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Rural Transportation System Design for Omnichannel Healthcare

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16. Abstract
This report investigates the deployment of Telehealth Kiosks (TKBs) as part of an omnichannel healthcare strategy to improve access and equity in rural areas. Using case studies from rural Missouri, the research integrates empirical data, discrete choice experiments, and optimization models to address critical barriers in healthcare accessibility. Travel time decay functions were calibrated to capture patient preferences for healthcare options, and these functions informed both continuous approximation and discrete optimization models to design optimal TKB networks. Key findings reveal the trade-offs between equity and efficiency, highlighting the importance of adaptive equity thresholds and strategic resource allocation. Practical implications for policymakers emphasize data-driven deployment strategies, scalable solutions, and leveraging emerging technologies. This study contributes a robust framework for designing equitable healthcare systems, offering insights to bridge access gaps in underserved rural regions.

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List of Abbreviations

Telehealth Kiosk/Booth (TKB)
Artificial Intelligence (AI)
Hybrid Discrete Choice (modeling framework) (HDC)
Gini Index (GI)
Latent Variable (LV)
Missouri (MO)
Accessibility Index (AI)

Disclaimer

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Abstract

This report explores the deployment of Telehealth Kiosks (TKBs) as a pivotal strategy to improve healthcare access and equity in rural areas. Leveraging case studies from rural Missouri, the research employs a comprehensive approach that combines empirical data, travel behavior analysis, and advanced modeling techniques. Travel time decay functions, calibrated using data from US adults, were integrated into both continuous approximation and discrete optimization models to guide the strategic placement of TKBs. The study examines key trade-offs between equity and efficiency, demonstrating how adaptive deployment strategies can address the unique challenges faced by underserved populations. Insights from the analysis highlight the critical role of equity thresholds, resource availability, and demographic factors in shaping optimal TKB networks, ensuring that the needs of vulnerable groups such as children and seniors are met while maximizing system-wide coverage and efficiency.

The findings underscore the potential of TKBs to transform rural healthcare delivery systems by reducing travel times, addressing demographic disparities, and complementing existing healthcare infrastructure. Case studies reveal significant benefits, such as travel time reductions and improved healthcare accessibility for large portions of rural populations. The report offers actionable recommendations for policymakers, including the use of dynamic equity metrics, investments in scalable solutions like mobile TKBs, and the integration of emerging technologies such as drones and AI to enhance service delivery. By bridging empirical insights with practical applications, this research provides a robust framework for designing equitable and efficient healthcare systems in rural regions, paving the way for innovative and inclusive solutions to healthcare access challenges.

Chapter 1 Introduction

Emerging technologies are revolutionizing healthcare delivery by enhancing access and equity, particularly in rural areas. Similar to how omnichannel retail provides customers with multiple ways to access products, omnichannel healthcare aims to deliver care through the most appropriate channel (physical or virtual), at the right location, time, and cost. This approach is crucial in rural regions, where significant challenges include long travel times and distances, a shortage of healthcare providers and facilities, and unique health needs of rural populations.

This research investigates the deployment of freestanding telehealth kiosks/booths (TKBs) in rural areas to improve healthcare access. A TKB is a publicly accessible automated facility offering various health services, such as providing health information, collecting clinical measurements, telemonitoring, teleconsultations (real-time communication with health professionals), dispensing tests, reporting test results, and even dispensing medication (Maramba et al., 2022; Zanjani et al., 2020; Letafat-nejad et al., 2020). Figure 1.1 illustrates two examples of TKBs. These kiosks can function with or without live synchronous staffing for teleconsultations and may also serve as sites for periodic in-person visits by health professionals. The market for TKBs is projected to exceed $4 billion globally by 2034 (KioskMarketplace, 2024).

TKBs are available in many different configurations with different functionalities, but in general a TKB can be defined as a self-contained healthcare unit equipped with digital and medical technology to facilitate remote clinical services. Features of a TKB generally include hardware/equipment (e.g., video monitor, video cameras, blood pressure monitor, thermometer, scale, stadiometer, pulse oximeter, glucometer, EKG/ECG, stethoscope, otoscope, dermascope, spirometer, high resolution cameras, etc.), software to manage the patient interface and ensure data security, and security and cleaning. TKBs can offer a wide range of healthcare services in the areas of: (i) diagnosis (e.g., consultation for respiratory symptoms, wounds, earaches, nausea, etc.), (ii) screening (e.g., blood pressure, glucose levels, mammograms), (iii) preventive care (e.g., health education, vaccination information, vaccine dispensing), and (iv) treatment (e.g., prescription management, mental health support, etc.). The services may be fully or partially automated, or augmented by on-site staff. Note that TKBs can also be mobile facilities that are easily repositioned. Thus, TKBs effectively allow self-service healthcare using technology to connect with remote resources and medical staff synchronously or asynchronously. This may help overcome the lack of providers and the challenges and limitations of telehealth from the home.

Figure 1.1 Examples of TKBs. Left image: “The OnMed kiosk offers an exam room and technologies such as soundproofing; ultraviolet lighting to keep air and surfaces clean; thermal imaging and an automated pharmacy.” from Maras (2020). Right image from Gupta (2022).

This research builds on existing advancements to investigate the optimized placement and integration of TKBs, with a particular focus on rural regions where challenges such as travel time decay, spatial equity, and healthcare access disparities are most pronounced. While other critical aspects of TKB deployment—such as legal, privacy, insurance, and cost considerations—are important, this study centers on the transportation and locational dimensions of implementing a TKB network and its impact on improving healthcare accessibility.

The research has two primary dimensions: empirical and analytical. The empirical phase incorporates both primary and secondary data collection. As detailed in Chapter 3, the secondary data collection focuses on case studies from rural Missouri, using two refined datasets that represent rural regions. These datasets provide accurate geographical centroids of US Census Block Groups, locational data for existing healthcare facilities, and travel distances derived from the Missouri road network. Developed for verification and validation purposes, they form a robust foundation for modeling healthcare access and equity.

The primary data collection, elaborated in Chapter 4, employs a survey instrument designed to engage potential users and evaluate the strategic placement, operation, and utilization of TKBs. Building on a comprehensive discrete choice experiment, the survey investigates preferences for TKBs versus traditional hospitals across four distinct age groups: Seniors, Middle Age, Young Adults, and School Age. Key factors such as travel time and consultation type are examined for their influence on healthcare decisions. The survey data are analyzed using Hybrid Discrete Choice models, which integrate latent behavioral variables like technology trust and health literacy. These models, estimated using Maximum Likelihood Estimation, yield travel time decay functions for each age group, illustrating how the perceived utility of healthcare options, including TKBs, diminishes as travel time increases. These decay functions provide valuable insights into population-specific responses to TKB accessibility and consultation types, enabling detailed predictions of patient preferences.

The finalized travel time decay functions serve as critical inputs for the location optimization models presented in Chapters 5 and 6. Chapter 5 employs a continuous approximation approach, while Chapter 6 introduces a discrete optimization framework. Both approaches aim to determine the optimal network of TKBs to enhance healthcare access and equity in rural areas. By incorporating various performance measures, these models provide a comprehensive assessment of proposed solutions, offering actionable insights for addressing disparities in healthcare access.

This research integrates empirical evidence with analytical rigor to tackle the complex problem of healthcare accessibility in underserved regions, providing a strategic framework for deploying TKBs that aligns with both equity and efficiency objectives.

Chapter 2 Background on Rural Healthcare Challenges and Omnichannel Solutions

The primary motivation for this research is the limited availability and poor quality of healthcare in rural America, driven by a shortage of healthcare providers and facilities, rural transportation challenges, and the unique needs of rural residents. According to the U.S. Census Bureau, rural areas are defined as all population, housing, and territory not included within an urban area—where urban areas are defined as densely developed territories with 50,000 or more people (urbanized areas) or at least 2,500 and less than 50,000 people (urban clusters). In the US, 19.3% of the population lives in rural areas, which account for 97% of the total land area (United States Census Bureau 2021). Rural residents tend to be older and experience worse health conditions than urban residents, with higher rates of obesity, smoking, and high blood pressure. They also face higher poverty rates and are less likely to have health insurance (CDC 2024). These factors, combined with demographic, economic, and social challenges, place rural populations at greater risk for leading causes of death, including heart disease, cancer, unintentional injuries (e.g., opioid overdose), chronic lower respiratory diseases, and stroke (CDC 2024). Compounding these challenges is the lack of broadband access, which restricts telehealth options from home.

Despite greater health needs, rural residents have lower access to healthcare services (Douthit et al. 2015). Rural hospital closures highlight this disparity—192 hospitals have closed since 2005, and 300 more are at immediate risk due to financial constraints (CHQPR 2024). Following closures, residents must travel approximately 20 miles farther for inpatient services and 40 miles farther for specialty care (United States Government Accountability Office 2023). Disparities are particularly stark for specialty services: urban areas have three times as many active physicians per capita and nearly seven to eight times more specialists such as cardiologists, dermatologists, and gastroenterologists compared to rural areas (Orgera et al. 2023). Federal and state programs provide incentives for physicians and support rural facilities, particularly through the Centers for Medicare & Medicaid Services (CMS), yet significant shortages persist.

Limited healthcare facilities in rural regions lead to longer travel times for care. Sparse populations and underdeveloped road networks exacerbate these delays, as rural residents travel over twice as far as urban residents for medical and dental care (Akinlotan et al. 2021). On average, rural residents spend 34.2 minutes traveling to healthcare, with late-night trips averaging 67 minutes. Older residents face even longer travel times—40 minutes for those over 65 compared to 28.2 minutes for younger adults (Akinlotan et al. 2021). Public transportation options are scarce, forcing older adults to rely on others for transport, especially for procedures that require someone to drive patients home (Lee et al. 2023). Transportation barriers further compound access issues (Krasniuk & Crizzle 2023; Dotse-Gborgbortsi et al. 2022; Syed et al. 2013; Mattson 2010).

Rural areas of the US remain critically underserved in terms of healthcare access, facilities, and providers, with significant travel burdens exacerbating these challenges. The *omnichannel paradigm* in healthcare delivery, presented in the following section, provides an opportunity to integrate multiple service channels, such as telehealth kiosks, to improve accessibility and reduce travel burdens for rural populations.

2.1 Omnichannel Paradigm in Health Care Delivery: Opportunities and Benefits

Digital technologies have unlocked new avenues for businesses to interact with consumers, such as self-service kiosks, remote monitoring devices, and mobile platforms (Diaz Baquero, 2021). This innovation has paved the way for the omnichannel strategy, which transcends traditional transactional models by delivering a cohesive and integrated customer experience across multiple channels. Rather than simply offering different ways to purchase goods and services, omnichannel strategies enable businesses to engage with customers seamlessly, ensuring convenience and consistency at every touchpoint (Min, 2021).

The omnichannel environment presents significant opportunities for healthcare organizations to revolutionize patient management by integrating more interactive and efficient processes (Moreira et al., 2023). This approach allows for the coordination of key operational tasks, including appointment scheduling, billing, and information verification. As an illustration, patients can now complete the preliminary stages of the registration process, verify their insurance coverage, and make the requisite payments via online platforms. Before the proliferation of omnichannel approaches to healthcare, patients were required to visit hospitals or clinics to receive medical care physically. As electronic devices become increasingly prevalent in healthcare provision, there is a clear indication that this traditional approach is set to undergo a significant shift. As more healthcare providers implement omnichannel strategies (Balestra, 2018), there is an increasing opportunity to improve patient outcomes and experiences. Incorporating diverse access points for coordinating and delivering care presents a promising avenue for optimizing the healthcare system (Reuveni, 2017).

A noteworthy advantage of an omnichannel strategy is the capacity for healthcare providers to integrate and harmonize their efforts across an expanded range of patient care channels (Varadarajan et al., 2021). This approach enhances efficiency within the healthcare system and its supply chain by giving patients greater control over their treatment options. It also significantly reduces unnecessary travel and minimizes patient wait times. By empowering patients to manage their care more autonomously, healthcare organizations can decrease hospital utilization, improve patient compliance with treatment plans, and use the healthcare human resources more efficiently (Dinesen et al, 2016). Furthermore, implementing an omnichannel approach can significantly enhance inclusivity and accessibility within healthcare systems, particularly for underserved populations and those residing in rural areas. If various digital platforms for appointment scheduling, access to medical records, and care delivery are also integrated, this strategy can then address key barriers to healthcare access, such as limited transportation and geographic isolation.

For low-income individuals or those in remote regions, who frequently encounter substantial challenges in reaching traditional healthcare services, omnichannel solutions can mitigate these disparities by offering alternative care delivery means, such as online portals or local kiosks. This improves operational efficiency and promotes healthcare equity by ensuring that vulnerable populations have access to timely, high-quality care, irrespective of their socioeconomic status or geographic location (Hermes et al, 2020).

Similarly, individuals living with conditions such as HIV/AIDS and cancer may benefit significantly from an omnichannel healthcare system, which facilitates discreet and private communication between physicians and patients—a critical feature for addressing sensitive healthcare needs (Lebel and Devins, 2008).

2.2 Omnichannel Healthcare: Essential Components, Platforms, Channels, and Devices

Telehealth is a cornerstone of the omnichannel healthcare system, crucial in bridging geographic gaps in care, particularly for rural populations. It reduces barriers such as time, distance, and geography, enabling patients to access healthcare services more efficiently and at lower costs (Kuziemsky et al., 2019). Marcin, Shaikh, and Steinhorn (2016) further argue that telemedicine facilitates real-time consultations between patients and specialists, reducing physical travel and improving access to expert care. This is especially vital for underserved communities and rural populations, where access to specialized care is often limited (Furrow, 2022). However, evidence also suggests that telehealth is increasingly applicable in urban settings, where it helps reduce the need for in-person visits and improves efficiency (Kuziemsky et al., 2019; Chang et al., 2023). Table 2.1 summarizes devices and platforms available for omnichannel healthcare delivery.

Table 2.1 Omnichannel healthcare devices/platforms

Type/Device/Platform	Context of Application/Functionalities	Selected Sources/References
Telemedicine platforms/software	Provide patients anywhere with synchronous access to doctors via voice, text, and video consultations, reducing geographical barriers, especially in rural areas.	Kuziemsky et al. (2019); Bashshur et al. (2014); Hilty et al. (2020)
Telehealth Kiosks/booths	Standalone physical unit equipped with technologies and tools like blood pressure monitors and pulse oximeters to facilitate remote diagnosis, patient monitoring and consultations. Commonly used in rural or underserved areas for point-of-care services.	Maramba et al. (2020); Courtney et al. (2010); Wise (2019)
Wearable Health Devices	Facilitates continuous health monitoring (e.g., heart rate, glucose levels), with the ability to upload data to the internet for remote access and analysis by healthcare staff or AI systems. These systems can also support two-way communication, enabling timely interventions such as notifying patients to seek in-person care when necessary.	Chang et al. (2023); Resnick et al. (2012); Ganesh et al. (2021)
AI-driven Diagnostic Systems	Enhances efficiency in telemedicine by providing automated diagnostics in fields like dermatology when in-person services are overwhelmed.	Baron, Chen, and Seidmann (2023); Subbhuraam and Panigrahi (2021)
Drones	Used for delivering medical supplies to rural sites, rapidly retrieving and transporting specimens, monitoring public health in remote areas, and performing diagnostic imaging during emergencies.	Nedelea et al. (2022); El-Sherif et al. (2022)

Telehealth platforms, whether synchronous (real-time) or asynchronous (delayed), offer a wide range of services, including consultations, diagnoses, and monitoring (Hilty et al., 2020). These platforms have broad applicability across medical fields, including radiology, dermatology, pathology, and psychology, and are particularly effective in managing chronic conditions such as diabetes, hypertension, and HIV (Bashshur et al., 2014; Pedersen et al., 2023; Ryu, 2012). The flexibility of telehealth solutions allows healthcare providers to tailor care delivery to patient needs, supporting the principles of precision medicine and ensuring that healthcare services are accessible, regardless of time or location.

It is possible to conduct initial teleconsultations via mobile phones (through calls or texts) or web-based platforms using personal computers (or smart phones) without requiring a health kiosk or booth. This approach enables patients to access fundamental healthcare services remotely; however, they may be required to travel to a medical facility for examination and to collect data on their health status (e.g., to measure blood pressure or other vital signs). More advanced telehealth platforms and kiosks equipped with integrated biometric and clinical measurement tools have been developed, creating a continuum of solutions. While platforms typically operate on patient-owned devices for use at home, TKBs function as facility-based systems located outside the patient's home. These advanced systems enable healthcare providers to remotely monitor patients' vital signs in real time, bridging gaps in accessibility and care delivery (Maramba et al., 2020). These kiosks allow for collecting crucial health data at the point of care, significantly improving the telehealth experience.

Several types of telehealth kiosks are available, enabling consultations and offering a range of services, from basic point-of-care measurements like blood pressure monitors, pulse oximeters, and stethoscopes to advanced diagnostics such as electrocardiograms, retinal imaging, ultrasound, and on-site lab testing for blood glucose and other analyses. These kiosks are particularly valuable in rural, remote, and underserved areas where healthcare access is limited. For instance, MedicSpot in the UK provides web-based GP services via kiosks in pharmacies, allowing patients to connect with physicians remotely (Wise, 2019; Maramba et al., 2020).

Similarly, Amwell in the US offers freestanding kiosks with features like a touchscreen interface, integrated camera, credit card reader, private audio handset, and sanitation tools (Lovett, 2020). These kiosks make healthcare more convenient and accessible, helping to reduce barriers for many patients.

Telehealth kiosks, as studied by Courtney et al. (2010), promote patient self-management and autonomy by providing convenient access to healthcare services in both rural and urban settings. They help reduce dependence on hospitals and clinics, thereby improving overall healthcare access. During the COVID-19 pandemic, telehealth kiosks became essential tools, easing the strain on healthcare facilities. For example, the H4D Consult Station was used to screen and detect suspected COVID-19 cases, significantly reducing nurses' intake time and protecting healthcare workers from exposure (Maramba et al., 2020). These kiosks proved vital in managing the increased demand for testing, serving as a critical public health strategy during periods of social distancing and overwhelmed healthcare systems (El-Sherif et al., 2022).

Stephens and Greenberg (2022) and Hayavi-Haghighi and Alipour (2023) emphasize the importance of integrating various digital systems and platforms into a broader healthcare system capable of managing the complexity of patient needs, from diagnosis to long-term care. They argue that omnichannel strategies must leverage the unique capabilities of each platform to ensure seamless care and improve patient outcomes. It is not surprising, then, that the integration of Artificial Intelligence (AI)—encompassing technologies such as machine learning, natural language processing, and predictive analytics—alongside emerging technologies like drones and blockchain represents a significant advancement in omnichannel healthcare. Baron, Chen, and Seidmann (2023) demonstrate how AI-driven systems can enhance telemedicine services, particularly in dermatology, by activating AI-based diagnostics when in-person care is overwhelmed. This approach ensures that patients continue to receive care without delays, improving both efficiency and accessibility by optimizing resource allocation and reducing bottlenecks in healthcare delivery.

For example, telehealth kiosks powered by Internet of Things (IoT)—a network of interconnected devices that collect and exchange data—and AI are advanced automated systems that use sensors to remotely monitor patients and deliver medical care (Subbhuraam and Panigrahi, 2021). In contrast, other kiosks, like those used for prescriptions, may have on-site staff such as clinicians or technicians. Increasingly, employers and insurers are setting up these kiosks in workplaces to provide employees with immediate access to offsite medical consultations when needed (Ganesh et al., 2021). Another area of potential integration is wearable health devices, which can be incorporated into telehealth kiosks and other existing healthcare service pathways, thereby enhancing the versatility of omnichannel healthcare strategies. These devices facilitate continuous monitoring of patient health metrics, enabling proactive care and reducing the necessity for frequent in-person visits (Chang et al., 2023; Resnick et al., 2012). When integrated with telehealth kiosks, wearables enable patients to upload health data, interact with clinicians remotely, and receive feedback without the need for travel. Such an integration allows patients to manage their own health more effectively, fostering greater autonomy while enhancing the accessibility and efficiency of healthcare services.

Drones are crucial in delivering medical supplies and monitoring public health, particularly in remote areas and during emergencies (Nedelea et al., 2022). When integrated with AI, drones can go beyond transporting medical supplies by collecting data, performing diagnostic imaging, and assessing health conditions in real-time. This combination allows for more proactive and timely medical interventions in underserved regions, where geographical and logistical challenges often limit access to healthcare. Additionally, blockchain technology can be embedded within various healthcare delivery channels to improve traceability, ensure the quality of care, and enhance the security of sensitive patient data. As Channi et al. (2022) highlight, blockchain strengthens privacy and facilitates secure communication between healthcare platforms, safeguarding patient information. This technology is particularly important as healthcare increasingly moves toward digital solutions, where concerns about data breaches can deter patients from fully utilizing telehealth services.

Hence, an omnichannel healthcare strategy integrates diverse technologies like telehealth kiosks, AI diagnostics, blockchain for data security, drones, wearable devices, and web-based platforms to create a patient-centered experience. These components, whether integrated or independent, complement traditional care methods, aiming to improve access and quality, especially for underserved populations. The next section focuses specifically on the role and potential of telehealth kiosks/booths (TKBs) in this paradigm.

2.2.1 TKB Use

Our focus in this research is on the transportation and location aspects associated with accessing a network of TKBs, which are telehealth kiosks or booths designed as facility-based systems that provide healthcare services and diagnostics at convenient, non-residential locations. We do not consider the micro-level design or location decisions for TKBs, but envision these being located in or near retail, government or public safety buildings. For research on TKB usage patterns, user acceptance and the physical design of TKBs, see Demeris et al. (2013), Bahadin et al. (2016), and Letefat-nejad et al. (2020). Public telehealth kiosks/booths (TKBs) have been available as far back as 1989 (Jones 2009), primarily as a means to provide health information. These have mainly been used in clinical settings and in urban areas (Joshi and Trout 2014).

While TKBs continue to provide services such as electronic patient registration, symptom collection and health information provision, advances in telecommunications and technological developments for self-service health measurements have changed TKB services to include more diagnostic and therapeutic services, with and without teleconsultations. Letefat-nejad et al. (2020) provide a review of 37 articles from 2001-2018 describing TKB use across 11 countries for a range of services, including automated measurement of vital signs, HIV testing, and diagnosis of urinary tract infections. Another survey of 134 studies of TKB use showed that the most common primary roles for TKBs are providing health information (35%), clinical measurements (21%), screening (13%) and telehealth (8%) (Maramba et al. 2022). This survey also noted that TKBs "outperform personal smart devices" in the collection of clinical measurements.

Interest in TKBs, along with all forms of telehealth, increased as a result of the COVID-19 pandemic. For example, North Carolina deployed five TKBs in rural Robeson County in 2021 with a goal to help communities with "inadequate broadband connections" (Administration for Strategic Preparedness and Response 2021). In another example, a TKB was deployed in the lobby of the sheriff's office in Milam County, Texas (a safe location open 24/7 with reliable internet access) (Hendrix 2020; Health Care Service Corporation 2020). This TKB connected patients to providers (e.g., clinicians and nurse practitioners) located in Florida, but licensed in Texas, and it included a variety of self-service tools for collecting health data from the patient. This TKB also included a pharmacy robot to dispense commonly prescribed medications. Following each visit, the TKB automatically sanitized itself using UV light. (No appointments were required and the cost for use was $65.) TKBs are also of interest to health insurers, large firms and public organizations for their own employees or covered individuals (Galewitz 2016).

These are private TKBs used by employees to address common conditions such as colds, sore throats, upper respiratory issues, earaches etc. Costs to patients are described as “either nothing or no more than $15 per session” and the kiosks themselves cost $15,000 to $60,000 (Galewitz 2016).

TKBs are also being used outside the US. Huet (2023) reports on a French TKB where “connected medical instruments allow patients to conduct their own physical exam while speaking to a doctor on a screen.” This cost 100,000 euros to install (in 2020) and was seeing “about 30 patients a week”, with a visit costing 25 to 30 euros, the “same as a normal visit to the doctor.” A comprehensive evaluation of a multisite network of TKBs covered visits from 1715 French patients in 2019-2020 (Falgarone et al. 2022). This included 31 TKBs, with most located in Paris or its suburbs and at large companies or local authorities. Results showed that 72% of TKB users were female, with the main users being younger women (mean age 38.7). The visits to a TKB were evenly distributed over the days of the week with a mean usage time of 18 minutes. The main reasons cited for visiting a TKB were cough disorders, pain, joint diseases and rhinitis. Some other studies have addressed more specialized uses of a TKB for managing chronic cardiovascular conditions in Singapore (Bahadin et al. 2016) and for teleopthamology in India (Delana et al. 2023). Detailed reports on the costs for using TKBs are limited, in part due to the customized nature of different TKBs and different government reimbursement schemes. Zanjani et al. (2020) reports that costs in the UK are “a bit less than what a typical visit to an office would cost” and “three times cheaper than an urgent care visit and vastly less expensive than a trip to an emergency department”. In summary, the literature includes a variety of reports on TKBs that provide a wide range of health services, but mostly from more urban areas and many for specialized situations.

