focused specifically on treatment centers, but it is possible that accessing other destination types may also be barriers to treatment success, including obligations like childcare, work, or court dates. Perhaps expanding transportation more generally could help offset burdens to treatment access even if done indirectly by helping individuals reach a network of destinations.

From the analysis as well as the literature review and conversations with practitioners, some initial recommendations have emerged for TDOT to begin to help individuals more easily access treatment facilities across the state. The following are initial recommendations for improved treatment access for Tennessee:

- In areas where transit exists, evaluate the connectivity to treatment facilities and whether service times align with facility hours.
- In areas where ridesharing exists and provides reliable service, consider subsidizing the ridesharing for individuals through working with treatment facilities to offer vouchers or other options to minimize the cost of transportation.
- In rural areas, one transportation service that has potential to be utilized by individuals is the paratransit service, which at present has limitations that would prevent OUD patients from utilizing the service. However, paratransit exists in all 95 counties.
- The western portion of the state has the majority of the counties in highest need based upon the current analysis; and therefore, efforts should be made to prioritize additional, local analysis toward optimal transportation options in those areas.
- One of the largest challenges as determined by the data is the lack of facilities in rural areas. While dedicated treatment facilities may not be feasible in many of these areas of high need, working with the Tennessee Department of Health to develop treatment services at County Health Departments may be an approach that is not transportation-

centric, but reduces the need for individuals to travel long distances for treatment. Each county has a public health department.

Again, data and additional analysis are needed at a localized level to properly evaluate both needs and opportunities to improve the outcomes for patients.

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Appendices

Appendices should be separated by category and may include correspondences, interview transcripts, non-textual elements, questionnaires or surveys, research instruments, sample calculations, or raw statistical data. Include raw data used in the making of the report. If the raw data is extensive and would be cumbersome to include, provide the documentation to TDOT Lead Staff and the Research Office in a separate, readable file. Deliverables that are separate from the research project should be provided separately in this manner as well.

Appendix A

Additional Indices Considerations for Weighting

Additional consideration of the various features and their impacts on overall index scores was performed as a means to test the sensitivity of the Indicies. Five additional indices to the original 3 were tested as described below and shown in the table that follows.

Index 4 uses min-max normalization for each of the seven features and combines them into a single index value using equal weights for each. Indices 5 through 8 use the same features and normalization as Index 4, but we vary the feature weights. Our weighting values always sum to one, and the weights were generated using feature grouping to represent potential prioritization preferences from the decision makers and allocated evenly to features within the groups. Index 5 prioritizes the opioids-specific features (fatal and nonfatal overdose rates, opioid prescription dispensing rates) with the highest weights, followed by the travel-relevant features (percentage of household with no vehicles and minimum travel time to a treatment facility), followed by the other two economic features (adult poverty rates, no health insurance rates). Index 6 alters this, prioritizing economic features first, followed by travel-relevant features, and ending with the opioids-specific features. Index 7 prioritizes travel, then opioid proxies, then economic vulnerability, and Index 8 prioritizes economic vulnerability, then opioid proxies, then travel data.

Table A-1: Indexes 4-8, including additional features and varying weights. Bold font used to indicate changes from previous index

Index #	Index components:	Index equation for each county's values
4	% no vehicles (VH), % adult poverty (AP), % uninsured (U) **Fatal overdoses per 10000 ($\boldsymbol{OD_F}$)** **Nonfatal overdoses per 1000 ($\boldsymbol{OD_{NF}}$)** **Opioid dispensing rates per 100 ($\boldsymbol{OP}$)** **Travel time in minutes to nearest SA or HRSA ($\boldsymbol{TT}$)**	Equal weights: $\frac{(VH + AP + U + OD_F + OD_{NF} + OP + TT)}{7}$ All min-max normalized
5	% no vehicles (VH), % adult poverty (AP), % uninsured (U) Fatal overdoses per 10000 (OD_F) Nonfatal overdoses per 1000 (OD_{NF}) Opioid dispensing rates per 100 (OP) Travel time in minutes to nearest SA or HRSA (TT)	**Varied weights: prioritizing opioid features, then travel features** $\mathbf{0.18(OD_F + OD_{NF} + OP) +}$ $\mathbf{0.13(VH + TT) +}$ $\mathbf{0.1(AP + U)}$ All min-max normalized

6	% no vehicles (VH), % adult poverty (AP), % uninsured (U) Fatal overdoses per 10000 (OD_F) Nonfatal overdoses per 1000 (OD_{NF}) Opioid dispensing rates per 100 (OP) Travel time in minutes to nearest SA or HRSA (TT)	**Varied weights: prioritizing economic vulnerability, then travel features** $\mathbf{0.2(AP + U) +}$ $\mathbf{0.15(VH + TT) +}$ $\mathbf{0.1(OD_F + OD_{NF} + OP)}$ All min-max normalized
7	% no vehicles (VH), % adult poverty (AP), % uninsured (U) Fatal overdoses per 10000 (OD_F) Nonfatal overdoses per 1000 (OD_{NF}) Opioid dispensing rates per 100 (OP) Travel time in minutes to nearest SA or HRSA (TT)	**Varied weights: prioritizing travel features, then opioid features** $\mathbf{0.19(VH + TT) +}$ $\mathbf{0.14(OD_F + OD_{NF} + OP) +}$ $\mathbf{0.1(AP + U)}$ All min-max normalized

8	% no vehicles (VH), % adult poverty (AP), % uninsured (U) Fatal overdoses per 10000 (OD_F) Nonfatal overdoses per 1000 (OD_{NF}) Opioid dispensing rates per 100 (OP) Travel time in minutes to nearest SA or HRSA (TT)	**Varied weights: prioritizing economic vulnerability, then opioid features** $\mathbf{0.19(AP + U) +}$ $\mathbf{0.14(OD_F + OD_{NF} + OP) +}$ $\mathbf{0.1(VH + TT)}$ All min-max normalized