2.3 Barriers to Adopting an Omnichannel Strategy for Rural Health

Omnichannel healthcare strategies offer numerous benefits, such as improved accessibility and care integration across various platforms, including telemedicine, e-platforms, TKBs, and in-person consultations. However, several barriers and challenges hinder the implementation of these strategies, which must be addressed to realize their full potential in healthcare (see Figure 3.1). One significant challenge is patient confidentiality and privacy. Telemedicine interactions may be more susceptible to privacy breaches than in-person consultations, raising concerns about data security. Cascella (2018) highlights that patients may be reluctant to fully embrace telemedicine due to the perceived risks of data breaches. These concerns are further compounded in underserved and rural areas, where reliable internet infrastructure may be lacking, creating vulnerabilities in data transmission. As Myers (2019) emphasizes, the successful adoption of omnichannel healthcare requires overcoming privacy and security issues, especially in remote areas where data protection measures may be harder to implement.

In addition to privacy concerns, personalized care is another challenge. Moreira et al. (2023) argue that omnichannel healthcare systems must provide patients with personalized information and services tailored to their individual preferences and needs. However, this also heightens the risk of data breaches, as more detailed information must be shared across various platforms. Balancing the need for personalization with stringent privacy measures is a complex task, particularly in the context of remote areas, where internet connectivity issues further complicate the delivery of personalized care. Another obstacle to adopting omnichannel strategies is the lack of integration between different channels of care. Barbosa and Casais (2022) note that without a unified system to manage services and inventories, healthcare providers struggle to offer seamless experiences to patients. If service channels are not properly integrated, patients may experience delays or shortages in care.

Table 2.2 Challenges in implementing omnichannel healthcare in rural areas

Barrier/Challenge	Impact/Explanation	Source/Reference
Patient confidentiality and privacy	Telemedicine poses higher risks for privacy breaches, making patients reluctant to adopt it, especially in rural areas with weak internet infrastructure.	Cascella (2018); Myers (2019)
Personalized care	Delivering personalized care requires sharing more detailed information, which increases the risk of data breaches, especially in rural areas with poor internet connectivity. Moreover, telemedicine cannot fully replicate in-person care, particularly for physical assessments and building long-term patient-provider relationships, further highlighting the need for a balanced approach to healthcare delivery.	Moreira et al. (2023); Balestra (2018); Yang & Kozhimannil (2016); Moulaei et al. (2023)
Telecommunication infrastructure challenges	Without proper integration of service channels, delays and shortages in care arise, making advanced services like telesurgery difficult due to network latency issues.	Barbosa & Casais (2022); Gupta, Shukla & Tanwar (2020)
Regulatory and legal barriers	Varying telehealth regulations and licensure requirements across states complicate omnichannel adoption, creating inconsistency in care and higher operational costs.	Gajarawala & Pelkowski (2021); Myers (2019)
Patient psychological resistance	Patients in remote regions feel isolated or suspicious of new technology, which limits telemedicine acceptance. Social interaction is essential for rural communities.	Hirano et al. (2023); Mohammadzadeh, Rezayi & Saeedi (2023)
Remote and geographical challenges	Rural areas face additional challenges, such as remote and geographical challenges, including difficulties in transporting necessary equipment, which hinder telemedicine implementation.	Mohammadzadeh, Rezayi & Saeedi (2023)

Gupta, Shukla, and Tanwar (2020) point out, telesurgery (an advanced form of telemedicine that holds great promise for providing specialized care in underserved regions) depends on real-time data transmission, which is challenging in rural healthcare systems with limited broadband access. Network latency can cause delays in data transmission between the surgeon and the robotic system, potentially compromising the precision of the surgery and leading to suboptimal outcomes. Also, regulatory and legal barriers further complicate the implementation of omnichannel healthcare. Gajarawala and Pelkowski (2021) highlight that varying state regulations in the US regarding telehealth make it difficult for providers to offer consistent care across state lines. For instance, while some states allow physical exams via electronic means, others still require in-person evaluations. This inconsistency confuses providers and adds additional costs, as they must navigate multiple licensure requirements.

Myers (2019) also identifies licensure, coverage, and reimbursement issues as significant obstacles for widespread adoption of omnichannel strategies. These barriers are particularly relevant for telehealth services, which often rely on multistate licensure and clear reimbursement frameworks to function effectively across different regions. Additionally, mental barriers, such as patients' feelings of isolation and suspicion toward new technology, further hinder the acceptance of telemedicine in remote regions (Hirano et al., 2023). According to Mohammadzadeh, Rezayi, and Saeedi (2023), telemedicine implementation in these locations faces unique challenges, such as harsh weather conditions, difficulty in transporting necessary equipment, and connectivity issues. Social factors, such as the importance of physical interaction, are particularly significant in rural areas, where residents may experience isolation due to geographic dispersion or rely on tight-knit, small communities for support. Therefore, broader adoption of omnichannel healthcare must consider these social dynamics in addition to addressing technological limitations. Telemedicine, for example, cannot fully replicate certain in-person care functions, particularly when a comprehensive physical assessment of the patient is required (Balestra, 2018).

Bearing in mind this social-physiological nature of rural communities, there is a concern that over reliance on telemedicine might compromise continuous care for patients requiring several hours of one-to-one services in a calendar day. Yang and Kozhimannil (2016) argue that virtual healthcare providers often lack the personal touch of in-person visits, essential for building long-term patient-provider relationships. Moulaei et al. (2023) support this by showing that many patients still prefer in-person consultations over telemedicine, citing better accuracy in diagnosis, physical examination, and treatment as their reasons. For omnichannel healthcare to succeed, it should complement, rather than replace, in-person care by addressing these relational barriers.

While not the primary focus of this research in its initial phase, overcoming these barriers is essential for the successful long-term implementation of omnichannel healthcare, particularly in rural regions where access challenges persist. Addressing critical factors such as system integration, patient trust, and technological limitations will be necessary to ensure that omnichannel strategies can effectively enhance healthcare delivery without compromising the benefits of in-person care. The next section focuses on modeling spatial accessibility to better understand and quantify the fitness of placing healthcare facilities, such as TKBs, to address some of these challenges effectively.

2.4 Modeling Spatial Accessibility

There are several approaches for measuring and modeling spatial accessibility to healthcare. Measures can address the presence or number of healthcare providers within a defined catchment area (i.e., availability), the percentage of potential users within the catchment of a healthcare facility (i.e., coverage), both the supply of healthcare and the demand from potential users (e.g., an accessibility index as in Luo and Wan (2003)), or spatial proximity (e.g., based on travel distance or time). Each of these approaches to measure accessibility can be used to provide descriptive measures for a spatially distributed health system or as an objective or constraint for prescriptive analytics, such as optimization modeling to design a network of facilities. Note that accessibility and coverage measures can be based on residents, potential users or geographic locations within one or more catchment areas of healthcare facilities, and travel time (distance) can be calculated for different populations (e.g., all residents, all potential users or actual users) and different geographic regions.

One important feature for evaluating and designing networks of healthcare facilities is the "distance decay effect". This captures the decline in a patient's willingness to travel to a facility (e.g., a TKB) as the travel time or distance increases. Because travel time is perhaps more important than travel distance, we use the term "travel time decay" as that more accurately reflects patient behavior. (We acknowledge that much of the literature focuses on "distance decay" models, where a simple conversion may be used to estimate travel time from travel distance.) Empirical studies of the travel time decay seek to identify the shape of the decay function with respect to travel time (or distance) and the catchment area, or the maximum travel time (or distance) patients are willing to travel. Empirical studies typically involve surveys of potential patients or analysis of data sets that include the patient and provider locations (e.g., addresses). The resulting decay behavior has been shown to depend on the type of healthcare facility and services, and the geographic and cultural setting. For example, Arcury et al. (2005) reported patients in rural North Carolina face a 5% decrease in the number of routine care visits for each additional kilometer that a patient must travel, as well as a lesser impact of travel time for acute and chronic care visits compared to routine care. McGrail et al. (2015) surveyed residents in rural Australia (1079 questionnaires) and found travel time decay depends on "degree of rurality", with a suggested maximum catchments of 60 minutes for "closely settled areas" and 120 minutes for "sparsely settled areas". Weinhold et al. (2022) showed how the travel time decay based on a German national health survey of 1598 participants depends on the patient age, region (urban vs small town/rural), and medical specialty, with 95% of the "small town/rural" patients traveling at most 33 minutes for a general practitioner and 61 minutes for orthopedists. Wood et al. (2023) reviewed Australian studies on accessibility to health care services and showed that most studies addressed accessibility in urban areas, with limited attention to "regional/rural/remote" areas. In summary, empirical studies to assess travel time decay generate situation specific results and tend to require time consuming data collection efforts.

A travel time decay function is important to translate potential users into willing system users based on their locations relative to the facilities (or providers), and it addresses two important issues: (i) identifying catchment areas; i.e., travel time limits, and (ii) identifying the shape of the decline in willingness to visit a facility as travel time increases. A wide variety of travel time decay functions have been presented in the literature, including continuous functions (exponential, gaussian, log-logistic, power, piecewise linear, etc.) and discontinuous (step) functions. While the value of properly calibrating the travel time decay function is widely recognized, it has often been ignored in academic studies. McGrail (2012) states "there is little empirical evidence to guide the choice of one decay function over another" and "many authors have developed distance-decay functions which are smoother and continuous in their decay;

however without any empirical evidence.” Similarly, Wan, Zhan, Zhou and Chow (2012) noted that “researchers have used arbitrarily determined impedance [distance decay function] coefficients in previous studies…” and Wang et al. (2021) state “…selection of a particular distance decay function…should be determined empirically in order to most accurately represent actual patterns.” Note this could be done prospectively by asking potential or actual patients how far they are willing to travel for healthcare, or retrospectively by analyzing data on healthcare utilization for actual trips.

Wang (2012) reviews healthcare accessibility methodologies and assesses a range of functions proposed for modeling travel time decay. Stacherl and Sauzet (2023) review gravity-type models for travel time decay, similar to those from spatial interaction or retail modeling. Step functions have also been used to model distance decay, as in the two-step floating catchment area (2SFCA) model and its extensions (e.g., McGrail 2012; Wan, Zou and Stenberg 2012). Wang et al. (2021) examined five continuous distance decay functions for cancer care in nine states in Northeastern US using travel between pairs of 5,969 zip codes They found that 85% of patients traveled 60 minutes or less, and 99.6% of patients traveled 180 minutes or less. Jia et al. (2019) analyzed travel for hospital inpatient care in Florida from over two million hospital discharge records in a state database. They compared four distance decay functions and showed a log-logistic function was a slightly better fit to the data than an exponential function. The data showed that rural patients traveled an average of 50.9 minutes versus 16.9 minutes for non-rural patients. Jia et al. (2017) fit four distance decay functions for travel to hospitals from over 2.5 million patient visits related to cardiovascular or neurological surgery in a state database. The log-logistic function was the best fit to the data, though the cardio and neuro patients showed different distance decay effects. These studies illustrate how empirical data leads to different catchment areas and different decay functions in different settings.

A very common accessibility measure for healthcare is the two-step floating catchment area (2SFCA) model (Luo and Wang 2003). This defines accessibility from the patient perspective using the "Accessibility Index", which is defined in two steps. The first step is to calculate the ratio of healthcare providers (or provider capacity) to population within a specified catchment of each facility. Because a patient site may be in the catchment area for several facilities, that patient site population can enter into the calculation of the ratio for several facilities. The second step calculates the Accessibility Index for each patient site as the sum of the ratios for all provider facilities within the specified catchment of the patient site. Luo and Wang (2003) illustrated the accessibility index for primary healthcare in the Chicago region with a catchment of up to 50 minutes of travel time. The use of a catchment area in the 2SFCA effectively defines travel time decay in a binary fashion with "no decay" for those within the catchment and "total decay" (zero willingness to use a facility) for those outside the catchment.

The 2SFCA has been used extensively for analyzing accessibility of existing healthcare systems and as a springboard for a number of extensions (McGrail 2012; Gu et al. 2023). The lack of travel time decay behavior is a known weakness of the basic 2SFCA model, and the extended-2SFCA (E2SFCA) model computes accessibility to healthcare facilities on the basis of several concentric catchment areas, where the likelihood that a patient travels to a facility decreases with the distance or travel time to the facility (Luo and Qi 2009). This can be viewed as a discrete approximation to a continuous travel time decay function. Wan, Zhan, Zou and Chow (2012) use the E2SFCA model with four catchments, where the farthest is at 60 minutes, for computing Accessibility Indices to primary care providers in a region of Texas. McGrail

(2012) compares two step functions and a continuous power weighting function for computing Accessibility Indices from the E2SFCA for travel to general practitioners in Victoria, Australia using a maximum catchment of 60 minutes. Results showed "relatively minor differences…particularly in more sensitive rural areas" between the Accessibility Indices from the step and continuous decay functions. Bauer and Groneberg (2016) develop a variation of the 2SFCA that defines a different distance decay function for each patient location, so there are variable catchment sizes, with a case study for primary care physicians in Berlin, Germany. Tao et al. (2020) extend the E2SFCA to a generalized version GV2SFCA for analyzing delivery care at hospitals in China, with variable catchment sizes allowing travel up to 170 minutes. Ghorbanzadeh et al. (2021) compare the basic 2SFCA model and the E2SFCA model for access to treatment for COVID-19 in Florida, where the E2SFCA uses weights of 1, 0.6, and 0.22 for three catchments of 10, 20 and 30 minutes (i.e., 100% of patients within 10 minutes, 60% of patients between 10 and 20 minutes, and 22% of patients between 20 and 30 minutes will get treatment). Gu et al. (2023) present a "balanced 2SFCA" model for hospital accessibility in China with a travel time of 80 minutes for the farthest catchment. They also use the Gini index to measure equity. Another example of measuring equity with the Gini index is in Cheng et al. (2020) where the basic 2SFCA is used to analyze accessibility for elderly residents in Nanjing, China.

Each travel time decay model requires deciding on values of one or several parameters to calibrate the model and determining one or more catchment limits. This calibration can be done based on data collected from surveys, secondary sources (e.g., Medicare data in the US) and/or stakeholder or expert opinions (e.g., focus groups). As noted earlier, a major concern is that parameters for the distance decay models are often not calibrated using empirical data, in spite of studies showing these parameters vary with the location, types of health services provided, and characteristics of the potential users. The data needed to calibrate continuous decay models can be challenging to acquire as it may require considerable data collection efforts, and primary or secondary data collection in the area of healthcare may need to overcome limited access and privacy regulations. Continuous functions can also be challenging for stakeholders (e.g., patients, healthcare staff) to interpret and the proper functional form is not known in advance,, as many different forms could potentially fit a given dataset.

For our study, we seek to measure accessibility for a particular type of new healthcare service (TKBs in a rural area) in light of other healthcare options (travel to other facilities or not seeking care). Thus, one cannot use empirical utilization data based on patient visits to rural TKBs to calibrate the travel time decay model, as such data is not available to be collected directly or extracted from secondary sources (like Medicare data). Further, as the literature notes, it can be challenging to determine the best continuous decay function, and simpler functions that are easier to estimate and understand can provide useful results. For example, it is likely more practical and easier for a group to understand and estimate a piecewise linear function or a step function with few steps using defined catchment travel times, rather than to define a particular continuous decay function.

Thus, in our research, we adopted an alternative efficient approach to estimate the travel time decay more accurately using a discrete choice experiment with an online survey of potential TKB users. This approach includes "decision makers" (i.e. potential TKB users) who choose among a set of alternatives (e.g., travel to a TKB, travel to another healthcare facility) under the assumption that decision makers seek to maximize their "utility" (Train 2009). Discrete choice models are widely used in transportation modeling (Ben-Akiva and Bierlaire 1999), and have been used for modeling a wide variety of healthcare decisions, such as healthcare mode choice in China (Jiang et al. 2020), emergency care choice in the UK (Bhattarai et al. 2019), and COVID-19 vaccine choices among young people (McPhedran et al. 2022). Our survey provided potential TKB users with a set of scenarios, where in each scenario they choose between visiting a TKB with a specified travel time or visiting a hospital with a specified travel time. Scenarios were designed to reflect rural areas were the hospital is likely to be farther than the TKB. We used the survey results to develop discrete choice random utility models for four different age groups to model an individual's likelihood to use a TKB. Chapter 4 contains details on the discrete choice experiments, including details on the survey and the multinomial logit modeling. The result of the discrete choice modeling is a continuous travel time decay function, expressed as a probability of a resident choosing to visit a TKB if they have to travel for a given time. This travel time decay function provides valuable insights into the factors influencing individuals' willingness to travel for healthcare, which are further explored in the following subsection.

2.4.1 Willingness to Travel for Healthcare

Willingness to travel for healthcare depends on several factors, including transportation availability, psychological motivations, cost, safety, waiting times, and clinical quality. While transportation services aim to improve healthcare access, they do not always yield the desired outcomes (Syed et al., 2013; Lyeo et al., 2024; Solomon et al., 2020). Psychological motivations, such as social interactions during travel, can improve well-being (Hua et al., 2024). However, long travel distances and extended travel times remain critical barriers to accessing care, significantly limiting the ability of individuals in underserved areas to receive timely and adequate healthcare services (Zhong et al., 2021; Balia et al., 2020).

Patients' willingness to travel is influenced by demographics and clinical severity. Younger and more severely ill patients are more likely to wait or travel longer distances for higher-quality care (Bruni et al., 2021). Telehealth has emerged as an alternative for reducing travel, particularly for weight management and consultations requiring frequent interactions (Rauch et al., 2022). However, telemedicine faces limitations for certain healthcare needs, such as palliative care and conditions like HIV and cancer, where privacy concerns or the need for in-person interactions may prompt patients to travel longer distances to access specialized care (Johnson & Samson, 2024; Zigah et al., 2023; Maroju et al., 2023).

Patients' willingness to travel for healthcare is often influenced by the need for specialized care, the reputation of healthcare facilities, and the perceived quality of services. For elective procedures, many individuals are willing to travel farther to minimize risks and access highly skilled providers, particularly older adults or those seeking specific expertise (Bühn et al., 2020). This growing willingness to travel for healthcare highlights the importance of strategically locating health facilities to balance accessibility, quality of care, and patient preferences, a topic we explore further in the next section.

2.5 Optimization Models for Locating Health Facilities

While much of the research on healthcare spatial accessibility focuses on descriptive analytics, there is a large body of work on prescriptive optimization for healthcare facility location. However, little research addresses optimal location modeling for telehealth kiosks/booths (TKBs) of the type considered here. Alcaraz et al. (2009) empirically compared TKB placements and found that kiosks located at neighborhood health centers and public libraries had the highest usage. Interestingly, while both laundromats and libraries offered the shortest average travel distance to users, usage remained highest at libraries and health centers.

Strategic facility location models often focus on coverage, a concept introduced by Church and ReVelle (1974) in the seminal Maximal Covering Location Problem (MCLP), which seeks to maximize demand coverage within defined catchment areas. Extensions, such as the Weighted Benefit MCLP (Church & Roberts, 1983) and the Generalized MCLP (Berman & Krass, 2002), incorporate travel time decay using step functions. Gradual coverage models with alternative decay functions (e.g., linear, exponential) and continuous location versions have been explored as well (Berman et al., 2003, 2010; Drezner et al., 2004; Karasakal & Karasakal, 2004; Karatas & Eriskin, 2021).

While partial coverage is well-studied in facility location problems, Ahmadi-Javid et al. (2017) reported that only 10% of healthcare location papers surveyed incorporated partial coverage, mostly for emergency applications. Related models for partial coverage in various transportation systems have addressed railway station siting (Chanta & Sangsawang, 2021), transport hubs (Peker & Kara, 2015), retail (Küçükaydın & Aras, 2020), and fire stations (Wang et al., 2016). Despite the prevalence of MCLP-based models, there is limited focus on transportation access, spatial equity, and proximity in healthcare location research (Shehadeh & Snyder, 2023).

More recent healthcare optimization models integrate travel time or distance decay. Lim et al. (2016) modeled vaccine distribution with step-function decay across three catchments. Luo et al. (2022) presented a multi-objective EMS station location model addressing urban-rural inequalities. Vicencio-Medina et al. (2023) optimized mobile unit placements for COVID-19 patients in Mexico using a mixed-integer programming model. Almeida et al. (2024) located neonatal screening centers in Brazil using gravity-based decay functions, while Wu et al. (2024) formulated a robust EMS location model incorporating equity and random demand. Mendoza-

Gómez and Ríos-Mercado (2024) applied piecewise linear decay to locate facilities for multiple health services in Mexico, and Erdogan et al. (2024) addressed clinic placement for bladder cancer screening with a distance decay Gompertz function.

2.6 Research Gap and Conclusion

While omnichannel healthcare holds significant promise for improving access and integrating various services, numerous barriers must be addressed to realize its full potential. It is important to avoid assuming that the same factors—whether opportunities, benefits, or barriers—will lead to successful implementation across different healthcare systems and regions. The impact of these factors is highly context-dependent, influenced by patient demographics, the types of channels employed (e.g., telehealth kiosks, drones, online platforms, remote surgery systems, and AI-based tools), the functional capabilities of these channels, and the range of health conditions they aim to address.

A "one-size-fits-all" approach is ineffective for designing omnichannel healthcare strategies. Further empirical research is required to identify the most significant barriers to integrating multiple care delivery channels—such as telehealth kiosks, drones, and virtual consultations—to improve healthcare access and equity, particularly for rural and underserved populations. For instance, while recent studies (e.g., Nedelea et al., 2022; Baron, Chen, and Seidmann, 2023) highlight the potential of drones and AI to complement telehealth systems during emergencies by providing real-time monitoring and public health support, their deployment in non-emergency contexts remains limited. Additionally, there is insufficient data on how these technologies can be effectively integrated to reduce healthcare inequality, especially in rural settings. Similarly, the use of Telehealth Kiosks/Booths (TKBs) in rural areas as part of an omnichannel healthcare system warrants further research to understand their role in addressing healthcare disparities, optimizing resource allocation, and complementing other delivery channels like drones and virtual consultations.

Existing studies lack a comprehensive approach that integrates empirical analysis with modeling and analytics to address healthcare access challenges in rural areas. In this report, we focus specifically on the deployment of Telehealth Kiosks/Booths (TKBs) in rural areas as a means to enhance healthcare access and equity, addressing critical gaps in current research and practice. Specifically, there is a gap in understanding:

1. How travel time decay influences patient preferences for telehealth kiosks (TKBs) as an alternative healthcare channel.
2. How empirical insights can inform the optimal location modeling and network design of TKBs to improve access and equity.
3. How these models can incorporate real-world data to address the unique spatial and demographic characteristics of rural healthcare systems.
4. What are the characteristics of optimal TKB networks for rural areas, including the ideal number of TKBs based on factors like population, geography, demographics, and cost, and the best strategies for their distribution—whether clustered in population centers or spread more evenly to balance accessibility and efficiency.

This study addresses these gaps by combining empirical analysis, through discrete choice experiments and survey data, with modeling and analytics approaches to estimate travel time decay functions and model optimal TKB placements. By leveraging these methods, the research provides a robust framework for designing integrated telehealth networks that enhance healthcare accessibility and equity in rural and underserved regions.

Chapter 3 Rural MO Data sets

In this chapter, we developed two case study datasets for Missouri to serve as the foundation for modeling healthcare accessibility and equity in rural areas and for verification and validation of the models of TKB networks to ensure their accuracy and applicability. We used the Missouri dataset for this research because Missouri closely mirrors the national trends where rural residents face significantly lower levels of access to healthcare. In Missouri, where the population is 6.2 million, approximately one-third of the population (2.06 million) lives in rural areas, with 99 of Missouri's 115 counties being rural (Missouri Department of Health and Senior Services 2024). Seniors (65 & older) comprise 19.4% of the population in rural areas, versus 16.2% in urban areas (Missouri Department of Health and Senior Services 2024). Missouri had 12 rural hospitals close in the period 2014-2023 which left 50 counties (43% of Missouri's counties) without a hospital (Missouri Department of Health and Senior Services 2024; Missouri Department of Health and Senior Services 2023). Furthermore, the remaining rural hospitals tend to offer less specialized services. For example, Missouri has 56 rural hospitals, but none with a Level 1 Trauma Center, Pediatric Trauma Center, Stroke Center or STEMI Center. In contrast, Missouri's urban areas have 133 hospitals with 95 (71%) at Level 1 or Level 2. In terms of Missouri's health outcomes and behaviors, life expectancy is 2.4 years lower in rural areas compared to urban areas, and rural Missourians generally have poorer nutrition, less physical activity, higher tobacco use and less insurance coverage than urban residents (Kuhns and Low 2021). A survey of rural Missouri healthcare reported that the three most commonly cited barriers to healthcare were transportation (16%), lack of healthcare providers (16%) and limited service offerings (13%) (Missouri Rural Health Association 2022).

3.1 Development of Case Study Regions

Two target regions were identified to investigate healthcare accessibility and equity in rural Missouri. The first region, located in West-Central Missouri, encompasses a seven-county area situated between Columbia and Kansas City. This region includes the counties of Carroll, Lafayette, Saline, Howard, Pettis, Cooper, and Moniteau. It was selected due to its predominantly rural characteristics, coupled with limited healthcare infrastructure and a sparse presence of hospitals, Federally Qualified Health Clinics (FQHCs), and Rural Health Clinics (RHCs). The second region in Southern Missouri included 10 counties. Like the West-Central region, Southern Missouri is marked by its rural nature, where healthcare facilities are particularly scarce, and access to services remains a significant challenge for residents. The 10-county southern region includes only rural counties, while the seven-county West-Central region includes both rural and non-rural counties. Figure 3.1 provides a map of the two case study regions. The population density for these regions is on average 35.6 (persons per square mile) for the seven-county West-Central region and 14.8 (persons per square mile) in the 10-county Southern region. The density of potential TKB users may be somewhat smaller than the population density, depending on the types of services provided by the TKBs. In the case studies we use the population density values to indicate potential TKB users.

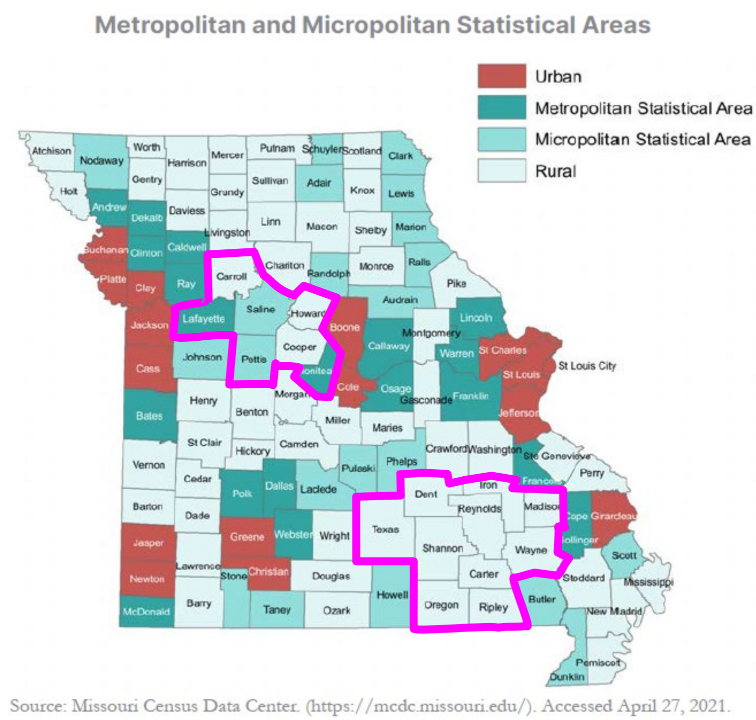


Figure 3.1 West-Central and Southern Missouri Case Study Regions

Table 3.1 provides detailed information about the seven-county region in Missouri, including population, area, density, and the number of FQHCs (Federally Qualified Health Centers). FQHCs are federally funded nonprofit clinics located in medically underserved areas, which offer insight into healthcare availability. While FQHCs provide vital services, their distribution may not reflect a balanced spread across the region as multiple FQHCs are often clustered in towns. Furthermore, TKBs, as proposed, are expected to operate with significantly broader hours (potentially 24 hours a day) compared to typical FQHCs. Table 3.2 presents similar data for the 10-county region, including population, area, density, and the number of FQHCs.

Table 3.1 Characteristics of 7-county West-Central case study

County	Population (2022)	Area (mi^2)	Population Density (persons/ mi^2)	Number of FQHC
Cooper	16,722	565	29.6	0
Howard	10,168	466	21.8	0
Moniteau	15,220	417	36.5	1
Lafayette	32,961	629	52.4	6
Saline	23,007	756	30.4	1
Carrol	8,423	694	12.1	1
Pettis	43,353	685	63.3	3
Total	149,854	4212	35.6	12

Source for FQHCs is
https://data-msdis.opendata.arcgis.com/datasets/76b8ca49558b44d197ae5fb372d1529a_0/about

Table 3.2 Characteristics of 10-county Southern case study

County	Population (2022)	Area (mi^2)	Population Density (persons/ mi^2)	Number of FQHC
Reynolds	6,006	811	7.4	3
Shannon	7,193	1004	7.2	1
Carter	5,268	508	10.4	1
Oregon	8,732	792	11.0	1
Ripley	10,703	630	17.0	3
Texas	25,336	1179	21.5	3
Dent	14,467	754	19.2	2
Iron	9,414	551	17.1	3
Wayne	10,792	761	14.2	1
Madison	12,753	497	25.7	0
Total	110,664	7487	14.8	15

Source for FQHCs is
https://data-msdis.opendata.arcgis.com/datasets/76b8ca49558b44d197ae5fb372d1529a_0/about

Both regions were deliberately chosen for their rural demographics, the absence of comprehensive healthcare infrastructure, and the evident disparities in access to essential healthcare services. The limited availability of hospitals and critical healthcare facilities, such as FQHCs, highlights the pressing need for targeted solutions to address healthcare inequities in these underserved areas (see Figure 3.2).

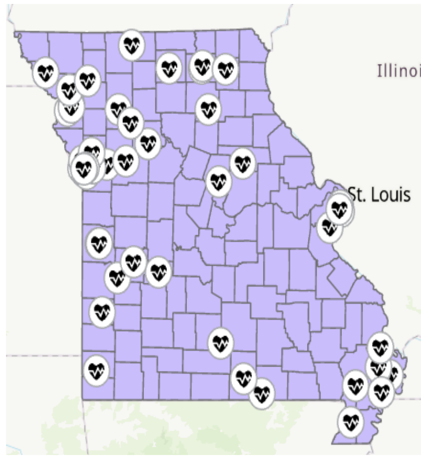


Figure 3.2 Distribution of Federally Qualified Health Centers (FQHCs) in Missouri.

We also collected data on the age distributions in the two case study regions from state government sources (https://health.mo.gov/data/mica/profiles/SocialandEconomic/index.html) because we were interested in examining the willingness of different age groups to use a TKB. Table 3.3 shows age distributions in the two regions, along with data for the US as a whole. The West-Central region is quite similar to the US, while the more rural Southern region shows a greater percentage of Seniors and smaller percentage of Young Adults.

Table 3.3 Age distributions in the case study regions

Age range	Southern region	West-Central region	US
0-4 (Preschool)	5.5%	6.2%	5.5%
5-18 (School age)	17.3%	18.6%	17.5%
19-29 (Young Adults)	11.3%	13.8%	14.4%
30-64 (Middle Age)	44.6%	43.9%	44.9%
65+ (Seniors)	21.2%	17.5%	17.7%

Source for US data: https://www.census.gov/data/tables/time-series/demo/popest/2020s-national-detail.html

3.2 Data Sources and Compilation

To develop the two case study datasets for rural Missouri, we utilized a comprehensive approach that integrated geographic, demographic, and healthcare infrastructure data from reputable public sources. These data were compiled, processed, and visualized using ArcGIS Pro to ensure accuracy and usability for further analysis of healthcare accessibility and equity.

The county boundaries for Missouri were obtained from the Missouri Spatial Data Information Service (MSDIS, 2024). The shapefiles were imported and visualized in ArcGIS Pro, where the target counties for each case study region were carefully extracted as new layers. For the West-Central Missouri region, this included Carroll, Lafayette, Saline, Howard, Pettis, Cooper, and Moniteau counties. This step established clear geographic boundaries for the analysis, ensuring a targeted and accurate scope for the study.

To identify population demand points, Census Block Group centroids were acquired from the US Census Bureau Centers of Population dataset (US Census Bureau, 2024). These centroids represent the geographic population centers within each Census Block Group, providing a granular view of where residents are concentrated across the target regions. Geographic coordinates, including latitude and longitude, were extracted and converted into XY event layers in ArcGIS Pro. This enabled precise visualization and spatial analysis of population nodes within the identified counties. These centroids served as demand points for modeling healthcare accessibility and travel distances to healthcare facilities.

The locations of healthcare facilities—including hospitals, FQHCs, and RHCs—were integrated into the datasets from multiple sources. Shapefiles for Missouri hospitals and RHCs (as nodes, i.e., latitude and longitude coordinates) were obtained from MSDIS (MSDIS, 2024), ensuring consistency in geographic data collection. RHCs may be nonprofit or for-profit healthcare facilities designated for underserved rural populations, and they generally provide outpatient primary care, basic laboratory services, and some “first response” services. Some RHCs are specialized, as for pediatric care or OB/GYN services, and thus may not be good matches for the services at a TKB. For FQHCs, geographic coordinates were obtained from publicly available federal health databases and imported into ArcGIS Pro. These data were processed and converted into spatial layers to align with the Census Block Group centroids. Given the sparse distribution of healthcare infrastructure in rural Missouri, the datasets included healthcare facilities both within and adjacent to the case study regions to capture realistic travel patterns. Thus, we included behavior for residents in a case study region who traveled for healthcare to a facility in an adjoining county outside the case study region.

By combining accurate county boundaries, detailed population distributions, and healthcare facility locations, the resulting datasets provided a robust foundation for analyzing healthcare accessibility and spatial equity in rural Missouri. The meticulous compilation and processing of these data ensured that both case study regions—West-Central and Southern

Missouri—were accurately represented, supporting further empirical research and modeling to address healthcare access disparities.

3.3 Distance and Travel Time Analysis

To assess healthcare accessibility in the two case study regions, we used ArcGIS Pro's Network Analysis tools with the Missouri road network to calculate travel distances and times. We defined demand points for healthcare services as the geographical centroids of US Census Block Groups, providing 229 demand points in the Southern region and 140 in the West-Central region (on average 20-23 points per county). This approach allowed us to quantify the proximity of residents, represented by these centroids, to healthcare facilities and evaluate broader spatial accessibility between demand points and providers.

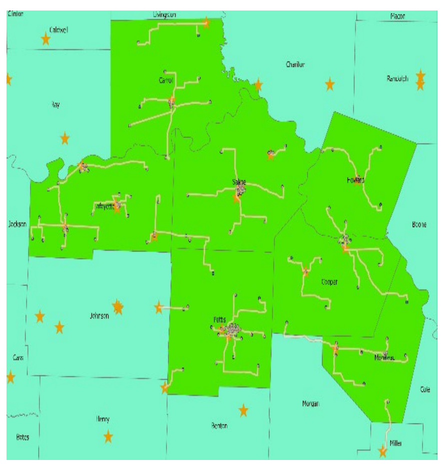


Figure 3.3 Proximity of Census Block Group Nodes to the Closest Hospital in West-Central region.

The Closest Facility analysis identified the nearest healthcare resource—hospital, Rural Health Clinic (RHC), and Federally Qualified Health Center (FQHC)—for each Census Block Group centroid (for example see Figures 3.3 and 3.4). These centroids served as proxies for population demand points, while healthcare facilities were treated as destinations. For each centroid, the analysis provided:

- The name of the closest healthcare facility,
- The total travel distance (miles), and
- The estimated travel time (minutes) based on the Missouri road network.

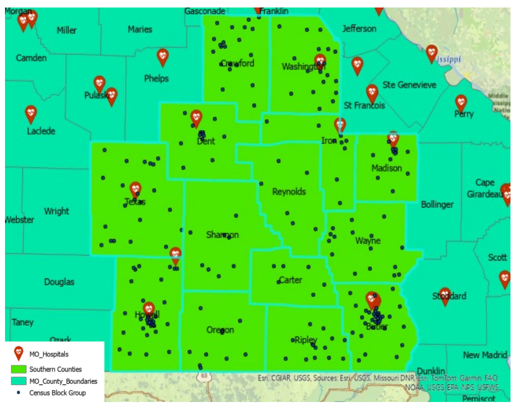


Figure 3.4 Proximity of Census Block Group Nodes to the Closest Hospital in Southern region.

Results revealed the sparse and uneven distribution of healthcare facilities in rural Missouri, with many residents relying on facilities outside their counties. This reflects the limited healthcare infrastructure in rural regions, where proximity to healthcare remains a significant challenge. Outputs from the analyses were exported to CSV files for both case study regions—West-Central Missouri and Southern Missouri—providing foundational datasets for further accessibility modeling.

To complete spatial accessibility analysis, a pairwise distance and travel time analysis was conducted using ArcGIS Pro's Origin-Destination (OD) Cost Matrix tool. This analysis calculated travel distances and times between every pair of Census Block Group centroids (population nodes) and healthcare facilities to allow the right incorporation of geographical locations to be incorporated in optimization modeling where potential locations for TKBs correspond to block group centroids.

The OD analysis was performed separately for the three healthcare facility types (hospitals, RHCs, and FQHCs), capturing road travel distances along the Missouri transportation network, and estimated travel times accounting for road conditions and speeds.

This detailed analysis of rural travel revealed that the average speed for trips from Census Block Group centroids to the nearest healthcare facility (hospital, FQHC, or RHC) was 37.8 mph in the Southern region and 35.4 mph in the West-Central region. As expected, longer trips generally occur at higher speeds, with trips to hospitals being the longest on average.

In terms of accessibility, 30.7% of the population in the Southern region and 9.6% in the West-Central region would need to travel more than 20 minutes one-way to reach the nearest healthcare facility. For trips exceeding 30 minutes one-way, the percentages drop to 19.5% for the Southern region and just 0.5% for the smaller and less rural West-Central region, highlighting the greater access challenges faced by residents in the Southern region.

Additionally, the ratio of road travel distance to straight-line distance (calculated from latitude and longitude) was approximately 1.4 for both regions. Based on these findings, the case studies assume an average travel speed of 35 mph and a travel circuity factor of 1.4 (indicating road travel is 1.4 times farther than the straight-line distance), reflecting the rural road network characteristics in these Missouri regions.

3.4 Data Validation, Refinement, and Significance

Following the initial data compilation, the datasets underwent a rigorous validation process to ensure accuracy and completeness. Errors in locational data and travel times were identified and corrected, enhancing the reliability of the data. The finalized datasets incorporate the following key components:

- Accurate geographical centroids for Census Block Groups, representing population demand points.
- Precise locational data for existing healthcare facilities, including hospitals, Rural Health Clinics (RHCs), and Federally Qualified Health Clinics (FQHCs).
- Verified travel distances and times derived from the Missouri road network using ArcGIS Pro tools, including (1) the distance and time from each demand node (block group centroid) to the nearest facility of each of the three types of healthcare facilities, and (2) the distance and time between each pair of demand nodes (block group centroids).

In Chapters 5 and 6, these datasets serve as essential inputs for both modeling and analysis. Specifically, they underpin location optimization models that aim to enhance healthcare delivery by improving spatial accessibility and equity.

Chapter 4 Empirical Survey and Discrete Choice Experiments

This chapter employs experimental and modeling frameworks to explore these relationships systematically. By leveraging stated preference methods and discrete choice models, the analysis identifies the key factors influencing medical facility selection, with a focus on patient age cohorts and consultation types. The findings contribute to understanding how Technology Trust and Health Literacy intersect with demographic and contextual variables, shaping preferences for traditional and modern healthcare options. These insights provide a foundation for designing interventions to improve healthcare accessibility and technology adoption across diverse patient populations.

The decision-making process behind selecting a medical facility is multifaceted, shaped by an intricate interplay of individual characteristics, experiences, and the attributes of available options. At its core, this process reflects patients' familiarity with healthcare systems, their trust in technology, their ability to navigate complex medical settings and to handle the incurred costs. Trust in automated technologies and health literacy are two critical factors, influencing preferences and acceptance of various healthcare consultation modes. Additionally, contextual factors such as facility type, consultation mode, and travel time interact with demographic variables like age to refine these preferences, further highlighting the complexity of healthcare decision-making. This chapter explores these dynamics using a conceptual framework that integrates dispositional, skill-based, and contextual factors.

A key concept in understanding medical facility choice is Technology Trust, defined as individuals' confidence in the reliability and efficiency of automated systems. This trust is shaped by personality traits, past experiences, and attitudes toward technology. Individuals with high Technology Trust are more likely to engage with modern technologies, perceiving them as capable and reliable. On the other hand, those with lower trust may exhibit skepticism, questioning the safety and utility of automated systems. The role of Technology Trust in influencing preferences for innovative healthcare options, such as artificial intelligence (AI) consultations, is a focal point of this analysis.

Similarly, Health Literacy plays a pivotal role in shaping healthcare preferences. Health Literacy encompasses the ability to understand medical terminology, communicate effectively with providers, and navigate healthcare systems. Individuals with higher health literacy are better positioned to make informed healthcare decisions and adapt to emerging technologies. As telemedicine and AI become integral components of modern healthcare, the interplay between health literacy and technology adoption becomes increasingly relevant.

The remainder of this chapter is organized as follows. Section 4.1 introduces the conceptual model, outlining the key factors influencing patient preferences for healthcare facilities, including demographic characteristics, consultation types, and latent variables such as Technology Trust and Health Literacy. Section 4.2 describes the experimental design, focusing on the development of stated preference methods to capture individual choices. Section 4.3 details the data collection process. Section 4.4 presents the discrete choice modeling framework used to analyze the data and derive travel time decay functions. Section 4.5 discusses the modeling results, emphasizing their implications for healthcare accessibility and equity. Finally, Section 4.6 concludes the chapter by summarizing the key findings and their significance for telehealth adoption and planning.

4.1 Conceptual Model

The decision to choose a medical facility is shaped by a multitude of factors that intertwine individual experiences, perceptions, and contextual elements. At the heart of these influences lies individuals' familiarity with navigating healthcare systems and their trust in automated technologies, both of which play a significant role in shaping preferences. Furthermore, characteristics of the facilities themselves, such as the type of consultation offered and the expected travel time, introduce practical considerations that can make certain options more appealing. Demographic factors, particularly the patient's age, further refine these preferences, highlighting the complexity of healthcare decision-making. Figure 4.1 illustrates the proposed conceptual model, offering a visual representation of the interconnected variables that inform these choices.

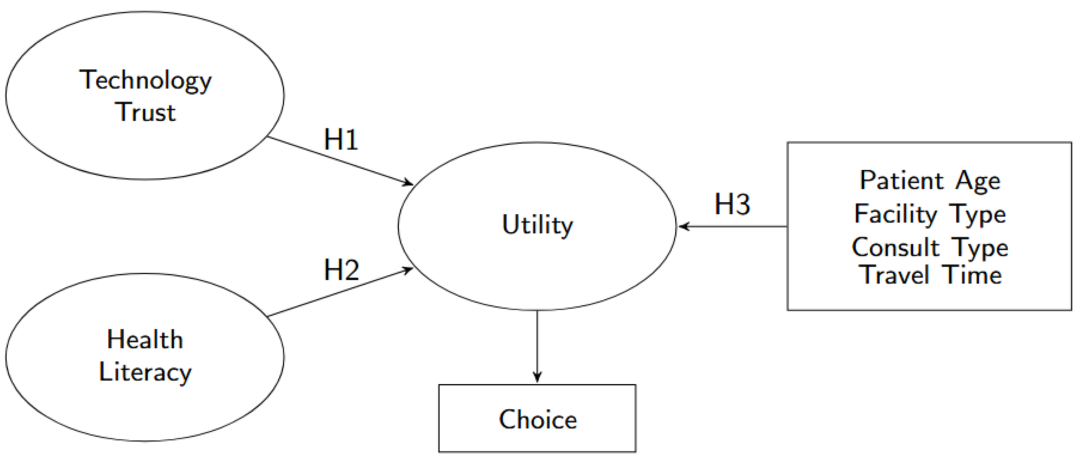


Figure 4.1 Conceptual Framework for Factors Influencing Medical Facility Choice

Technology trust reflects the degree of confidence and reliance individuals place on automated technologies and systems. This trust is inherently dispositional, arising from an individual's personality traits, previous experiences with technology, and overall attitudes toward its use (Jian et al., 2000; Merritt et al., 2013). Those with high levels of technology trust are more likely to perceive automated systems as reliable, efficient, and capable of executing tasks accurately. They engage with and depend on such systems more readily, embracing them as valuable tools in various domains. In contrast, individuals with low technology trust often exhibit skepticism, hesitancy, and heightened concerns regarding the reliability and safety of automated systems. This dispositional trust significantly influences how people interact with technology, shaping their openness to adopting new technological innovations and their willingness to integrate these systems into everyday activities. Given this, we propose our first hypothesis:

H1: Technology Trust Positively Influences Adoption of TKBs.

Health literacy pertains to an individual's ability to effectively navigate and manage the complexities of medical processes and settings. It encompasses a broad range of skills, including comprehension of medical terminology, recognition of symptoms, adherence to treatment protocols, effective communication with healthcare providers, and utilization of healthcare resources efficiently (Rudd, 2007; McCormack et al., 2010). Individuals with high health literacy are better equipped to make informed health decisions, ensuring that they can access and benefit from available healthcare services. These competencies are essential for successfully engaging with new healthcare technologies and environments. We then derive our second hypothesis:

H2: Health Literacy Positively Influences Adoption of TKBs.

Together, these hypotheses articulate the interplay between dispositional and skill-based factors that influence patients' acceptance of TKBs. In the next section, we outline the empirical framework developed to evaluate these propositions and test the proposed relationships systematically.

4.2 Experimental Design

Individuals' willingness to travel to different telehealth facilities was elucidated using stated preference methods, which are attitudinal valuation techniques based on hypothetical scenarios (Gkartzonikas and Gkritza, 2019). Choice experiments are ideal for studying preferences under controlled conditions. These experiments allow for the systematic manipulation and control of scenario attributes presented to respondents, which helps isolate the impact of each attribute on respondents' preferences.

In the experimental design, respondents were asked to choose between different types of healthcare facilities when faced with a health issue requiring medical intervention, with the choice scenarios designed hierarchically around two main facility types: hospitals and TKBs. Hospitals represent traditional healthcare facilities without specified consultation types, while TKBs offer modern telehealth options with three distinct consultation types: AI Consultation, providing medical advice via artificial intelligence; Medical Professional Consultation, where a healthcare professional is present; and Telemedicine Consultation, involving the provision of care through telemedicine technologies. This setting leads to a hierarchy of choices determined by facility and consultation types. Respondents had to consider these options with varying travel times and the age of the individual needing care to determine their preferences.

We developed an optimal experimental design to generate the choice scenarios to test our hypotheses regarding respondents' willingness to travel. This design aims to maximize the expected Fisher information, quantifying the amount of information an observable random variable carries about an unknown parameter (Kessels et al., 2006). To mitigate the sensitivity of choice designs to incorrect parameter guesses, we implemented a Bayesian efficient design, incorporating the researcher's uncertainty about the true parameters by specifying a prior distribution reflecting prior beliefs. To inform the prior distributions for the main experiment, we conducted a small-scale pilot study via Prolific (2024), a platform that recruits participants for online research, collecting 30 responses to the variables of interest. The respondents in the study were adults, while the patient scenarios included individuals across different ages. Patients were categorized into five mutually exclusive age groups: Preschool Children (0-4 years), School-Aged Children (5-17 years), Young Adults (18-29 years), Middle-Aged adults (30-64 years), and Seniors (65 years and older).

4.3 Data Collection and Sample Description

The research hypotheses were tested using data from an incentivized survey conducted through Prolific. The sample data was collected in May of 2024. Adult respondents (age 18 and over) in the United States whose first language was English were targeted, and 460 valid responses were collected. Table 4.1 shows the descriptive statistics for the socioeconomic characteristics of the respondents and the corresponding reference values for the US population (US Census Bureau 2024).

Table 4.1 Demographic and Socioeconomic Characteristics of the Sample

Attribute	N	(%)	US%	Attribute	N	(%)	US%
Gender				**Income**			
Female	229	49.8%	51.4%	Less than $25,000	75	16.3%	9.6%
Male	225	48.9%	48.6%	$25,000-$49,999	99	21.5%	14.9%
Non-binary	4	0.9%	-	$50,000-$74,999	82	17.8%	15.7%
Prefer not to say	2	0.4%	-	$75,000-$99,999	79	17.2%	13.9%
				$100,000-$149,999	73	15.9%	20.1%
Age				$150,000 or more	52	11.3%	25.9%
18-24	55	12.0%	9.3%				
25-34	118	25.7%	13.9%	**Race and Ethnicity**			
35-44	95	20.7%	12.6%	Asian	32	7.0%	6.7%
45-54	65	14.1%	12.7%	Black or African American	63	13.7%	13.9%
55-64	64	13.9%	12.6%	Hispanic or Latino	37	8.0%	19.1%
65-74	52	11.3%	10.2%	White	350	76.1%	69.6%
75 or older	11	2.4%	7.2%	Other	15	3.3%	9.7%
Residence				**Education**			
Rural	74	16.1%	14.0%	High School or Less	150	32.6%	54.6%
Suburban	246	53.5%	55.0%	College	222	48.3%	40.9%
Urban	140	30.4%	31.0%	Graduate Degree	88	19.1%	4.5%

Regarding age distribution, the sample has a higher representation of young adults. Notably, the 25-34 age group is significantly overrepresented in the sample, comprising 25.7% compared to being 13.9% of the US population. Additionally, individuals in the 35-44 age range make up 20.7% of the sample, which is higher than their US population representation of 12.6%. Regarding areas of residence, the sample is closely aligned with US patterns, with rural areas slightly overrepresented in the sample (16.1%) compared to the US population (14%). Income levels indicate a higher representation in lower income brackets in the sample. Those earning less than $25,000 make up 16.3% of the sample versus 9.6% of the US population. However, higher income brackets, such as those earning $150,000 or more, are underrepresented in the sample (11.3%) compared to the US (25.9%). Education levels indicate that those with a graduate degree are overrepresented in the sample (19.1%) compared to the US population (4.5%). In contrast, those with only a high school education or less are underrepresented (32.6% vs. 54.6%).

The differences between our sample and the broader US population suggest that we cannot generalize the descriptive statistics of the variables under study to all US adults. However, this limitation does not hinder the generalizability of the causal effects estimated by our modeling efforts. This is because we have an exogenous sampling situation, where the variations in sampling are independent of the outcome variables (Wolf et al., 2013).

We assessed the quality and usefulness of the measurement instruments using confirmatory factor analysis (CFA) to evaluate the data's fit with the proposed measurement model (Brown 2015). The results show all factor loadings were close to or above the recommended 0.50 threshold, with critical ratios exceeding 1.96, indicating coherence between observed variables and latent constructs (Dunn and Waller 1994; Segars and Grover 1998). We estimated the Average Variance Explained (AVE) for each latent construct (Brown 2015), showing all constructs had AVE values above 0.417, demonstrating clear differentiation. Comparing AVE with construct correlations suggested items were more related within constructs than between constructs (Segars and Grover 1998), indicating convergent validity.

4.4 Choice Modeling

The Hybrid Discrete Choice (HDC) modeling framework is an extension of traditional discrete choice models that integrates Latent Variables (LVs)—unobserved factors such as attitudes, perceptions, or preferences—into the decision-making process. By incorporating these LVs into the systematic utility of alternatives, the HDC framework provides a more comprehensive understanding of how both observed attributes (e.g., cost, distance) and unobserved psychological or behavioral factors influence choices (Ben-Akiva et al., 2002). The latent variables econometrically capture the combined influence of behavioral factors such as respondents' attitudes and perceptions. Incorporating latent variables allows for the inclusion of effects that cannot be directly quantified or observed. Attitudinal and perceptual survey questions act as indicators of these latent behavioral factors. The HDC model consists of two main components: the latent variables model and the choice model, depicted in Figure 4.2.

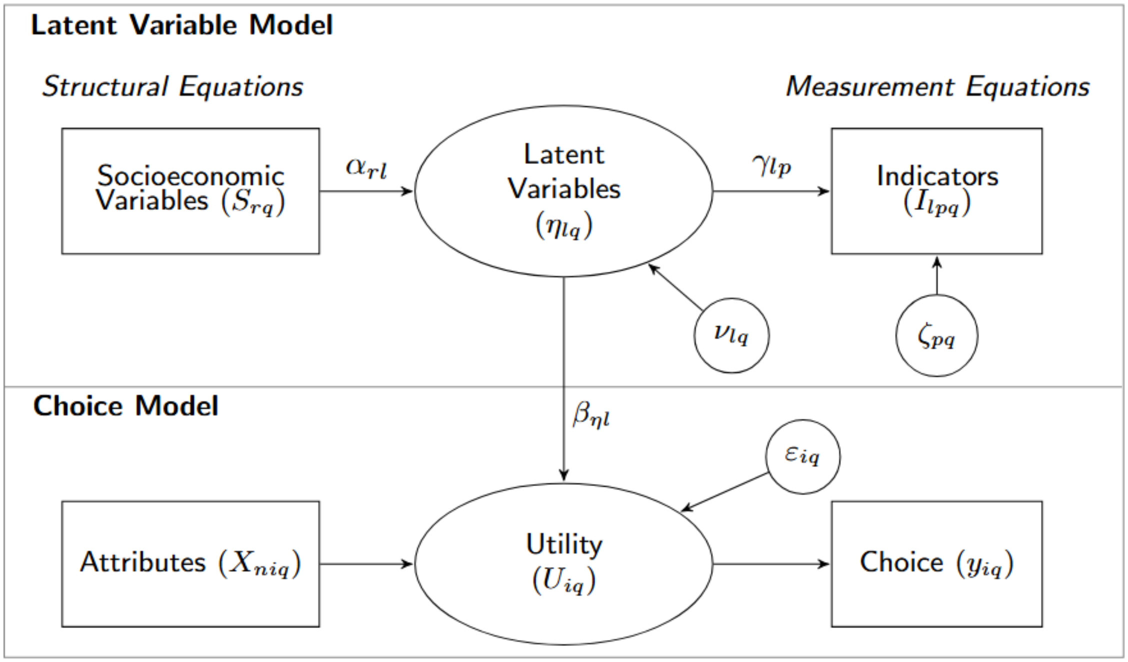


Figure 4.2 Integrated Latent Variable and Choice Model Framework

The latent variables model is further divided into two parts: structural equations and measurement equations. The structural model equations capture the causal relationships among observable explanatory variables, attitudinal factors, and latent variables, as expressed in Equation 4.1:

$$\eta_{lq} = \sum_{r} \alpha_{rl} S_{rq} + \nu_{lq} \tag{4.1}$$

where η_{lq} represents the dependent latent variable l for individual q, S_{rq} is the socioeconomic variable r, α_{rl} is a parameter to be estimated, and ν_{lq} represents the error terms, which is assumed to assumed to be normally distributed with zero mean.

The measurement equations establish the relationships between a latent variable and its attitudinal indicators. Given the ordered nature of these observed indicators, the measurement equations are specified as heteroskedastic ordered logit models, as demonstrated in equation 4.2:

$$z_{pq}^* = \sum_l \gamma_{lp}\eta_{lq} + \zeta_{pq} \tag{4.2}$$

where z_{pq}^* corresponds to the attitudinal indicator p for individual q, γ_{lp} is a parameter of the measurement equation to be estimated, and ζ_{pq} is the error term, which is assumed to follow a logistic distribution. The underlying assumption is that each discrete response k observed within each indicator p, which has K levels, is obtained through a censoring mechanism that defines different categories of response, according to equations 4.2 and 4.3, where each categorical response in the indicator z_{pq} is defined by a set of threshold parameters τ; in consequence, the ordered model includes the estimation of a set of threshold parameters that define the categorical responses.

$$z_{pq} = \begin{cases} 1 & \text{if } -\infty < z_{pq}^* \leq \tau_{p1} \\ \vdots & \vdots \\ K & \text{if } \tau_{p(k-1)} < z_{pq}^* \leq \infty \end{cases} \tag{4.3}$$

The discrete choice model estimates individual choices. In this setting, a nested logit (NL) model is proposed since the choice set presented to the individuals can be partitioned into subsets, referred to as nests. The two nests separate choices into those corresponding to the two facility types: hospitals and TKBs. The nested logit model is appropriate when the choice set facing a decision maker can be partitioned into nests (subsets) in such a way that for any two alternatives in the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives in the nest. And, for any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. Then, individual choices are expressed as a function of the utility for each alternative I and each nest k, as perceived by individual q, shown in equation 4.4:

$$U_{iq} = \sum_{n} W_{nk} + \sum_{n} \theta_{ni} X_{niq} + \sum_{l} \beta_{li} \eta_{lq} + \varepsilon_{iq} \tag{4.4}$$

where W_{nk} depends only on variables that describe nest k. These variables differ over nests but not over alternatives within each nest. Then, θ and β are associated with the individual's attribute and latent variable sets. The error term, ε_{iq}, is independent with a univariate extreme value distribution. However, the ε_{iq}'s are correlated within the nests. For any two alternatives q and p in nest B_k, ε_{iq} is correlated with ε_{ip}. For any two alternatives in different nests, the unobserved portion of utility is still uncorrelated. Parameters were estimated via Maximum Likelihood Estimation using Apollo software (Hess and Palma, 2019). Choice of TKB with an in-person consultation was set as the reference alternative to address identification issues in the modeling effort (Walker et al., 2007).

4.5 Modeling Results

This section presents the results of the modeling framework used to evaluate the factors influencing individuals' choices. The proposed Nested Logit (NL) structure was tested against the Multinomial Logit (MNL) specification to assess its appropriateness. Statistical tests revealed that the null hypothesis asserting the equivalence of the NL structure to the MNL specification could not be rejected. This outcome supports the validity of the MNL model in this context.

The robustness of the Independence of Irrelevant Alternatives (IIA) assumption was also examined. The IIA assumption, which underpins the MNL model, posits that the relative odds of choosing between any two alternatives remain unaffected by the inclusion or exclusion of other alternatives (McFadden, 1974). While this assumption is often a point of theoretical contention, the results demonstrate that the IIA assumption is not violated in this modeling scenario.

Given these findings, the analysis focuses on the MNL specification as it provides a sufficiently robust representation of the choice dynamics under investigation. The subsequent discussion highlights key insights from the estimated MNL model, shedding light on the relationships between explanatory variables and individual decision-making processes.

Table 4.2 provides parameter estimates and robust t-ratios for both structural and measurement equations within the modeling framework. Structural equation parameters describe the relationship between latent constructs (Technology Trust and Health Literacy) and their corresponding observed indicators, while measurement equation parameters capture the associations between individual demographic variables and the latent constructs. Parameters with robust t-ratios exceeding the critical threshold (e.g., ±1.96 for a 95% confidence level) indicate statistically significant relationships, shedding light on the factors influencing Technology Trust and Health Literacy.

Table 4.2 Parameter Estimates and Robust t-Ratios for Technology Trust and Health Literacy Model

Construct	**Variable**	**Estimate**	**Rob. t-ratio**
Structural Equation Parameters			
Technology Trust	TT01	3.114	8.27
	TT02	3.190	7.73
	TT03	2.085	8.37
	TT04	3.401	7.68
Health Literacy	HP01	1.284	8.10
	HP02	2.131	7.04
	HP03	2.390	6.51
	HP04	2.837	7.27
Measurement Equation Parameters			
Technology Trust	Aged 30 or less	-0.270	-1.56
	Race: Black	0.313	2.14
Health Literacy	Female	0.263	1.96
	Middle Age	0.491	3.43
	Senior	1.075	5.24
	High Income	0.350	1.96

The structural equation results indicate that all observed variables (TT01–TT04 and HP01–HP04) are strongly and positively associated with their respective latent constructs, as reflected by their parameter estimates and robust t-ratios exceeding six. These findings confirm that the indicators effectively capture the underlying constructs of Technology Trust and Health Literacy. For instance, the high estimate of TT04 (3.401, t-ratio = 7.68) underscores its strong contribution to measuring Technology Trust. Similarly, HP04 (estimate = 2.837, t-ratio = 7.27) plays a critical role in representing Health Literacy. These results affirm the validity of the constructs and support their inclusion in the modeling framework.

The measurement equation results highlight the demographic factors influencing Technology Trust. Being aged 30 or less is negatively associated with Technology Trust (estimate = -0.270, t-ratio = -1.56), though this relationship is not statistically significant. Conversely, being Black has a positive and statistically significant effect on Technology Trust (estimate = 0.313, t-ratio = 2.14). This suggests that racial identity may shape individuals' confidence in automated technologies, potentially reflecting cultural or experiential differences. These insights underscore the nuanced demographic influences on Technology Trust, warranting further exploration.

The measurement equation results for Health Literacy reveal notable demographic patterns. Being Middle-Aged (estimate = 0.491, t-ratio = 4.93) or a Senior (estimate = 1.075, t-ratio = 5.24) is significantly associated with higher Health Literacy. This suggests that older individuals are better equipped to navigate healthcare processes, potentially due to accumulated life experience or exposure to medical systems. Additionally, having a high income is positively and significantly related to Health Literacy (estimate = 0.350, t-ratio = 1.96), reflecting the role of socioeconomic factors in accessing and understanding healthcare resources. These findings emphasize the intersection of age and income in shaping individuals' Health Literacy, highlighting areas for targeted interventions.

Table 4.3 presents parameter estimates and robust t-ratios for the MNL and HDC models, examining factors influencing preferences for medical facility consultations (Hospital, TKB with AI (TKB-A), and TKB with Telemedicine (TKB-T)). Significant parameter estimates (indicated by robust t-ratios exceeding ±1.96) highlight key relationships between patient characteristics (e.g., age, time variables, health literacy, and technology trust) and their preferences for each consultation type. Comparing results across models provides insights into how additional latent concepts may refine our understanding of patient decision-making.

For Hospital consultations, both models demonstrate consistent findings. Time-related variables are significant for younger, School-Aged, and Middle-Aged cohorts, with positive coefficients indicating that these groups prefer hospital visits as travel time increases. Interestingly, the Senior cohort also shows significant preferences for hospitals as travel time increases, albeit to a lesser extent. These results suggest that traditional hospital consultations remain particularly appealing across age groups as travel time increases. The slightly lower intercept in the HDC model (-1.268) compared to the MNL model (-1.287) suggests that accounting for hierarchical dependencies slightly reduces the baseline disutility of hospital consultations.

Table 4.3 MNL and HDC Model Estimates for Factors Influencing Medical Facility Choice

	MNL Model		HDC Model	
Variable	**Estimate**	**Rob. t-ratio**	**Estimate**	**Rob. t-ratio**
Consult: Hospital				
Intercept	-1.287	-16.09	-1.268	-15.81
Time × School Age	0.057	12.27	0.056	12.33
Time × Young Adult	0.053	9.57	0.055	9.96
Time × Middle Age	0.045	9.86	0.044	9.65
Time × Senior	0.045	6.97	0.046	7.21
Consult: TKB-T				
Intercept	-0.153	-4.22	-0.173	-3.16
Time × School Age	-0.029	-7.22	-0.029	-7.30
Time × Young Adult	0.006	1.24	0.007	1.55
Time × Middle Age	0.006	1.67	0.005	1.34
Time × Senior	-0.002	-0.37	-0.003	-0.47
Technology Trust	-	-	0.178	3.54
Health Literacy	-	-	0.054	1.09
Consult: TKB-A				
Intercept	-1.040	-15.64	-0.996	-8.55
Time × School Age	-0.031	-6.09	-0.032	-6.14
Time × Young Adult	-0.019	-2.34	-0.018	-2.12
Time × Middle Age	-0.010	-2.43	-0.011	-2.63
Time × Senior	-0.004	-0.46	-0.002	-0.20
Technology Trust	-	-	0.716	5.84
Health Literacy	-	-	-0.199	-1.48
Panel Effect	0.561	13.44	0.433	9.79

TKB-T results reveal significant differences in preferences across age groups. The negative coefficient for School-Aged and Middle-Aged cohorts reflects a declining preference for TKB-T as travel time increases, particularly in the MNL model. In contrast, the HDC model adjusts these effects, slightly reducing the magnitude of disutility. The significant positive coefficient for Health Literacy (HDC model, estimate = 0.054, t-ratio = 1.09) underscores the role of individual capabilities in shaping telemedicine adoption. However, the low t-ratio for Health Literacy in the MNL model indicates variability in its influence depending on the modeling structure.

For TKB-A (a TKB with AI-based consultations), younger and middle-aged cohorts exhibit a slight aversion to this option as travel time increases, with negative coefficients in both models. Seniors show neutral preferences for TKB-A across time variables, perhaps highlighting their limited engagement with such technologies. Technology Trust, only included in the HDC model, significantly influences TKB-A preferences (estimate = 0.716, t-ratio = 4.86). This result emphasizes the importance of dispositional trust in driving adoption of cutting-edge, automated healthcare technologies, especially among younger cohorts.

Across the three consultation types, younger cohorts (School-Aged and Young Adults) exhibit a strong preference for hospital-based care, with significant positive coefficients for time variables. Middle-Aged patients show a mixed pattern, favoring hospitals but exhibiting declining preferences for telemedicine and AI consultations as travel time increases. Seniors consistently prefer hospital consultations but demonstrate neutral attitudes toward telemedicine and AI options, likely reflecting comfort with traditional systems and limited exposure to emerging technologies. The positive influence of Health Literacy and Technology Trust on telemedicine and AI adoption, respectively, suggests that addressing these factors could expand acceptance among Middle-Aged and Senior patients. This highlights the need for targeted interventions, such as training or familiarization programs, to bridge the gap in technology adoption across age groups.

4.5.1 Case Study Travel Time Decay Models

Based on the survey responses, utility equations (travel time decay function) for willingness to visit a TKB equipped with telehealth, U_T; a TKB equipped with artificial intelligence (AI), U_A; and a Hospital, U_H were derived as follows:

$$U_T(t) = 1.23759 - t(0.08392I_C + 0.06375I_Y + 0.067I_M + 0.07124I_S) \tag{4.5}$$

$$U_A(t) = -0.15241 - t(0.11187I_C + 0.08519I_Y + 0.07831I_M + 0.06559I_S) \tag{4.6}$$

$$U_H(t) = 0.73532 - t(0.02603I_C + 0.02932I_Y + 0.03398I_M + 0.02507I_S) \tag{4.7}$$

In these equations, the binary indicator I_* determines the age group, where C indicates School Age, Y indicates Young Adult, M indicates Middle-Aged adults and S indicates Seniors. From these utility values, for each age group the willingness to use a TKB (with either Telemedicine consultation or AI consultation) for a potential TKB user located at travel time t from the TKB (a probability for that age group) is given by

$$W_{TKB}(t) = \frac{e^{U_T(t)} + e^{U_A(t)}}{e^{U_T(t)} + e^{U_A(t)} + e^{U_H(t)}} \tag{4.8}$$

This provides four separate continuous functions for the likelihood of each age group to use a TKB based on the travel time to the TKB.

As this functional form (equation 4.8) can be non-intuitive for practitioners, we elected to use corresponding three-piece piecewise linear functions for each age group with catchment areas of 0-30 minutes, 30-60 minutes and 60-90 minutes. To define these, we fit a three-piece piecewise linear function to $W_{TKB}(t)$ as follows. First, for $t = 0$ to $t = 30$, we found the best fit line segment using LINEST in Excel, with t in one-minute increments. Then, for the pieces from $t = 30$ to $t = 60$ and from $t = 60$ to $t = 90$, we solved the nonlinear problems using Excel Solver to maximize the sum of the R^2 values for the two pieces using one-minute increments, while ensuring that the second piece joined the first at $t = 30$, and the third piece joined the second at $t = 60$. The slope and intercept for the resulting piecewise linear functions for each age group are shown in Table 4.4. This table also shows the R^2 values which verify the good fit between the piecewise linear functions and equation 4.8. Figure 4.3 plots the travel time decay functions from equation 4.8, while Figure 4.4 shows the corresponding piecewise linear functions (from Table 4.4). The travel time decay functions used in this study are based on a representative sample of US adults, capturing how their willingness to access healthcare services diminishes as travel time increases. These empirically derived functions provide a realistic foundation for understanding patient behavior in rural healthcare contexts. In Chapters 5 and 6, we apply these decay functions to our rural Missouri case study data, modeling the deployment of TKBs in rural US regions.

Table 4.4 Piecewise linear travel time decay functions for case studies in Missouri.

Age Group	**slope**	**intercept**	**Lower catchment time limit**	**Upper catchment time limit**	R^2
Senior	-0.010971	0.67654	0	30	0.9999
	-0.0078478	0.58283	30	60	0.9783
	-0.0027619	0.27768	60	90	0.9820
Middle Age	-0.0085400	0.67639	0	30	0.9998
	-0.0074843	0.64472	30	60	0.9931
	-0.0039186	0.43078	60	90	0.9911
Young	-0.0092220	0.67574	0	30	0.9999
Adult	-0.0075098	0.62438	30	60	0.9909
	-0.0036109	0.39044	60	90	0.9895
School Age	-0.014661	0.67105	0	30	0.9988
	-0.0062650	0.41916	30	60	0.9052
	-0.0012694	0.11943	60	90	0.9509

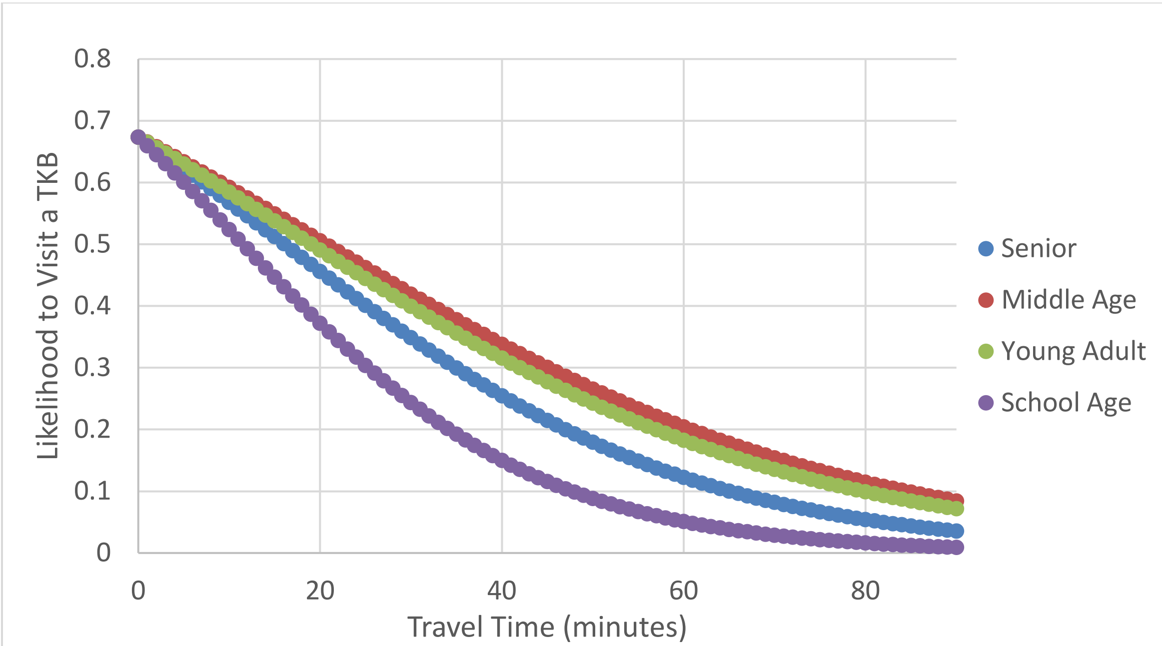


Figure 4.3 Travel time decay functions for case studies from equation 4.8.

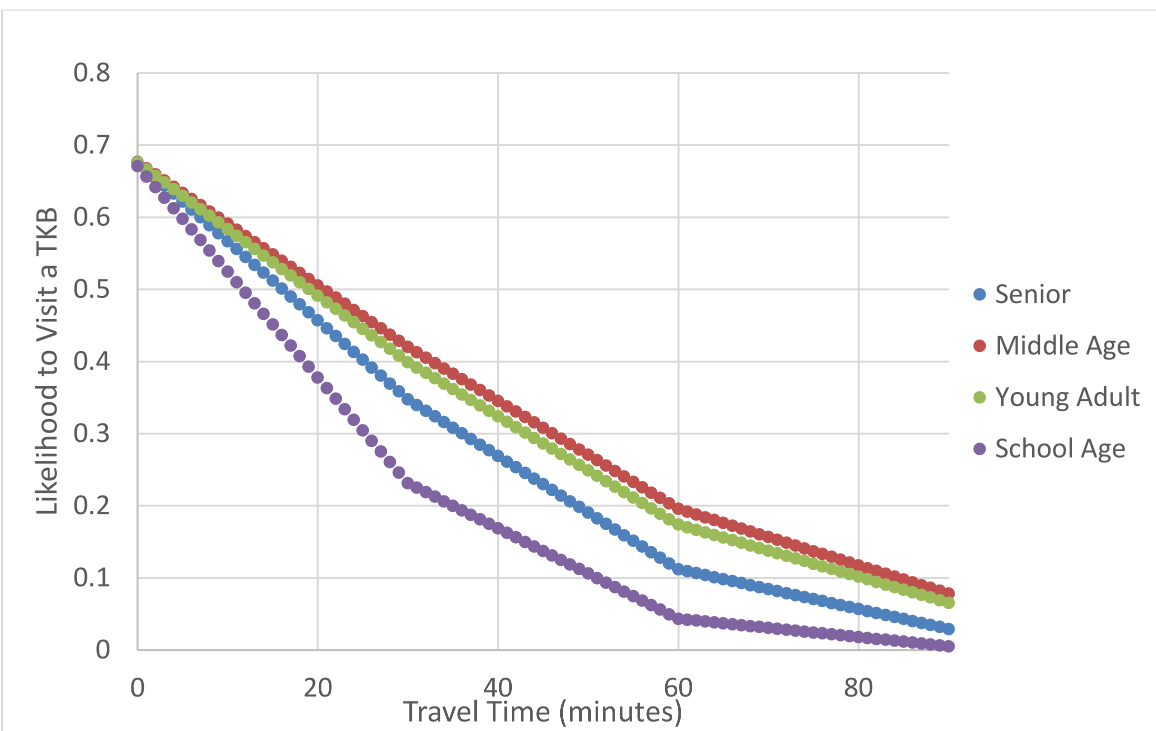


Figure 4.4 Piecewise linear travel time decay functions for case studies.

4.6 Concluding Remarks

This chapter presented empirical evidence on the factors influencing individuals' decisions when selecting medical facilities, highlighting the roles of personal characteristics, dispositional traits, and contextual variables. By examining Technology Trust and Health Literacy alongside facility attributes such as consultation type and travel time, this research provides a nuanced understanding of how patient preferences evolve within complex healthcare delivery systems.

The findings show that Technology Trust significantly influences the adoption of modern consultation modes, such as telemedicine and AI-based healthcare services. Individuals with higher trust in automated systems are more likely to adopt these innovations, perceiving them as reliable and efficient, whereas skepticism toward technology remains a barrier, particularly among older individuals and those with limited exposure to technology. These insights highlight the need for initiatives to build trust in technology, especially within AI-driven healthcare.

Similarly, Health Literacy emerged as a critical enabler for technology-enabled healthcare access. Higher health literacy was associated with greater willingness to adopt telemedicine services, suggesting that familiarity with healthcare processes empowers patients to make informed choices and overcome barriers to adopting innovative solutions.

Demographic analysis revealed notable variations across age cohorts. Younger and Middle-Aged individuals showed stronger preferences for hospital-based care, while Seniors demonstrated limited engagement with telemedicine and AI options. These differences reflect the influence of familiarity, comfort, and trust in shaping healthcare preferences. Interventions such as training programs or simplified interfaces could bridge the generational gap in technology adoption and promote equitable access.

In summary, this chapter underscores the interplay of trust, literacy, and demographics in shaping healthcare preferences. Addressing disparities in Technology Trust and Health Literacy is essential to ensuring inclusive access as healthcare systems increasingly integrate advanced technologies. Furthermore, this chapter develops realistic travel time decay functions through comprehensive analyses of patient behavior and accessibility patterns. By leveraging data from a representative sample of US adults, the chapter captures how the likelihood of accessing healthcare services decreases with increasing travel time. These functions provide an empirical basis for modeling healthcare access, ensuring that subsequent analyses reflect realistic behavioral responses to travel distances.

Chapter 5 Continuous Modeling

This chapter presents a strategic analysis aimed at evaluating the impacts on healthcare access in rural regions from deploying a network of publicly accessible telehealth kiosks/booths (TKBs). By bringing healthcare services closer to patients, strategically located TKBs have the potential to significantly improve health outcomes. We employ data-driven, analytical continuous approximation models to examine travel times, distances, coverage, and accessibility metrics for rural residents accessing TKBs. A key practical challenge addressed in this research is accurately modeling the "travel time decay" effect, which reflects the decreasing likelihood of individuals using a healthcare facility as travel time or distance increases. While much of the existing research on healthcare accessibility assumes a specific form of travel time decay, our approach uses both general decay models that capture different degrees of sensitivity to travel time, as well as decay models derived using empirical data from surveys and discrete choice experiments to capture people's willingness to travel to TKBs for healthcare services (see Chapter 4). The analysis in this chapter includes general findings as well as case studies specific to rural Missouri.

The primary contributions of this research are fourfold: (i) assessing the potential benefits of TKBs in enhancing healthcare access, (ii) examining how system performance measures evolve with varying numbers of TKBs, (iii) evaluating the sensitivity of system performance to different travel time decay behaviors, and (iv) analyzing how system performance is influenced by the availability of existing healthcare facilities. Additionally, the study offers managerial insights for effectively utilizing a network of TKBs in rural settings.

To achieve these objectives, we develop continuous approximation (CA) models that facilitate strategic evaluation of various deployment options and configurations. The analysis investigates the effects of several operational factors, including patient density, travel time decay, and the number of existing healthcare facilities, to provide a more comprehensive understanding of the potential for TKBs to address healthcare access in rural areas. The remainder of the chapter is organized as follows. Section 5.1 develops the continuous approximation models for transportation access and equity with TKBs. Section 5.2 provides general results for a variety of different scenarios. Section 5.3 provides results on case studies for two regions in Missouri as described in Chapter 3. Section 5.4 includes the conclusions of the research.

5.1 Methodology/Continuous Approximation Models

This section presents continuous approximation (CA) models to evaluate the deployment of a network of TKBs serving rural residents across a geographic region. CA modeling is particularly effective for identifying key trade-offs and relationships among design parameters and has been widely applied in the analysis of logistics and transportation systems (Janjevic et al., 2021; Ansari et al., 2018; Franceschetti et al., 2017; Langevin et al., 1996). The approach models demand for services, such as visiting a TKB, as a continuous density distributed over the region (e.g., potential TKB users per square mile). Expected transportation times and distances are calculated using geometric probability, providing insights into accessibility and equity for varying numbers of TKBs. These models help reveal trade-offs and dependencies through both analytical and numerical methods.

Previous research has demonstrated that the geometry of a service region has minimal impact on logistics costs, provided the region is not excessively elongated (Ansari et al., 2018; Daganzo & Newell, 1986). Although CA models are best suited for large-scale systems with gradually changing conditions, studies have shown that this approach can yield valuable managerial insights and approximations with high accuracy (within a few percentage points) even when these conditions are partially violated (Cui et al., 2010).

In our modeling, rural residents (potential TKB users) are assumed to be distributed across a compact rural service region with area A, characterized by a density δ of potential users per unit area and per unit time (e.g., per day or per year). This density is modeled as a continuous function that varies smoothly across the region. The objective is to design a system of TKBs that maximizes accessibility, with a particular focus on travel to and from the kiosks.

The section begins by presenting a continuous approximation model for the Accessibility Index, which accounts for the coverage of patients by multiple TKBs. Subsequently, we explore CA models that assume patients are served by the nearest TKB and evaluate key performance measures of healthcare access. This analysis provides a structured framework for optimizing the deployment of TKBs to enhance accessibility and equity in rural areas.

5.1.1 A CA Model for the Accessibility Index

In healthcare modeling, accessibility is often defined from the patient perspective using the Accessibility Index from the two-step floating catchment model (2SFCA). For a discrete set of facilities and patient sites, the Accessibility Index for site i, A_i was defined (Luo and Wang 2003) as

$$A_i = \sum_{j \text{ in catchment of site } i} R_j = \sum_{j \text{ in catchment of site } i} \frac{S_j}{P_j} \tag{5.1}$$

where S_j is the “supply” of healthcare at facility j and P_j is the population served from facility j, as determined by the catchment for facility j. The term R_j is effectively a ratio of providers (or provider capacity) to population for facility site j, and it relies on the specified catchment of facility j. Because a patient site may be in the catchment area for several facilities, that patient site can be entered into the calculation for several R_j's. The Accessibility Index for patient site i includes the R_j values for all provider facilities within the catchment of patient site i. In a discrete model, each patient site is a town, and each provider site is a facility (a TKB in our case).

For a continuous approximation approach with a uniform density of potential patients and provider sites, the concept is the same with facility j's catchment assumed to be a circular region around the facility. Likewise, a potential patient has a circular catchment area that indicates the facilities (TKBs) they may visit. To develop a continuous approximation version of the basic 2SFCA model, we assume there are k identical TKBs and the catchment of each TKB is a circular region of radius r (miles) that corresponds to how far potential patients are willing to travel to a TKB. Thus, the area served by each TKB is πr^2. To formulate the model of accessibility we introduce the notion of "i-cover", where a patent is "i-covered" if they are in the catchments of i different TKBs. Thus, 0-cover corresponds to a potential patient (or a region) not within distance r of any TKBs, and 2-cover is for potential patients (regions) within distance r of exactly 2 TKBs. With some TKBs there may be regions that are 0-covered, but with many TKBs the entire region can be covered and many subregions would have several (or many) TKBs within distance r. Let N_L be the smallest number of TKBs needed to provide a coverage area totaling at least A, so that

$$N_L = \left\lceil \frac{A}{\pi r^2} \right\rceil \tag{5.2}$$

In this analysis, we approximate hexagons, which are space-filling shapes, with circles for simplicity. While circles do not tessellate perfectly, they serve as a close approximation for hexagons when analyzing distances and catchment areas. Notably, circles and hexagons with equivalent areas yield nearly identical expected distances. The difference in expected distances, whether between two random points or between the center and a random point within the shape, is minimal—less than 0.3% (Stone 1991). This approximation allows for a more straightforward derivation of results without significant loss of accuracy.

For $k < N_L$, with no overlap of the TKB catchments, then the fraction of potential patients 1-covered, i.e., those within the catchment of a TKB is denoted f_1 and given by

$$f_1 = \frac{k\pi r^2}{A} \tag{5.3}$$

and the fraction 0-covered is

$$f_0 = 1 - \frac{k\pi r^2}{A} \tag{5.4}$$

For $\left\lceil \frac{A}{\pi r^2} \right\rceil \leq k < \left\lceil 2\frac{A}{\pi r^2} \right\rceil$, to provide more equitable access to a TKB we assume that the TKBs are distributed "evenly" across the region so that all covered subregions are 1-covered and none are 2-covered. In general, for $\left\lceil i\frac{A}{\pi r^2} \right\rceil \leq k < \left\lceil (i+1)\frac{A}{\pi r^2} \right\rceil$, there will only be subregions that are i-covered and $(i+1)$-covered. For example, if $A = 3000$ square miles and $r = 10$ miles, then $N_L = \lceil 9.55 \rceil = 10$, so for $k = 1, 2, \ldots 9$ there is 0-coverage and 1-coverage, while for $k = 10, 11, 12 \ldots 19$ there is 1-coverage and 2-coverage (note that 1-coverage ends with $k < N_L = \left\lceil 2\frac{A}{\pi r^2} \right\rceil = 20$) , for $k = 20, 21, \ldots 28$ there is 2-coverage and 3-coverage, etc. We can then write the high level of coverage in terms of k as

$$c_1(k) = \left\lceil k\frac{\pi r^2}{A} \right\rceil \tag{5.5}$$

and the low level of coverage as

$$c_2(k) = \left\lceil k\frac{\pi r^2}{A} \right\rceil - 1 = \left\lfloor k\frac{\pi r^2}{A} \right\rfloor. \tag{5.6}$$

Further, the fraction of potential patients (or of the region) with the high level of coverage is

$$f_1(k) = k\frac{\pi r^2}{A} - \left\lfloor k\frac{\pi r^2}{A} \right\rfloor \tag{5.7}$$

and the fraction of potential patients (or of the region) with the low level of coverage is

$$f_2(k) = \left\lceil k\frac{\pi r^2}{A} \right\rceil - k\frac{\pi r^2}{A} \tag{5.8}$$

Let the "supply" for a TKB be S units in equation (5.1), so the R_j values are $\frac{S}{\delta \pi r^2}$ for each TKB and the Accessibility Index with k TKBs in the continuous approximation model, denoted $AI(k)$, is

$$AI(k) = \begin{cases} AI_1(k) = \left\lceil k\frac{\pi r^2}{A} \right\rceil \frac{S}{\delta \pi r^2} & \text{For high level of coverage} \quad (5.9)\text{a} \\ AI_2(k) = \left(\left\lceil k\frac{\pi r^2}{A} \right\rceil - 1 \right) \frac{S}{\delta \pi r^2} & \text{For low level of coverage} \quad (5.9)\text{b} \end{cases}$$

Clearly, as k increases the accessibility index increases (as expected), yet the range of accessibility indices (maximum minus minimum) in this model stays the same at

$$Range_{AI} = \frac{S}{\delta \pi r^2} \tag{5.10}$$

We can compute the average accessibility index $\bar{A}(k)$ across the service region using the fraction of potential patients (or the region) with the different levels of coverage $f_i(k)$ as

$$\overline{AI}(k) = \sum\nolimits_{i=1}^{2} AI_i(k) f_i(k) = \frac{S}{\delta \pi r^2} k \frac{\pi r^2}{A} = \frac{kS}{\delta A} \tag{5.11}$$

Note that when the patient population and the TKBs are continuously and evenly distributed over the region, the Accessibility Index has one of two values across the service region for a given number of TKBs.

Figure 5.1 plots the average accessibility $\overline{AI}(k)$ as a function of the number of TKBs for an example with $A = 3000$, $r = 10$, $\delta = 1$ and $S = 1$. This shows the linear increase in average accessibility index with each added TKB. While the high and low levels of the accessibility index are a step function, the average is a linear function as the proportion of patients subject to the high and low levels changes with each added TKB.

We assumed the TKBs were spread across the service region to achieve equity, but an alternative (extreme) approach would concentrate the TKBs in the same location. From the perspective of the accessibility index, this would increase the accessibility index for a small number of potential patients (i.e., a small part of the service region) as k increases, with $AI(k) = k\frac{S}{\delta\pi r^2}$ for the covered region which is a fraction $\frac{\pi r^2}{A}$ of the potential patients (and region), and $AI(k) = 0$ everywhere else. The average accessibility index would then be $\frac{kS}{\delta A}$, the same as equation (5.11) for an evenly distributed set of TKBs. However, equity, as measured by the range of the accessibility indices, would be $\frac{kS}{\delta\pi r^2}$, in contrast to the constant range of $\frac{S}{\delta\pi r^2}$ (equation 5.10) for the evenly distributed TKBs.

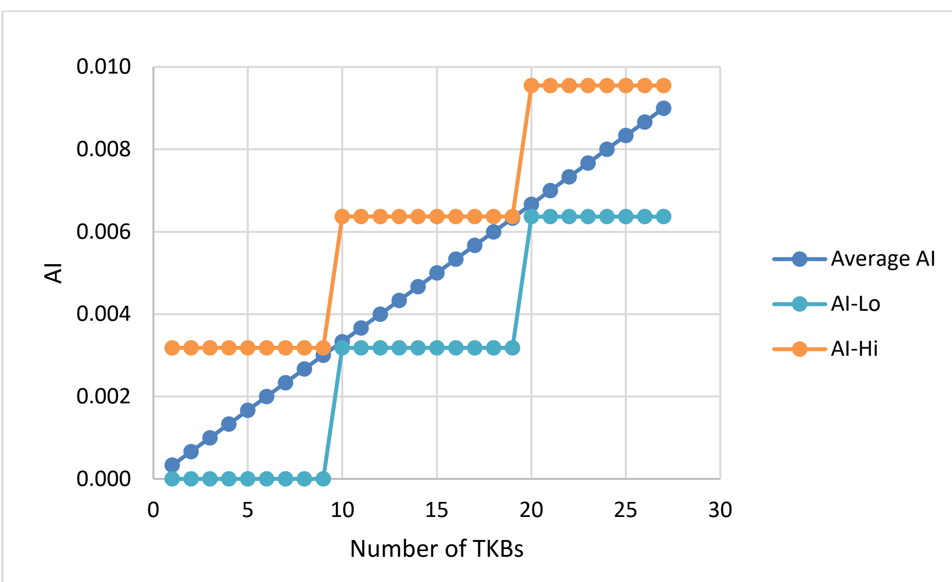


Figure 5.1 Accessibility Index as the number of TKBs increases

The accessibility index model described above accounts for multiple coverages, capturing the overlap of catchment areas where potential patients may access multiple facilities. However, it does not explicitly determine which TKB a patient would choose to visit. To address this, the subsequent analysis focuses on models where potential patients are assumed to travel to their nearest TKB. This allows us to evaluate performance measures specifically related to travel times and distances, providing a more precise assessment of accessibility and equity.

5.1.2 CA Models for Travel Time with Travel Time Decay

With k TKBs located in the service region of area A, we model service by assuming that TKBs are uniformly distributed across the service region, and that potential patients travel to the closest TKB (shortest travel time), but not farther than a travel time of T to reach a TKB. We let v be the average speed for patient travel and use $\alpha > 1$ as the circuity factor to reflect the sparse nature of rural road networks. Thus, a straight-line distance of d implies an average road travel distance of αd and an average travel time of $\frac{\alpha d}{v}$. Each TKB is modeled as serving the potential patients closest to it; i.e., within its catchment defined as a circular region of radius

$$r_{\max}(k) = \min\left\{\sqrt{\frac{A}{k\pi}}, \frac{v}{\alpha}T\right\} \tag{5.12}$$

The corresponding maximum travel time is given by

$$t_{max}(k) = \min\left\{\frac{\alpha}{v}\sqrt{\frac{A}{k\pi}}, T\right\} \tag{5.13}$$

This approach divides the overall service region, with a total area A, into multiple subregions, each assigned to a single TKB at most. When there are not enough TKBs to cover the entire service region, i.e., when $k < \frac{A}{\pi T^2}\left(\frac{\alpha}{v}\right)^2$, then each TKB serves potential patients up to distance

$\frac{v}{\alpha}T$ (i.e., for travel time T), and some potential patients in the service region are too far from a TKB to be served. On the other hand, with enough TKBs, i.e. when $k \geq \frac{A}{\pi T^2}\left(\frac{\alpha}{v}\right)^2$, then all potential patients are less than travel time T from a TKB. In this case, each TKB is modeled as serving potential patients up to a distance $\sqrt{\frac{A}{k\pi}}$, which corresponds to travel time $\frac{\alpha}{v}\sqrt{\frac{A}{k\pi}}$. Thus, as k increases (more TKBs), the maximum (and average) travel time for potential patients decreases.

We note that the spatial density of δ potential TKB users per square mile can also be viewed in terms of the travel time. With an average speed of v mph and a circuity factor of α, the spatial density per hour of travel is

$$\delta' = \delta\left(\frac{v}{\alpha}\right)^2 \tag{5.14}$$

potential TKB users per hour of travel squared. If speed v is measured in miles per hour and travel time is measured in minutes, then this is

$$\delta' = \delta\left(\frac{v}{60\alpha}\right)^2 \tag{5.15}$$

For example, if $\delta = 10$ potential TKB users per square mile, $v = 30$ mph, and $\alpha = 1.4$, then $\delta' = 4591.84$ potential TKB users per hour of travel squared. In one hour of travel a user covers 30 miles which takes them $\frac{30}{1.4} = 21.43$ miles from their starting point due to the road circuity. Thus, we can view the density of potential TKB users in terms of either the geographic area using δ or in terms of travel time using δ'.

Healthcare accessibility is strongly influenced by the distance patients must travel, making the inclusion of a travel time decay function a critical component of our model. A wide variety of travel time decay functions have been presented in the literature. Figure 5.2 shows a continuous exponential function approximated by a 3-step step function that models a situation where 65% of residents within 30 minutes of a facility visit the facility, 30% of residents between 30-60 minutes travel from a facility visit the facility, 15% of residents between 60-90 minutes travel from a facility visit the facility, and no one travels more than 90 minutes to access the facility.

Using a travel time decay function requires calibrating the relevant parameters. For step functions, this involves determining the step levels and the corresponding catchment limits. Continuous decay functions, on the other hand, necessitate one or more "impedance" parameters, along with defining a maximum distance or time (the catchment limit). Calibrating continuous models can be challenging, as it often demands extensive data collection and may be difficult for stakeholders, such as patients or healthcare providers, to interpret. Additionally, the appropriate functional form is not always clear, as many different forms can be fitted to a given dataset.

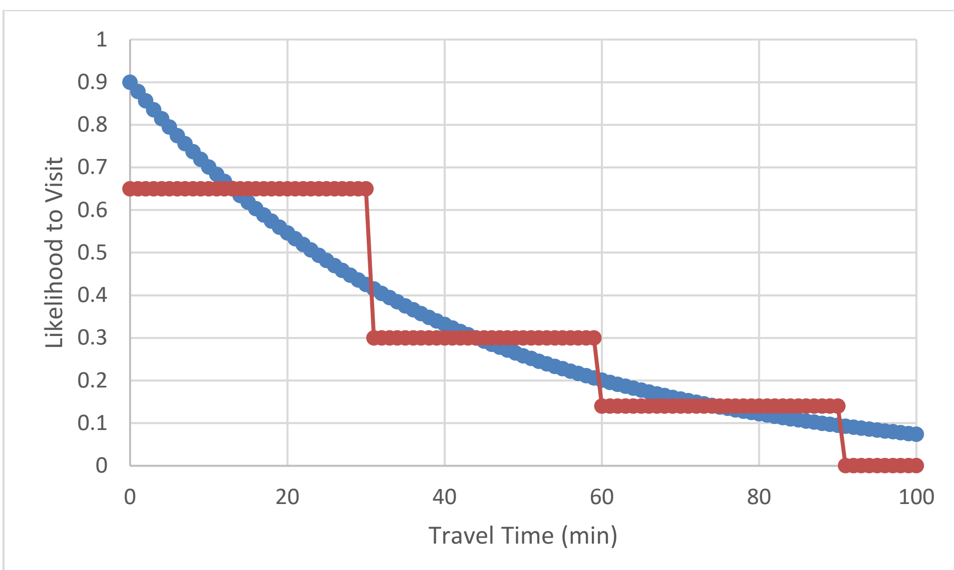


Figure 5.2 A continuous exponential function approximated by a 3-step step function

However, any continuous function can be approximated using either a piecewise linear function or a step function, both of which tend to be more straightforward for users to understand. Step decay functions in particular are relatively simple to calibrate when stakeholders (e.g., through focus groups or surveys) can provide estimates for step levels and catchment distances or travel times. Similarly, piecewise linear decay functions with only a few segments are easier to calibrate and interpret. For these reasons, we focus on step functions and piecewise linear functions in the subsequent modeling to represent travel time decay.

We first derive some connections between these two models. Let $F(t)$ be a continuous function of travel time t that describes travel time decay. Thus, $F(t)$ is the likelihood for a potential TKB user to visit the TKB if they must travel time t to the nearest TKB. While any continuous function can be closely approximated by a step function with numerous small steps, this approach risks introducing artificial precision, as it remains an approximation of inherently complex and variable patient behavior. Thus, we adopt a three-step step function as an approximation as that is able to capture a wide range of decay behavior while preserving managerial clarity for communication. We define this step function $S(t)$ for travel time t using three catchment travel time limits t_1, t_2, and t_3, where $t_3 = T$, as follows:

$$S(t) = \begin{cases} s_1 \text{ for } 0 \leq t \leq t_1 \\ s_2 \text{ for } t_1 < t \leq t_2 \\ s_3 \text{ for } t_2 < t \leq t_3 \\ 0 \text{ for } t_3 < t \end{cases} \tag{5.6}$$

5.1.2.1 Converting a piecewise linear travel time decay to a step function.

Suppose we are given the function $F(t)$ for a healthcare setting where patients travel to the closest facility and we wish to generate the corresponding step function $S(t)$. First, note that a good approximation requires the level of the steps to depend on the limits of the catchments. For example, in Figure 5.2 the farthest catchment extends to 90 minutes of travel, but if there are enough TKBs in a region, then the farthest travel to a TKB may be less than the maximum catchment limit. Thus, if the farthest travel is 70 minutes, then the 3rd step in Figure 5.2 should be higher to more accurately model the situation. The appropriate level of the step then depends on the area each TKB serves, and hence the number of TKBs in use. Because our CA model of travel time decay is in 3-D space, the step function should be rotated around the origin (TKB), so the three steps are really three rings of different levels around the TKB location, as patients travel to the TKB from all directions.

To determine the level of the steps that approximate the patient's likelihood to travel to a TKB, we equate the population served by a particular step with the population served by the continuous function for the same range of travel times. Since $F(t)$ describes the travel time decay in all directions when traveling a time t to the TKB, the total number of potential TKB users is $\int_0^{min\{t_3, t_{max}(k)\}} 2\pi t\delta' F(t)\, dt$, where δ' is the spatial density of potential TKB users in terms of the travel time.

Now we set the population served by the i^{th} step for $i = 1, 2, 3$ equal to the population served by the continuous function for the same range of travel times. To simplify the notation, we set $t_i'(k)$ to be the upper limit of the travel time for catchment i, which is the minimum of the catchment limit and the maximum travel time from equation (5.13):

$$t_i'(k) = \min\{t_i, t_{max}(k)\} \quad \text{for } i = 1, 2, 3 \tag{5.17}$$

So, for all steps i such that $t_{i-1} < t_{max}(k)$, where $t_0 = 0$, we set

$$\int_{t_{i-1}}^{t_i'(k)} 2\pi t\delta' F(t)\, dt = \int_{t_{i-1}}^{t_i'(k)} 2\pi t\delta' s_i\, dt \tag{5.18}$$

Where

$$\int_{t_{i-1}}^{t_i'(k)} 2\pi t\delta' s_i \, dt = \pi\delta' s_i[(t_i')^2 - t_{i-1}^2] \text{ for } t_{i-1} < t_{max}(k) \tag{5.19}$$

The level for the step s_i is then given by

$$s_i = \frac{2\int_{t_{i-1}}^{t_i'(k)} tF(t)\, dt}{\left(t_i'(k)\right)^2 - t_{i-1}^2} \text{ for } i \text{ such that } t_{i-1} < t_{max}(k) \tag{5.20}$$

For any i such that $t_{i-1} \geq t_{max}(k)$, $s_i = 0$ (i.e., there will be no potential TKB users).

The three levels in the step function as calculated above depend on the function $F(t)$ and the catchment limits. Note that any continuous function can be approximated by linear pieces, so consider $G(t)$ to be the piecewise linear approximation to $F(t)$ as follows

$$G(t) = \begin{cases} m_1 t + b_1 & \text{for } 0 \leq t \leq t_1 \\ m_2 t + b_2 & \text{for } t_1 < t \leq t_2 \\ m_3 t + b_3 & \text{for } t_2 < t \leq t_3 \\ 0 & \text{for } t_3 < t \end{cases} \tag{5.21}$$

One could set the slopes and intercepts (m and b values) such that $G(t)$ is continuous, or it could be discontinuous.

Consider the general case with a linear function $m_i t + b_i$ for $t_{i-1} < t \leq t_i$. We set the level of a single step s_i in the range $t_{i-1} < t \leq t_i$ such that the (ring) step includes the same number of potential TKB patients as the (ring) defined by the linear function

$$\int_{t_{i-1}}^{t_i'(k)} 2\pi t\delta'(m_i t + b_i)\, dt = \int_{t_{i-1}}^{t_i'(k)} 2\pi t\delta' s_i \, dt \tag{5.22}$$

which gives

$$s_i = b_i + \frac{2m_i}{3}\frac{(t_i'(k))^3 - t_{i-1}^3}{(t_i'(k))^2 - t_{i-1}^2} = b_i + \frac{2m_i}{3}\frac{(t_i'(k))^2 + t_i'(k)t_{i-1} + t_{i-1}^2}{t_i'(k) + t_{i-1}} \tag{5.23}$$

Note that because of the circular service region, the level of the step is not halfway between the endpoints of the linear function. For example, if $t_1 = 30$, $t_2'(k) = 60$, $b_2 = 1.2$ and

$m_2 = -1/60$, then the level of the step is $s_2 = 0.4222$ (42.22%). The values of $G(t)$ at the endpoints of the line segment are 0.7 (70%) and 0.2 (20%), so the step likelihood is slightly lower than the midpoint likelihood at 45%. For the same linear function, if the step range was shorter (due to a shorter farthest travel time from having more TKBs), then a higher step is used; for example, if $t_1 = 30$, $t_2'(k) = 45$, $b_2 = 1.2$ and $m_2 = -1/60$, then the level of the step is $s_2 = 0.5667$ (56.67%).

This modeling of the step function allows the number of potential TKB users for each step in the step function to match the number of potential TKB users for each piece of a piecewise linear function as the service region varies with the number of TKBs in the region. When more TKBs are in a region, the maximum travel time to the closet TKB (i.e., $t_{max}(k)$) decreases, thereby effectively cutting off the right side of Figure 5.2. For example, if enough TKBs are located so that the maximum travel time to a TKB is 45 minutes, then the 3rd catchment area (from 60-90 minutes) is no longer relevant and the TKB users would come from the two catchment areas from 0-30 minutes and from 30-45 minutes.

5.1.2.2 Converting a step travel time decay function to a piecewise linear function

Suppose instead of knowing a piecewise linear travel time decay function, we are given (e.g., by stakeholders) a set of three step levels (likelihood of patronizing a TKB) s_1, s_2, and s_3 corresponding to three travel time ranges defined by catchment travel time limits t_1, t_2, and t_3 (i.e., $S(t)$). Suppose we are also given a maximum patronage level b_1, effectively corresponding to a travel time of zero. We wish to derive a continuous piecewise linear function $G(t)$ that matches this step function in terms of the demand captured by each catchment level. We do this iteratively, starting with the first step ($i = 1$). For each step we determine the linear segment corresponding to the same number of potential TKB users as for the step.

To equate the population served by the first step with the population served by a linear function of slope m_1 and intercept b_1, we solve the following to determine m_1:

$$\int_0^{t_1} 2\pi t\delta'(m_1 t + b_1)\, dt = \int_0^{t_1} 2\pi t\delta' s_1\, dt \tag{5.24}$$

This gives

$$m_1 = \frac{3}{2}(s_1 - b_1)\frac{1}{t_1} \tag{5.25}$$

To make the piecewise linear function continuous, we set the right endpoint of piece $i - 1$ equal to the left endpoint of piece i, so that

$$m_{i-1}t_{i-1} + b_{i-1} = m_i t_{i-1} + b_i \tag{5.26}$$

This allows b_i to be expressed in terms of the known slope and intercept for piece $i - 1$ and the unknown slope for piece i

$$b_i = -m_i t_{i-1} + m_{i-1}t_{i-1} + b_{i-1} \tag{5.27}$$

For the slopes of the second and subsequent pieces of the piecewise linear function, m_i for $i = 2, 3$, we set the population served by the step of level s_i equal with the population served by a linear function of slope m_i and intercept b_i:

$$\int_{t_{i-1}}^{t_i} 2\pi t\delta'(m_i t + b_i)\, dt = \int_{t_{i-1}}^{t_i} 2\pi t\delta' s_i\, dt \text{ for } i = 2, 3 \tag{5.28}$$

Substituting b_i from equation (5.27) into equation (5.28) and solving for m_i gives

$$m_i = \frac{(t_i^2 - t_{i-1}^2)\left(\frac{s_i}{2} - \frac{b_{i-1}}{2} - \frac{m_{i-1}}{2}t_{i-1}\right)}{\frac{1}{3}(t_i^3 - t_{i-1}^3) - \frac{1}{2}t_{i-1}(t_i^2 - t_{i-1}^2)} \text{ for } i = 2, 3 \tag{5.29}$$

This allows m_i to be calculated based only on the known step level s_i, the previously calculated line segment (i.e., m_{i-1} and b_{i-1}) and the known catchment limits. Thus, given the initial level b_1 along with the step function $S(t)$ (i.e., the pairs s_i and t_i), equations (5.25), (5.29) and (5.27) can be used iteratively to calculate each piece of the piecewise linear function $G(t)$.

For example, suppose the step function has three levels of $s_1 = 0.8$, $s_2 = 0.4$, and $s_3 = 0.1$ for 30-, 60-, and 90-minute catchments and $b_1 = 0.9$ (maximum likelihood to visit a TKB is 90%). The corresponding piecewise linear function is

$$G(t) = \begin{cases} -0.005t + 0.9 & \text{for } 0 \leq t \leq 30 \text{ minutes} \\ -0.021t + 1.38 & \text{for } 30 < t \leq 60 \text{ minutes} \\ -0.0012t + 0.19 & \text{for } 60 < t \leq 90 \text{ minutes} \\ 0 & \text{for } t > 90 \text{ minutes} \end{cases} \tag{5.30}$$

The step function with steps at 0.8, 0.4 and 0.1 and the corresponding piecewise linear function are shown in Figure 5.3. The above equations provide a way to construct matching travel time decay functions in the form of a step function and a piecewise linear function. If we are given one function (e.g., based on empirical data) we can construct the other. We consider both a piecewise linear function and a step function to model travel time decay.

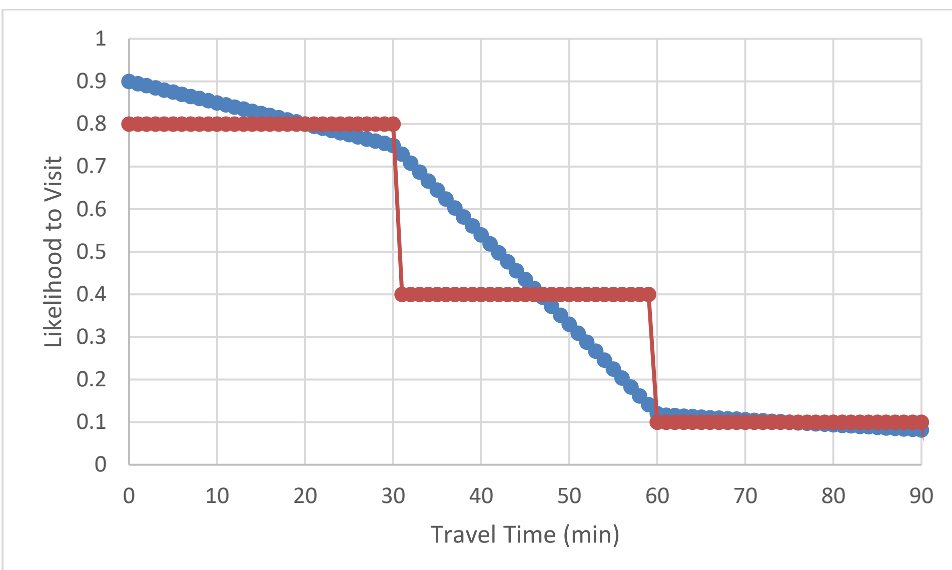


Figure 5.3 Step function and corresponding piecewise linear function.

- Piecewise linear (L) – the function is either given (slopes and intercepts for each piece) or the slopes and intercepts are calculated from a given step function and b_1 value using equations (5.25), (5.29) and (5.27).
- Step function (S) – step levels are either given or defined from a piecewise linear decay function using equation (5.23). Note that the step levels s_i in equation (5.23) depend on k, the number of TKBs, since the t_{max} (equation 5.13) depends on k. To use fixed step levels that do not depend on k, one can replace t_i' with t_i in equation (5.23).

5.1.3 Performance Measures

This section derives expressions for relevant performance measures associated with a collection of k identical TKBs serving a region of area A. We first calculate the expected travel times to a TKB for the piecewise linear and step travel time decay function. Consider the piecewise linear function $G(t)$ as defined in equation (5.21). For catchment i such that $t_{i-1} < t_{max}$, the expected number of potential TKB users willing to use the TKB in catchment i, denoted $P_L(i)$, is

$$\begin{aligned} P_L(i) &= \int_{t_{i-1}}^{t_i'(k)} 2\pi\delta' t(m_i t + b_i)dt \\ &= 2\pi\delta'\left[\frac{1}{3}m_i((t_i'(k))^3 - t_{i-1}^3) + \frac{1}{2}b_i((t_i'(k))^2 - t_{i-1}^2)\right] \end{aligned} \tag{5.31}$$

With the piecewise linear distance decay function, the total expected round trip travel time for potential TKB users in catchment i for $t_{i-1} < t_{max}(k)$, denoted $T_L(i)$ is

$$\begin{aligned} T_L(i) &= 2\int_{t_{i-1}}^{t_i'(k)} t2\pi\delta' t(m_i t + b_i)dt \\ &= 4\pi\delta'\left[\frac{1}{4}m_i((t_i'(k))^4 - t_{i-1}^4) + \frac{1}{3}b_i((t_i'(k))^3 - t_{i-1}^3)\right]. \end{aligned} \tag{5.32}$$

For a step function $S(t)$ defined in equation (5.16), we can use equations (5.31) and (5.32) with $m_i = 0$ and $b_i = s_i$. Thus, for catchment i such that $t_{i-1} < t_{max}(k)$, the expected number of potential TKB users likely to use the TKB with $S(t)$ in catchment i, denoted $P_S(i)$, is

$$P_S(i) = \pi\delta' s_i((t_i'(k))^2 - t_{i-1}^2) \tag{5.33}$$

and the total expected round trip travel time for potential TKB users in catchment i for $t_{i-1} < t_{max}(k)$, denoted $T_S(i)$, is

$$T_S(i) = \frac{4}{3}\pi\delta' s_i((t_i'(k))^3 - t_{i-1}^3)\,. \tag{5.34}$$

Let $M = \{L, S\}$ denote the travel time decay function where L indicates piecewise linear and S indicates the step function. With k TKBs, the total expected number of potential TKB users likely to use a TKB is then

$$P_m(k) = k\sum_{i\ s.t. t_{i-1} < t_{max}(k)} P_m(i) \text{ for } m \in M \tag{5.35}$$

This depends on the number of TKBs, k, as indicated by equation (5.13), since having more TKBs once $t_{max} > T$ gives each a smaller service area and thus reduces the maximum distance and time patients travel. To simplify the presentation we here-on refer to the “number of potential TKB users willing to use a TKB” as the “number of patients served by a TKB”. The average number of patients served by each TKB is

$$P_m^{TKB}(k) = \frac{P_m(k)}{k} \text{ for } m \in M \tag{5.36}$$

Population coverage $C_m^P(k)$ with k TKBs is defined as the percentage of the total potential TKB users served by a TKB, given the distance decay function m. Thus,

$$C_m^P(k) = \frac{P_m(k)}{\delta A} \text{ for } m \in M \tag{5.37}$$

Area coverage $C_m^A(k)$ with k TKBs is defined as the percentage of the total area served by a TKB, given the distance decay function m. Thus,

$$C_m^A(k) = \frac{k\pi(r_{max})^2}{A} \text{ for } m \in M \tag{5.38}$$

Similar to the expected number of patients served by a TKB, the total expected round trip travel time served by the collection of k TKBs is

$$T_m(k) = k \sum_{i\ s.t. t_{i-1} < t_{max}(k)} T_m(i) \text{ for } m \in M \tag{5.39}$$

The expected round trip travel time per patient for decay model m denoted $T_m^p(k)$ is $\frac{T_m(k)}{P_m(k)}$, so

$$\begin{aligned} T_L^p(k) &= \frac{T_L(k)}{P_L(k)} \\ &= 2\frac{\sum_{i\ s.t. t_{i-1} < t_{max}(k)} \left[\frac{1}{4} m_i((t_i'(k))^4 - t_{i-1}^4) + \frac{1}{3} b_i((t_i'(k))^3 - t_{i-1}^3)\right]}{\sum_{i\ s.t. t_{i-1} < t_{max}(k)} \left[\frac{1}{3} m_i((t_i'(k))^3 - t_{i-1}^3) + \frac{1}{2} b_i((t_i'(k))^2 - t_{i-1}^2)\right]} \end{aligned} \tag{5.40}$$

And

$$T_S^p(k) = \frac{T_S(k)}{P_S(k)} = \frac{4}{3} \frac{\sum_{i\ s.t. t_{i-1} < t_{max}(k)} s_i((t_i')^3 - t_{i-1}^3)}{\sum_{i\ s.t. t_{i-1} < t_{max}\ (k)} s_i((t_i')^2 - t_{i-1}^2)} \tag{5.41}$$

The maximum round trip travel time for a patient served at a TKB is

$$T^{pmax}(k) = 2t_{max}(k) \tag{5.42}$$

As a measure of travel time variability, the maximum minus average round trip travel time for patients served at a TKB is

$$TV_m^{pmax}(k) = T_m^{pmax}(k) - T_m^p(k) = 2t_{max}(k) - T_m^p(k) \text{ for } m \in M \tag{5.43}$$

Note that the range (maximum minus minimum) of the round trip travel time (or distance) for patients served at a TKB is equal to the maximum round trip travel time (or distance) for a patient served at a TKB since our CA model allows a patient to be located very near a TKB (with travel distance and time = 0).

We now define several other performance measures related to travel distance, similar to those above for travel time. The expected total round trip travel distance for patients visiting TKBs with k TKBs is

$$D_m(k) = \frac{T_m(k)}{v} \text{ for } m \in M \tag{5.44}$$

and the average round trip travel distance per patient is

$$D_m^p(k) = \frac{T_m^p(k)}{v} \text{ for } m \in M \tag{5.45}$$

The maximum round trip travel distance for a patient served at a TKB is

$$D^{pmax}(k) = \frac{2t_{max}(k)}{v} \tag{5.46}$$

The travel distance variability is defined as the maximum minus average round trip travel distance for patients served at a TKB is

$$DV_m^{pmax}(k) = D^{pmax}(k) - D_m^p(k) = \frac{2t_{max}(k)}{v} - \frac{T_m^p(k)}{v} \text{ for } m \in M \tag{5.47}$$

The final performance measure is the total expected travel time savings with k TKBs compared to the situation when all those who are served by a TKB would be served instead by travelling to a single centrally located healthcare facility (e.g., an existing facility). To conservatively estimate the travel distance to a single centrally located facility, we assume the facility is located at the center of a circle of area A (the area of the service region). The expected travel distance from a randomly located point in the circle to its center is two-thirds the radius. With many TKBs, then each patient served at a TKB can be treated as distributed according to the original spatial distribution, so the expected round trip travel time per patient to the central facility in our setting can be approximated as $2 \times \frac{2}{3} \times \sqrt{\frac{A}{\pi}} \times \frac{\alpha}{v} = \frac{4\alpha}{3v}\sqrt{\frac{A}{\pi}}$. The total travel time for all $P_m(k)$ patients served by the k TKBs would be $\frac{4\alpha}{3v}\sqrt{\frac{A}{\pi}}P_m(k)$. The total travel time savings with k TKBs, $TSAV_m(k)$, is then

$$TSAV_m(k) = \frac{4\alpha}{3v}\sqrt{\frac{A}{\pi}}P_m(k) - T_m(k) \text{ for } m \in M \tag{5.48}$$

The total travel distance savings with k TKBs, $DSAV_m(k)$, is

$$DSAV_m(k) = \frac{4\alpha}{3}\sqrt{\frac{A}{\pi}}P_m(k) - D_m(k) \text{ for } m \in M \tag{5.49}$$

From equations (5.48) and (5.35), the total round trip travel time savings per patient served at a TKB with k TKBs, $TSAV_m^p(k)$, is

$$TSAV_m^p(k) = \frac{TSAV_m(k)}{P_m(k)} \text{ for } m \in M \tag{5.50}$$

Similarly, from equations (5.49) and (5.35), the total round trip travel distance savings per patient served at a TKB with k TKBs, $DSAV_m^p(k)$, is

$$TSAV_m^p(k) = \frac{TSAV_m(k)}{P_m(k)} \text{ for } m \in M \tag{5.51}$$

Using the derivations above, and those in previous sections for the Accessibility Index, we summarize the performance measures in Table 5.1 associated with a collection of k identical TKBs serving a region of area A. Subscript m identifies the travel time decay model (either L for piecewise linear or S for step function).

Table 5.1 Performance Measures

#	Measure	Notation	Equation(s)
1	Total number of patients served at a TKB	$P_m(k)$	5.35 with 5.31 or 5.33
2	Number of patients served per TKB	$P_m^{TKB}(k)$	5.36
3	Population coverage	$C_m^P(k)$	5.37
4	Area coverage	$C_m^A(k)$	5.38
5	Total round trip travel time for all patients served at a TKB	$T_m(k)$	5.39 with 5.32 or 5.34
6	Round trip travel time per patient served at a TKB	$T_m^p(k)$	5.40 or 5.41
7	Maximum round trip travel time for patients served at a TKB	$T^{pmax}(k)$	5.42
8	Travel time variability for patients served at a TKB	$TV_m^{pmax}(k)$	5.43
9	Total round trip travel distance for all patients served at a TKB	$D_m(k)$	5.44
10	Round trip travel distance per patient served at a TKB	$D_m^p(k)$	5.45
11	Maximum round trip travel distance for patients served at a TKB	$D^{pmax}(k)$	5.46
12	Travel distance variability for patients served at a TKB	$DV_m^{pmax}(k)$	5.47
13	Maximum accessibility index	$AI_1(k)$	5.9a
14	Minimum accessibility index	$AI_2(k)$	5.9b
15	Average accessibility index	$\overline{AI}(k)$	5.11
16	Total travel time savings	$TSAV_m(k)$	5.48
17	Total travel distance savings	$DSAV_m(k)$	5.49
18	Average travel time savings per patient served at a TKB	$TSAV_m^p(k)$	5.50
19	Average travel distance savings per patient served at a TKB	$DSAV_m^p(k)$	5.51

5.2 General Results

This section presents a series of analyses to evaluate healthcare accessibility using a network of TKBs in a rural area. Section 5.2.1 explores the effects of varying degrees of travel time decay on accessibility. Section 5.2.2 investigates how changes in the number (or density) of potential TKB users within the region influence outcomes. Lastly, Section 5.2.3 examines scenarios where potential TKB users are unevenly distributed across the service area.

5.2.1 Impact of Decay – No Decay, Weak Decay and Strong Decay

This section examines the impact of varying travel time decay levels on system performance measures as the number of TKBs in the service region increases. Table 5.2 outlines the parameters used in the analysis. The service region spans 7,000 square miles and includes 70,000 potential TKB users.

Table 5.2 Parameters to analyze impact of travel time decay

	Measure	Value
A	Service region area (square miles)	7000
δ	Density of potential TKB users (people per square mile)	10
v	Speed (miles per hour)	35
α	Circuity factor	1.4
t_1	Catchment travel time limit 1 (hours)	0.5
t_2	Catchment travel time limit 2 (hours)	1
t_3	Catchment travel time limit 3 (hours)	1.5

The travel time decay is divided into three catchment areas. The closest catchment (up to 0.5 hours) covers 11.11% of the total area and serves 11.11% of potential users. The middle catchment (0.5 to 1.0 hours) encompasses 33.33% of the area and serves 33.33% all users. The farthest catchment (1.0 to 1.5 hours) accounts for 55.56% of the area and 55.56% of users. The maximum catchment size of 1.5 hours corresponds to a travel distance of 52.5 miles at an average speed of 35 mph. Accounting for a circuity factor of 1.4, this results in an effective circular radius of 37.5 miles around each TKB.

The total area within the maximum travel time catchment is 4,417.8 square miles, covering 63% of the service region. With the placement of two or more TKBs, the entire service region falls within the farthest catchment area, ensuring full coverage.

The three levels of travel time decay are modeled with three step functions, and are: (i) No Decay, (ii) Weak Decay, and (iii) Strong Decay. No Decay has a single step with value 0.9 (90% likelihood to use the TKB) up to the 1.5 hour travel time; thus for No Decay $s_1 = s_2 = s_3 = 0.9$. Weak Decay has three steps with the likelihood declining from 90% to 70% to 50%, so $s_1 = 0.9$, $s_2 = 0.7$, and $s_3 = 0.5$. Strong Decay has three steps with the likelihood declining from 90% to 30% to 10%, so $s_1 = 0.9$, $s_2 = 0.3$, and $s_3 = 0.1$.

Figure 5.4 illustrates the total number of patients served at a TKB as the number of TKBs increases from 1 to 30. Under the "No Decay" scenario, the maximum population is reached with two or more TKBs, serving 90% of the total potential TKB users, or approximately 63,000 patients. In contrast, under "Weak Decay" and "Strong Decay" scenarios, the likelihood of patients visiting a TKB decreases with increasing travel time, resulting in fewer patients being served. The maximum population served in these cases is not achieved until at least 14 TKBs are deployed. At this point, the proximity of the TKBs ensures that all potential patients fall within the closest catchment area, where the likelihood of visiting a TKB remains at 90%, regardless of the decay level.

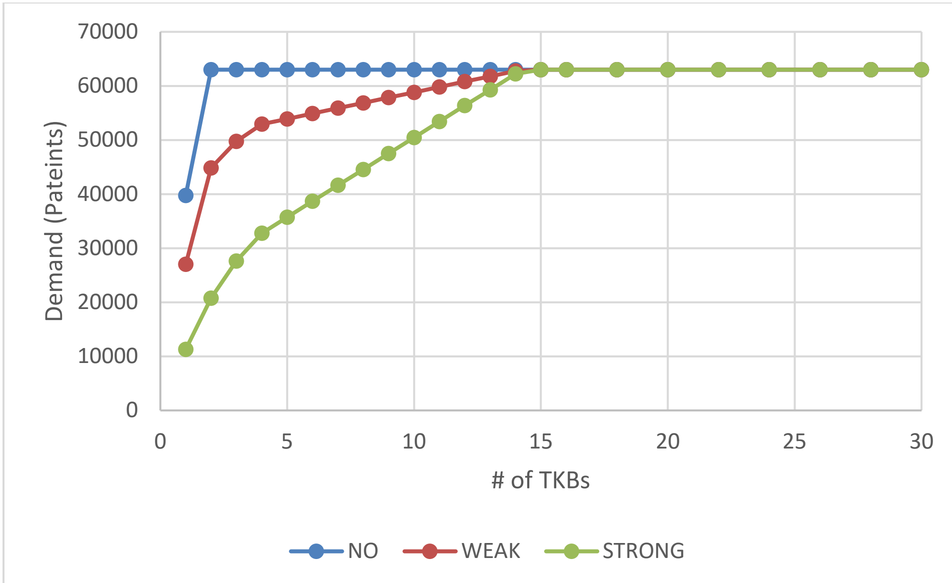


Figure 5.4 Total number of patients served at a TKB (Performance measure 1).

Figure 5.5 shows the number of patients served per TKB as the number of TKBs increases from 1 to 30. Under the "No Decay" scenario, demand per TKB is initially very high, with up to 40,000 patients per TKB when only one is deployed. This corresponds to approximately 4.54 visits per hour if TKBs operate 24/7 year-round, highlighting the impracticality of such assumptions without capacity constraints. As more TKBs are added, demand per TKB decreases, and the results for the three decay scenarios become more aligned. With 10 TKBs, patient demand per TKB ranges from 5,045 to 6,300, equating to 13.8 to 17.2 visits per day (assuming year-round operation). Once the number of TKBs reaches 14 or more, the results converge across all decay scenarios, as all potential patients fall within the closest catchment area, where the likelihood of visiting stabilizes at 90%.

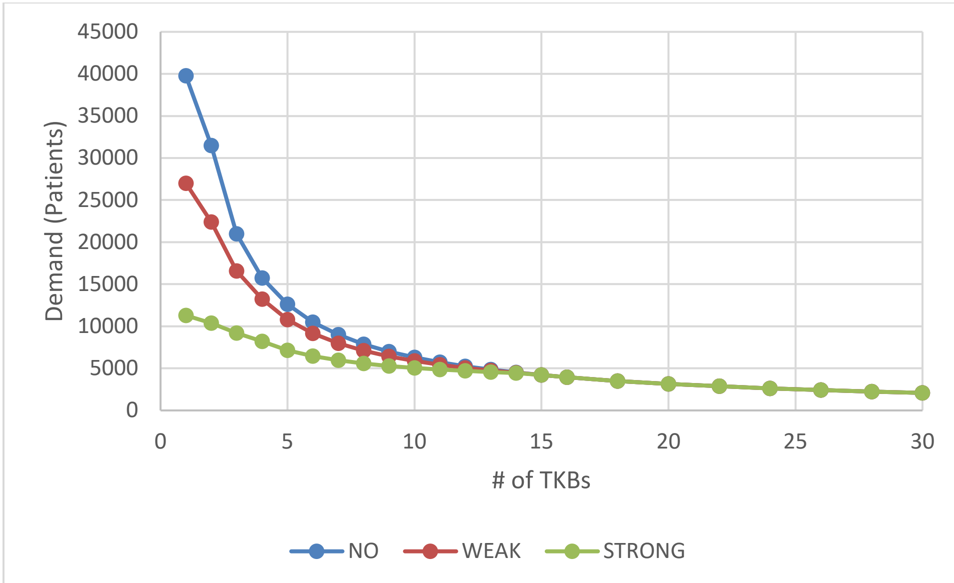


Figure 5.5 Number of patients served per TKB (Performance measure 2).

Figure 5.6 shows the population and area coverage, with area coverage (the top line in Figure 5.7) being the same for all three levels of travel time decay. Note that the maximum population coverage is only 90%, while area coverage reaches 100% with just two TKBs. The curves for the population coverage have the same shape as for the three levels of travel time decay in Figure 5.4 since the total potential demand for a TKB is fixed.

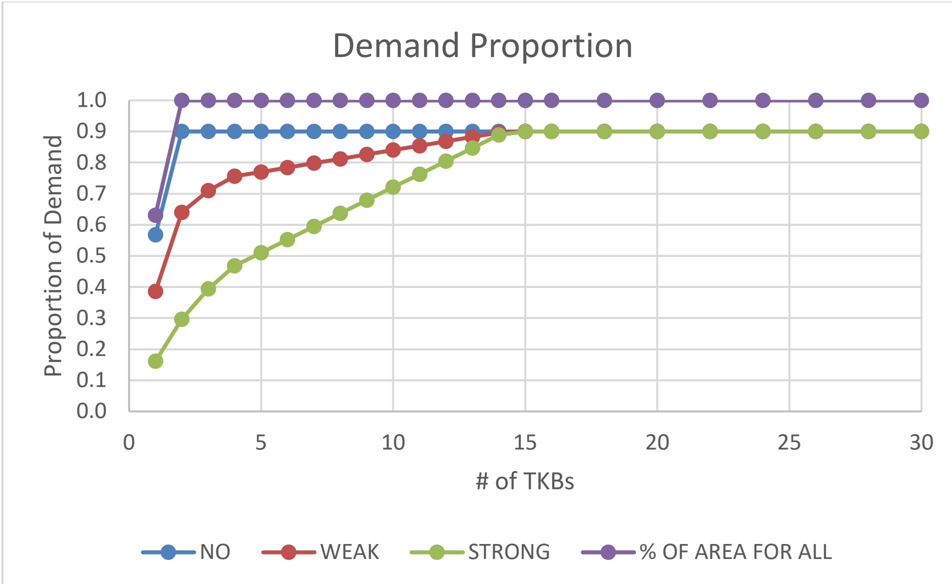


Figure 5.6 Population and area coverage (Performance measures 3, 4).

Figure 5.7 illustrates the total round-trip travel time for all patients served at TKBs. Greater levels of travel time decay result in lower total travel times (up to 14 TKBs) due to fewer patients being served, as shown in Figure 5.5. Initially, total travel time increases with additional TKBs because more patients are served. For instance, with No Decay, adding a second TKB increases the number of patients served, but with three or more TKBs, the total served reaches its maximum and remains constant. As the number of TKBs increases, fewer patients are in the farthest catchments, reducing total travel time as patients are closer to their nearest TKB. With Weak and Strong Decay, each additional TKB up to the 14th reduces the size of the farther catchments (lower likelihood areas) and increases the nearer catchments (higher likelihood areas), thereby serving more patients. This leads to an initial increase in total travel time. However, shorter travel times for some patients with additional TKBs can offset this increase, creating a mixed effect on total travel time, as depicted in Figure 5.7.

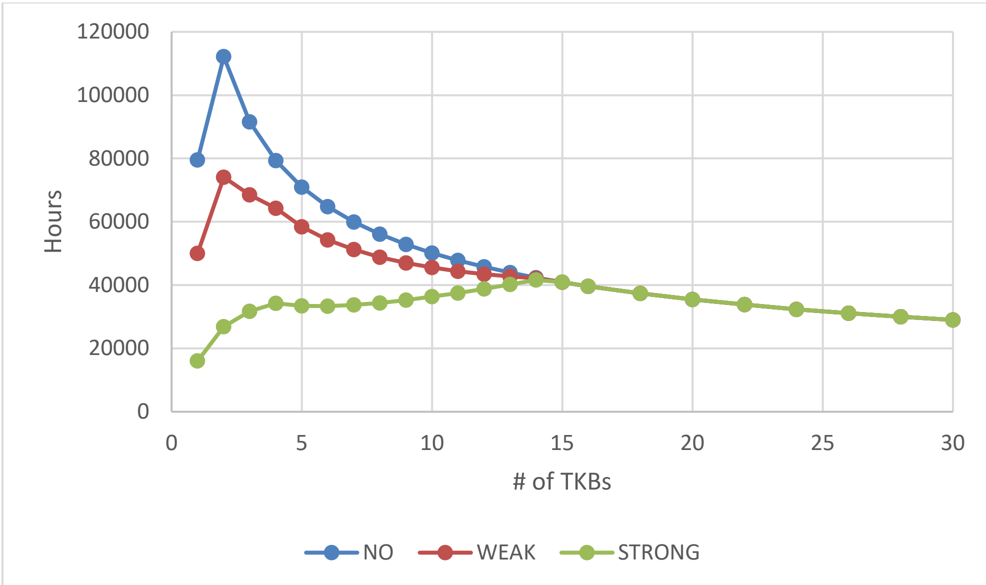


Figure 5.7 Total round trip travel time for all patients served at a TKB (Performance measure 5).

Figure 5.8 illustrates the average round-trip travel time per patient served at a TKB (lower three lines) and the maximum round-trip travel time for any patient (top line). As expected, both average and maximum travel times decrease as more TKBs are added, with longer trips replaced by shorter ones. Adding TKBs also shifts some regions from farther catchments to closer ones, increasing the number of patients served, as closer catchments have higher likelihoods of TKB use. The rate of decline in the lines reflects these dual effects: shorter trips for more patients in closer catchments and fewer patients in farther catchments. Strong Decay yields the lowest average travel time, but as Figure 5.4 shows, this occurs with fewer patients served. Figures 5.8 and 5.4together highlight a tradeoff: serving fewer, closer patients with Strong Decay versus serving more patients, including those at farther distances, with weaker decay levels. Importantly, the shape of the travel time decay function could be influenced by initiatives such as introducing new services, reducing costs, or marketing or training efforts to encourage TKB use.

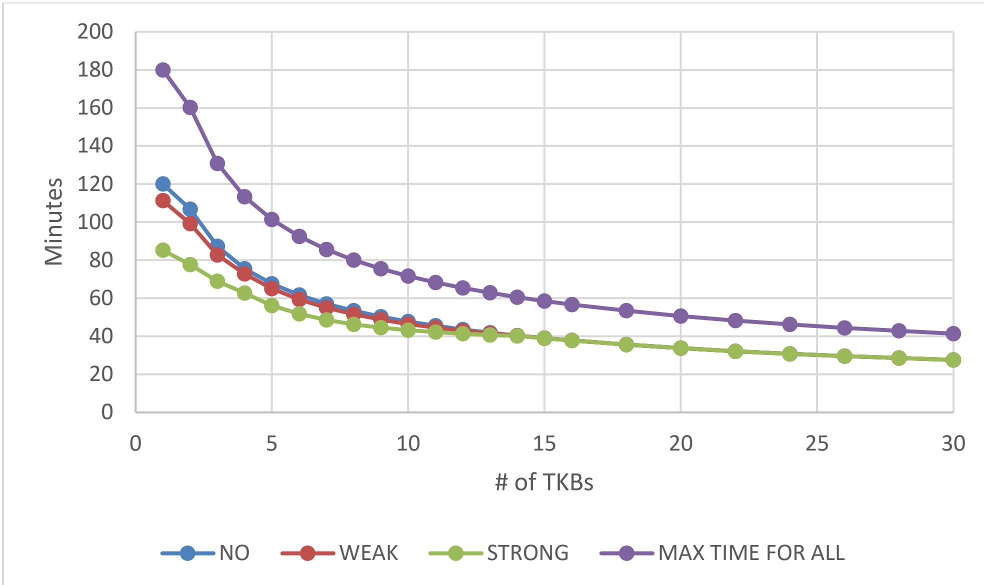


Figure 5.8 Round trip travel time per patient served at a TKB and Maximum round trip travel time for patients served at a TKB (Performance measures 6, 7).

Figure 5.9 illustrates travel time variability, defined as the difference between the maximum and average round-trip travel times per patient served at a TKB. The results highlight greater inequity with Strong Decay: while average travel times are shorter (Figure 5.8), some patients still experience significantly longer trips (top line in Figure 5.9). Conversely, with No Decay and Weak Decay, variability is lower, indicating more equitable travel times, but the average travel time is higher (Figure 5.8). The more equitable No Decay scenario results in longer average travel times but also serves a greater number of patients at TKBs.

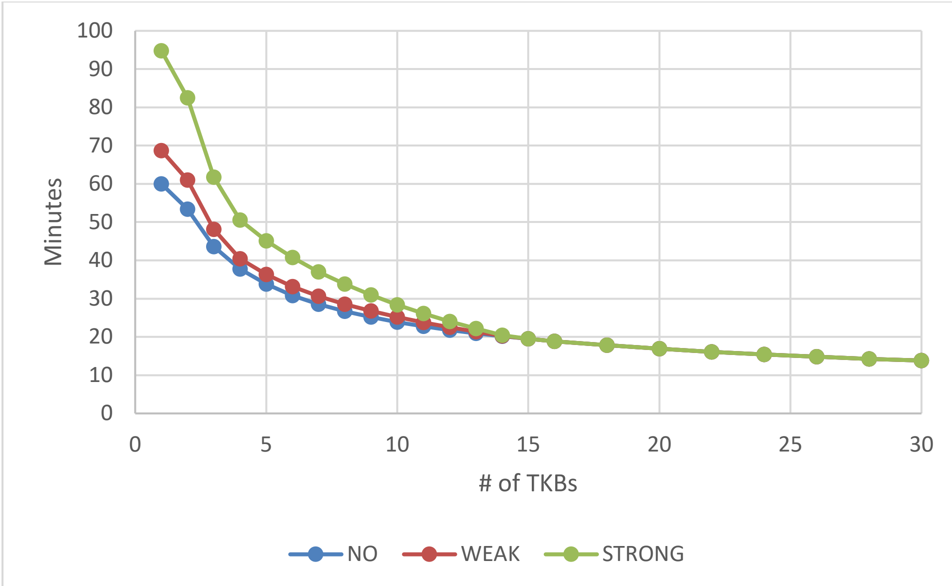


Figure 5.9 Travel time variability for patients served at a TKB (Performance measure 8).

Figures 5.10, 5.11, and 5.12 present travel distance performance measures corresponding to those for travel time shown in Figures 5.7-5.9. The patterns in these figures mirror those of the travel time measures, as the only difference lies in dividing by the constant speed parameter. Therefore, the analysis and insights discussed for Figures 5.7-5.9are directly applicable to Figures 5.10-5.12.

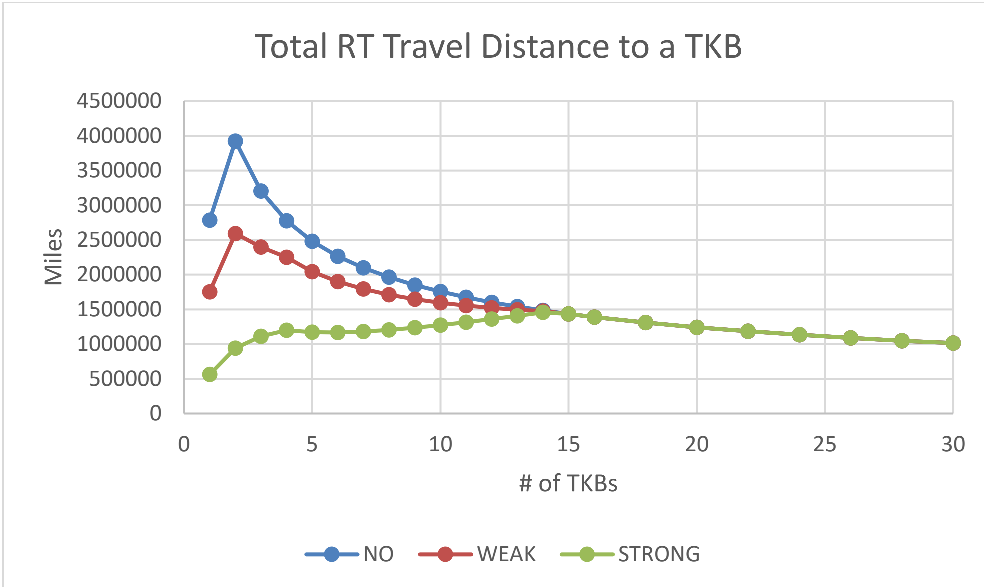


Figure 5.10 Total round trip travel distance for all patients served at a TKB (Performance measure 9).

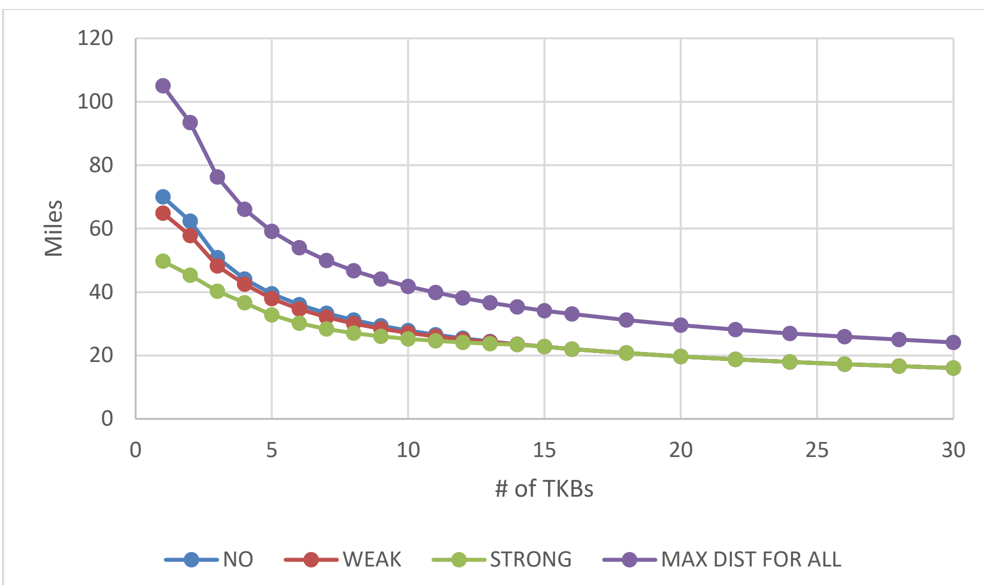


Figure 5.11 Round trip travel distance per patient served at a TKB and Maximum round trip travel distance for patients served at a TKB (Performance measures 10, 11).

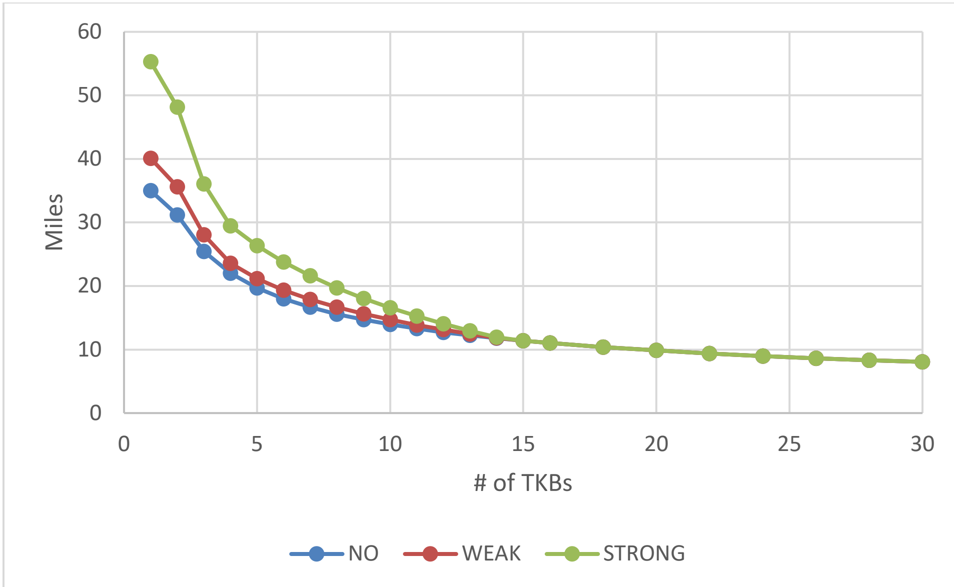


Figure 5.12 Travel distance variability for patients served at a TKB (Performance measure 12).

Figure 5.13 shows the maximum, average and minimum Accessibility Indices as the number of TKBs increases from 1 to 30. As expected, accessibility improves with increases in the number of TKBs, and the average Accessibility Index is linear for the number of TKBs.

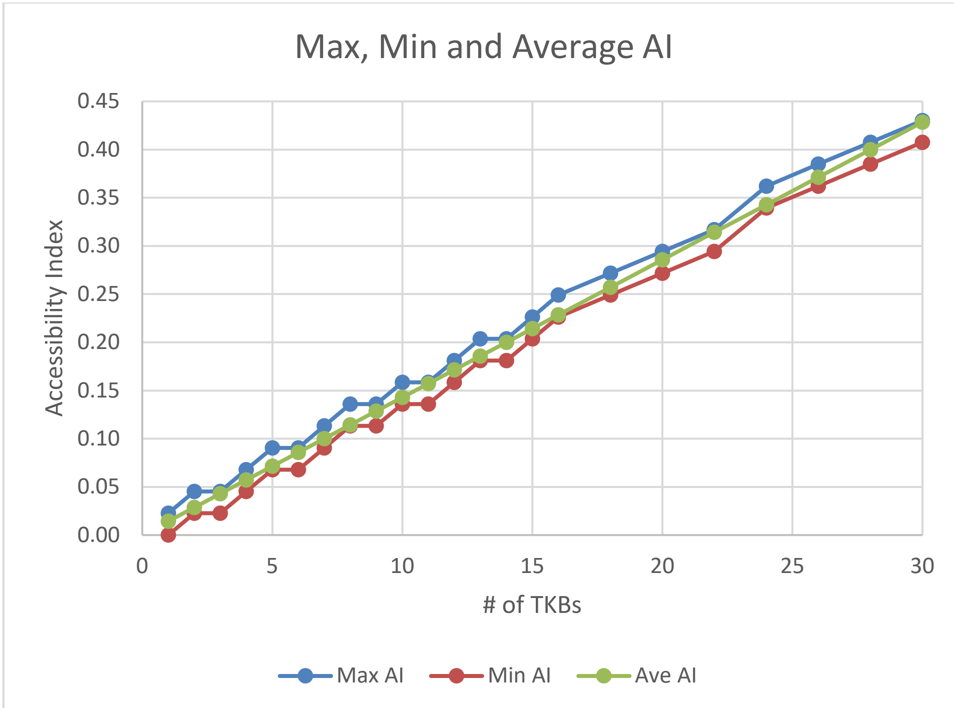


Figure 5.13 Maximum, Average and Minimum Accessibility Index.

Figures 5.14 and 5.15illustrate the total travel savings in hours and miles, respectively, achieved by using a network of TKBs compared to patients traveling to a single central healthcare facility. In this 7,000 square mile region, the expected round-trip travel time to a central facility (assuming randomly distributed patients) is 151 minutes (2.52 hours or 44 miles round-trip). This estimate corresponds to a one-way travel distance of 1.4 times two-thirds of the radius of a circle with an area of 7,000 square miles. Figure 5.14 shows that total travel time savings increase as more TKBs are deployed. With one TKB, travel savings range from approximately 12,388 hours (Strong Decay) to 17,899 hours (Weak Decay). These savings grow significantly, reaching nearly 130,000 hours with 30 TKBs. This is due to both shorter travel distances and an increasing number of patients served as TKB density rises. For instance, with

30 TKBs, the average one-way travel time drops to just 13.8 minutes, resulting in substantial time savings.

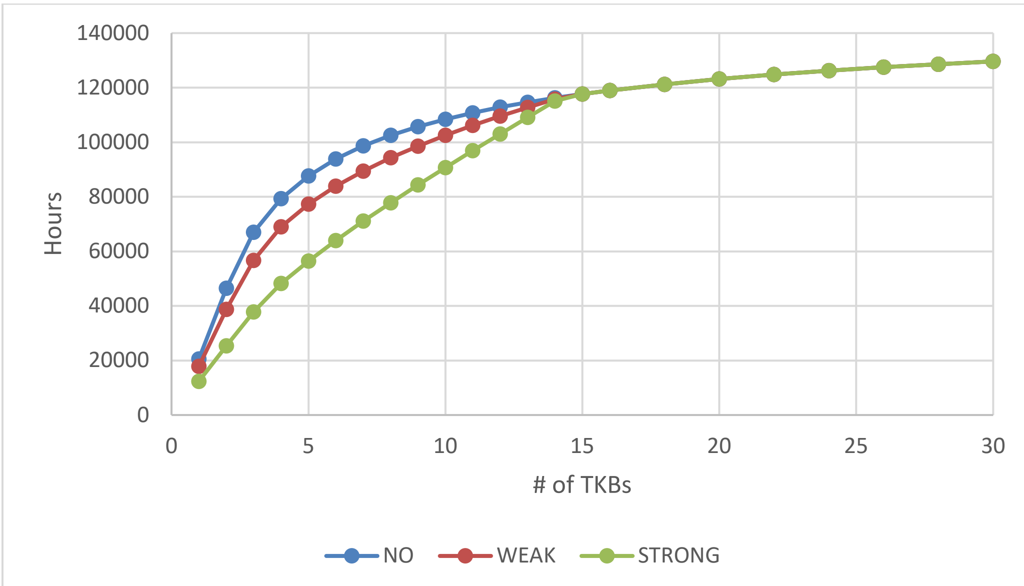


Figure 5.14 Total travel time savings compared to one existing healthcare facility.

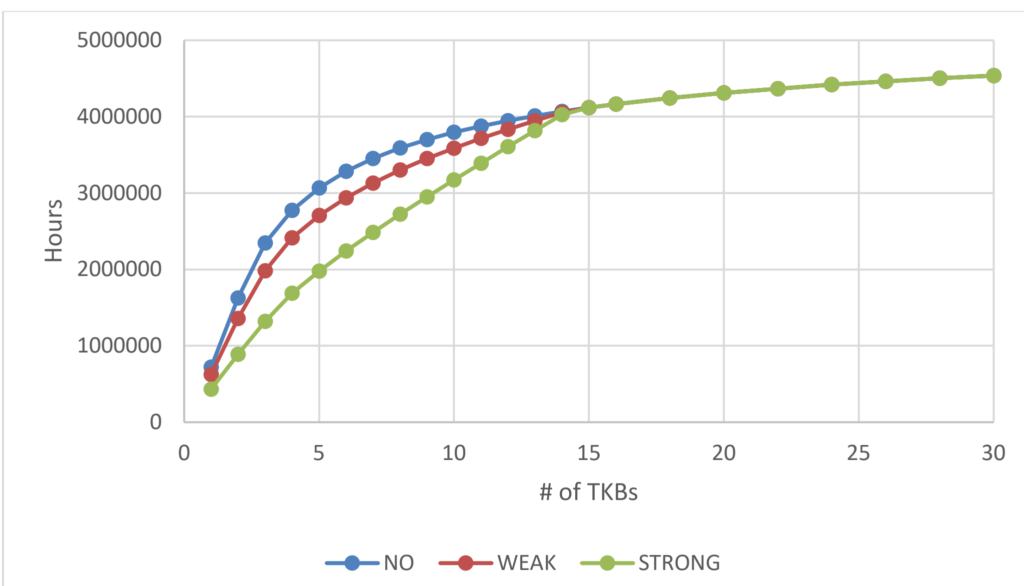


Figure 5.15 Total travel distance savings compared to one existing healthcare facility.

Similarly, Figure 5.15 reports round-trip distance savings, showing a total savings of 4.54 million miles with 30 TKBs. These savings reflect the number of trips made by potential patients, as determined by the population density (δ). For example, if δ is 10 potential patients per square mile and each patient makes one annual trip to a TKB, the values in Figures 5.14 and 5.15 represent annual savings.

Figures 5.16 and 5.17 report the travel time and distance savings on a per patient basis. Again, note that this effectively reflects one trip per year to a TKB. These two charts have the same shape as they differ only by a constant factor of the speed. However, note that Figures 5.14 and 5.15 show the largest total savings are from No Decay, in part because that serves the largest number of patients. On the other hand, the largest average savings per patient are with Strong Decay, since that favors patients close to a TKB who have a shorter travel distance.

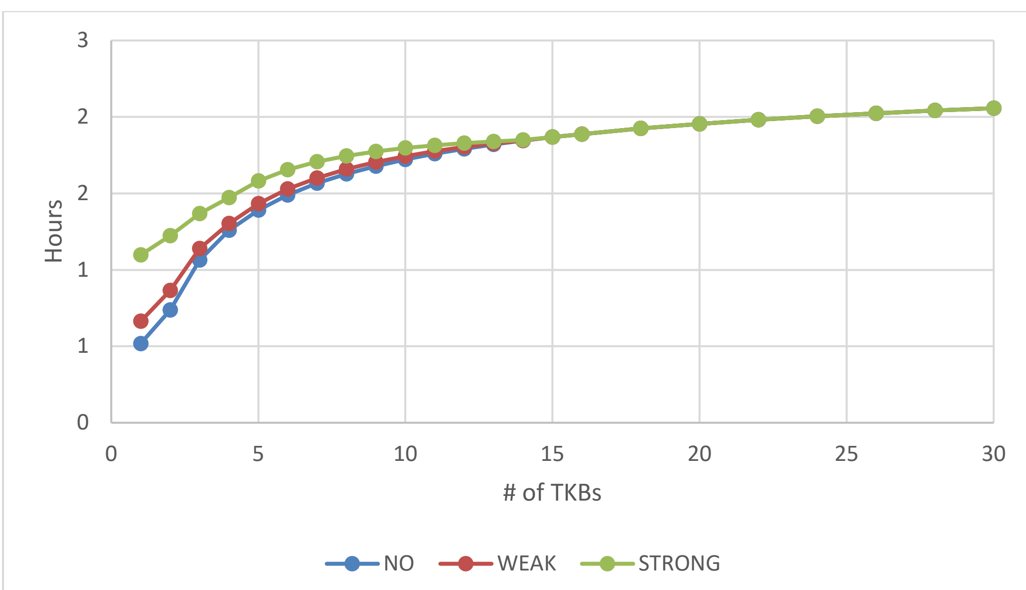


Figure 5.16 Per patient round trip travel time savings compared to one existing healthcare facility.

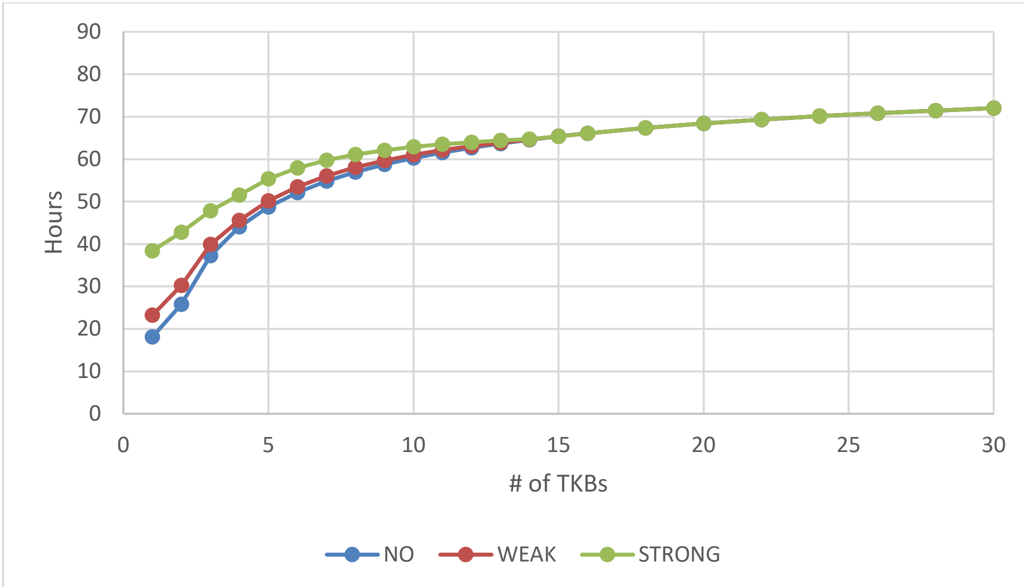


Figure 5.17 Per patient round trip travel distance savings compared to one existing healthcare facility.

The curves in Figures 5.14-5.17 highlight the substantial benefits of deploying the first few TKBs, with diminishing returns as more are added. To provide additional insight, Figure 5.18 illustrates the marginal percentage increase in total travel time savings as the number of TKBs grows. For No Decay and Weak Decay, the savings increase by at least 10% per additional TKB up to five TKBs, while for Strong Decay, this threshold extends to sevenTKBs. Lesser incremental savings occur as more TKBs are added, and beyond 16 TKBs, the incremental savings for each additional TKB drops below 1%.

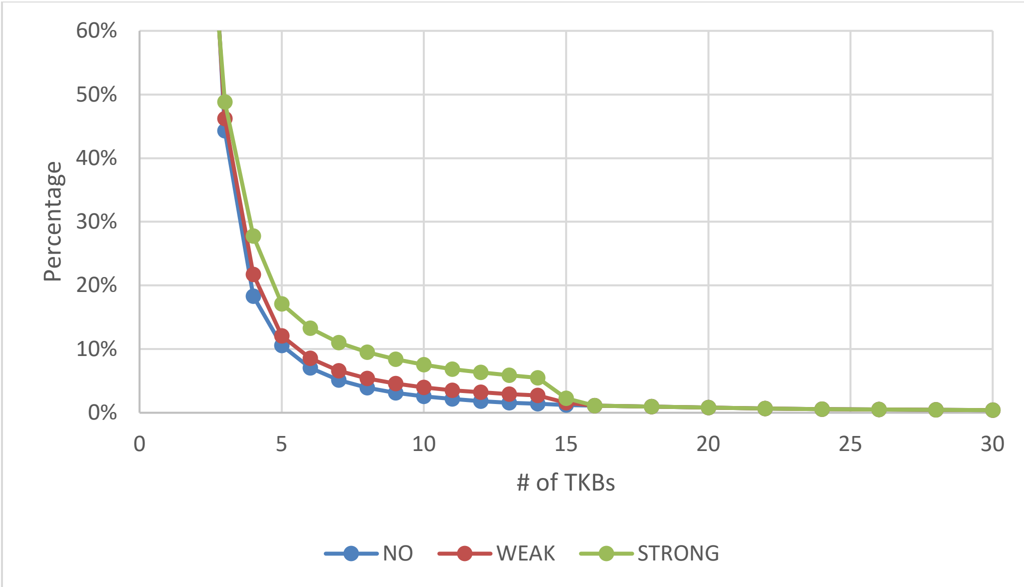


Figure 5.18 Marginal (%) savings in total travel time with each added TKB.

5.2.2 Impact of Changes in Density of Potential Patients

This section examines the impact of increasing the density of potential TKB users while retaining the parameter values from the previous section. Performance measures, as formulated in Section 5.1.3, are either proportional to patient density or independent of it (e.g., per-patient averages). To illustrate, we analyze three density levels: δ=10 (as in the previous section), δ=20, and δ=40, focusing on Weak Decay.

Figure 5.19 shows total travel time savings compared to one existing healthcare facility for the three density levels. The lowest curve corresponds to the middle curve in Figure 5.14. The savings are proportional to density, with $\delta = 40$ yielding four times the savings of $\delta = 10$. This indicates that regions with higher potential TKB users experience greater total savings.

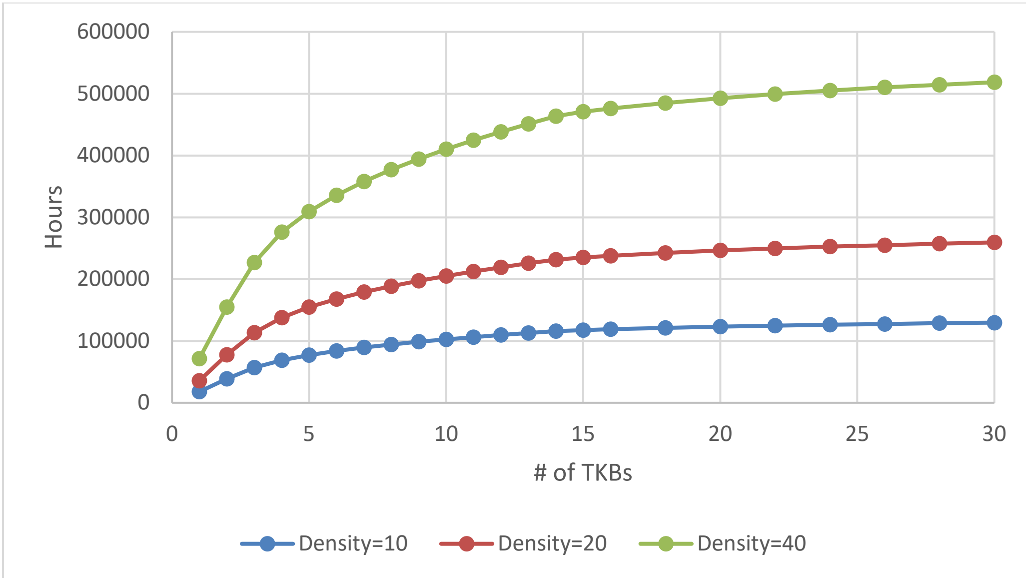


Figure 5.19 Total travel time savings compared to one existing healthcare facility with three density values and Weak Decay.

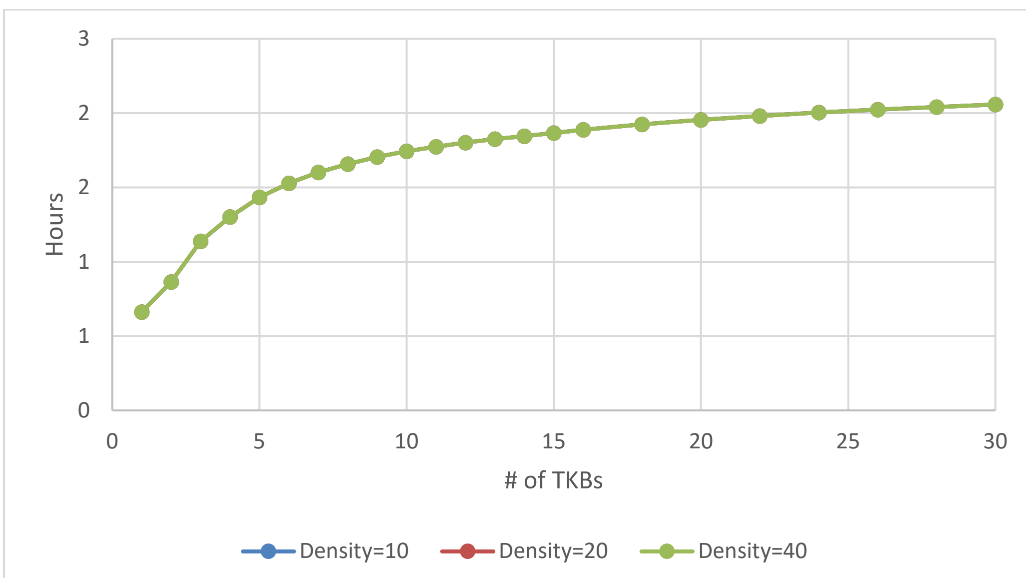


Figure 5.20 Per patient round trip travel time savings compared to one existing healthcare facility with three density values and Weak Decay. (all three lines overlap)

However, savings per patient remain constant across densities, as shown in Figure 5.20 (matching the middle curve in Figure 5.16 for Weak Decay). Other performance measures either exhibit proportional scaling with density or remain unchanged for per-patient metrics, mirroring the trends from the previous section.

5.2.3 Uneven Density of Potential TKB Users

This section considers the impact of having an uneven distribution of potential TKB users across the service region using CA modeling. Suppose one half of the service region has a uniform density of δ potential TKB users, while the other half has a larger uniform density of $h\delta$ potential TKB users for $h \geq 1$. We use Ld and Hd to denote the low-density and high-density regions respectively. We consider two options for the deployment of a set of k TKBs: "even" and "proportional". For the even distribution, regions Ld and Hd both have $k/2$ TKBs uniformly distributed across a region of area $A/2$. For the proportional distribution, the TKBs are distributed proportional to the demand, so that region Ld has $k/(1+h)$ TKBs and region Hd has $kh/(1+h)$ TKBs, with each set of TKBs serving a region of area $A/2$. We can use the performance measure equations derived earlier to analyze the even and proportional distribution of TKBs. Table 5.3 summarizes key performance measures for the even and proportional distribution of TKBs. This includes three sections with the top being three rows for general values, then separate sections for the even distribution of TKBs and proportional distribution of TKBs. The right two columns show the values for the Ld and Hd subregions, or a central value for the average across the entire region (calculated by multiplying the regional values by the regional fraction of potential TKB users in row 4).

Table 5.3 Performance measures for evenly distributed TKBs with varying patient density distributions, including proportional and uneven allocations

	Region Ld	Region Hd
Area (square miles)	$A/2$	$A/2$
Density of potential TKB users (per square mile)	δ	$h\delta$
Fraction of potential TKB users	$\frac{1}{1+h}$	$\frac{h}{1+h}$
Even Distribution of TKBs		
Number of TKBs	$k/2$	$k/2$
Area per TKB	$\frac{A}{k}$	$\frac{A}{k}$
Round trip distance per patient to nearest TKB by subregion (miles)	$\frac{4}{3}\sqrt{\frac{A}{k\pi}}$	$\frac{4}{3}\sqrt{\frac{A}{k\pi}}$
Average round trip distance per patient to nearest TKB for entire region (miles)	$\frac{4}{3}\sqrt{\frac{A}{k\pi}}$	
Average Accessibility Index by subregion	$\frac{k}{\delta A}$	$\frac{k}{h\delta A}$
Average Accessibility Index for entire region	$\frac{k}{\delta A}\frac{2}{1+h}$	
Proportional Distribution of TKBs		
Number of TKBs	$k/(1+h)$	$kh/(1+h)$
Area per TKB	$\frac{A}{k}\frac{1+h}{2}$	$\frac{A}{k}\frac{1+h}{2h}$
Round trip distance per patient to nearest TKB by subregion (miles)	$\frac{4}{3}\sqrt{\frac{A}{k\pi}}\sqrt{\frac{1+h}{2}}$	$\frac{4}{3}\sqrt{\frac{A}{k\pi}}\sqrt{\frac{1+h}{2h}}$
Average round trip distance per patient to nearest TKB for entire region (miles)	$\frac{4}{3}\sqrt{\frac{A}{k\pi}}\frac{1+\sqrt{h}}{\sqrt{2(1+h)}}$	
Average Accessibility Index by subregion	$\frac{2k}{\delta A(1+h)}$	$\frac{2k}{\delta A(1+h)}$
Average Accessibility Index for entire region	$\frac{k}{\delta A}\frac{2}{1+h}$	
Area per TKB	1	100

Figure 5.21 illustrates the minimum and average Accessibility Index (AI) for both even and proportional distributions of TKBs across varying levels of demand unevenness (h). While both distributions result in the same average AI ($\overline{AI}$), this value decreases as demand unevenness (h) increases. For proportional TKB distribution, the Accessibility Index is uniform across regions, resulting in zero variability, with $\overline{AI}$ equaling both the maximum and minimum values. In contrast, the even TKB distribution achieves the same average AI but with a fixed maximum value independent of h and a lower minimum value compared to the proportional distribution. This leads to a wider range of AI values and greater inequity under the even TKB distribution.

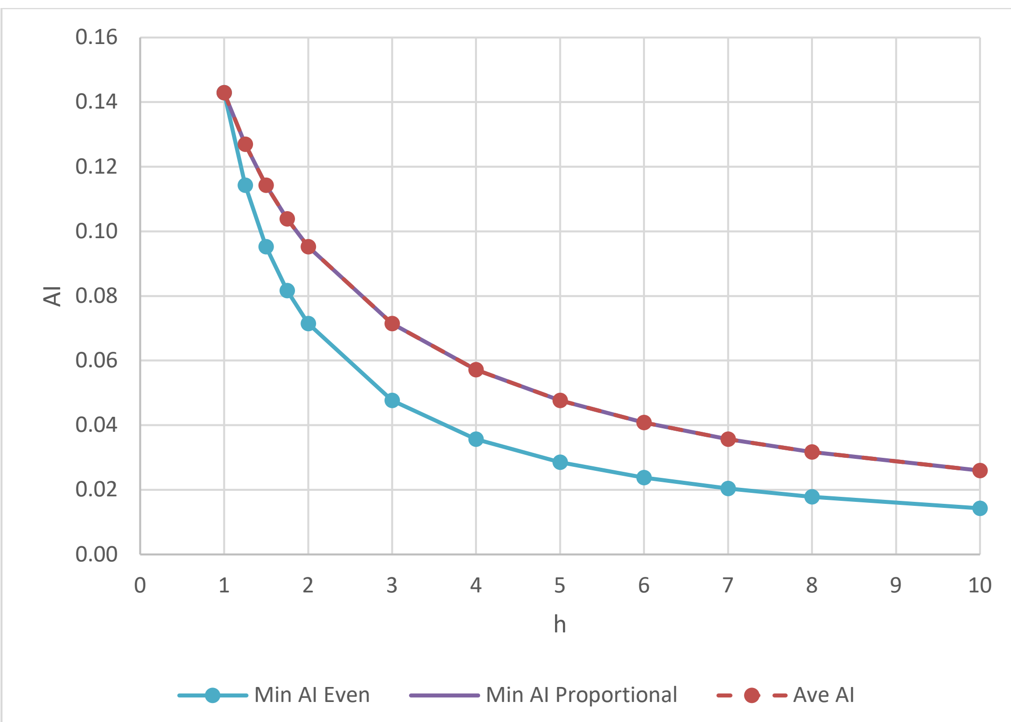


Figure 5.21 Minimum and average Accessibility Index for even and proportional TKBs.

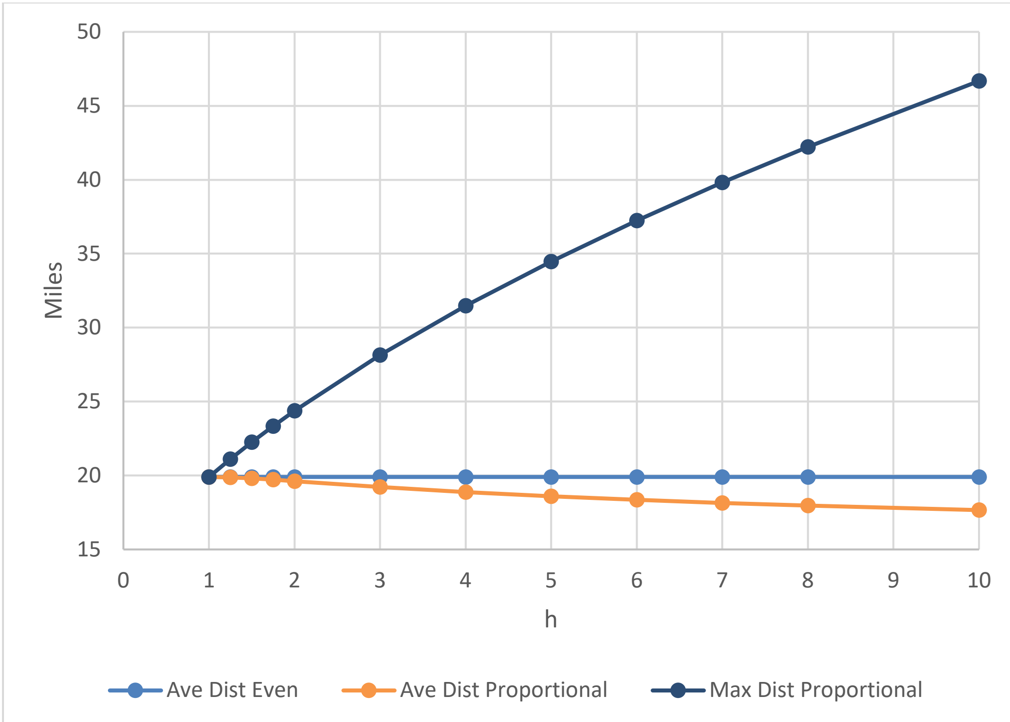


Figure 5.22 Average and maximum round trip travel distance for even and proportional TKBs.

Figure 5.22 compares the average and maximum round trip travel distances for even and proportional TKB distributions. The even distribution maintains a constant average travel distance, regardless of demand unevenness (h). In contrast, the proportional distribution achieves a lower average travel distance, with the gap increasing as h grows. However, the maximum travel distance for the proportional distribution (in the Ld region) becomes significantly larger with increasing h, though it affects a smaller fraction of demand.

This analysis highlights a tradeoff: the proportional distribution minimizes Accessibility Index inequity but creates substantial travel distance inequities (24% for h=2 and 67% for h=4). Conversely, the even distribution minimizes travel distance inequity but results in significant Accessibility Index disparities, with the minimum AI falling 25% below the average AI for h=2 and 38% below for h=4. Decision-makers must balance these competing priorities based on the desired equity goals for accessibility and travel distance.

5.3 Results for Case Studies

This section provides results using the CA models for access to TKBs for the case studies presented in Chapter 3 with the Southern and West-Central Missouri data sets. For each region, the service region area and density of potential TKB users are taken from the "Total" row in Tables 3.1 and 3.2. The speed is 35 mph and the circuity factor is 1.4. Travel time decay is modeled as presented in Table 4.4for each age group and the number of potential TKB users are aggregated over the four age groups using the age group percentages from Table 3.3.

We first provide results for the Southern case study, which highlight key trends in potential TKB user demographics. Figure 5.23 shows that Middle-Aged users dominate, which is not surprising as they comprise 44.6% of the population (see Chapter 3) and have the highest likelihood of visiting a TKB (see Figures 4.3 and 4.4). The interaction between population fraction and likelihood to visit a TKB determines TKB patronage. Notably, the ordering of age groups changes as TKBs are added; for example, Young Adults outnumber School-Aged users with six or fewer TKBs, but School-Aged users surpass Young Adults when seven or more TKBs are available.

Figure 5.24 illustrates population coverage by age group. With fewer TKBs, coverage is low due to the reduced likelihood of visiting a TKB at greater distances (see Figure 4.4). However, as TKBs are added, travel times decrease, leading to higher likelihoods of use and significant increases in population coverage, especially with the first few TKBs. Coverage grows more gradually as additional TKBs are deployed, eventually reaching 52% to 59% across all age groups with 60 TKBs. This value reflects the maximum likelihood of using a TKB, which is under 68% (see Table 4.4 or Figures 4.3 and 4.4).

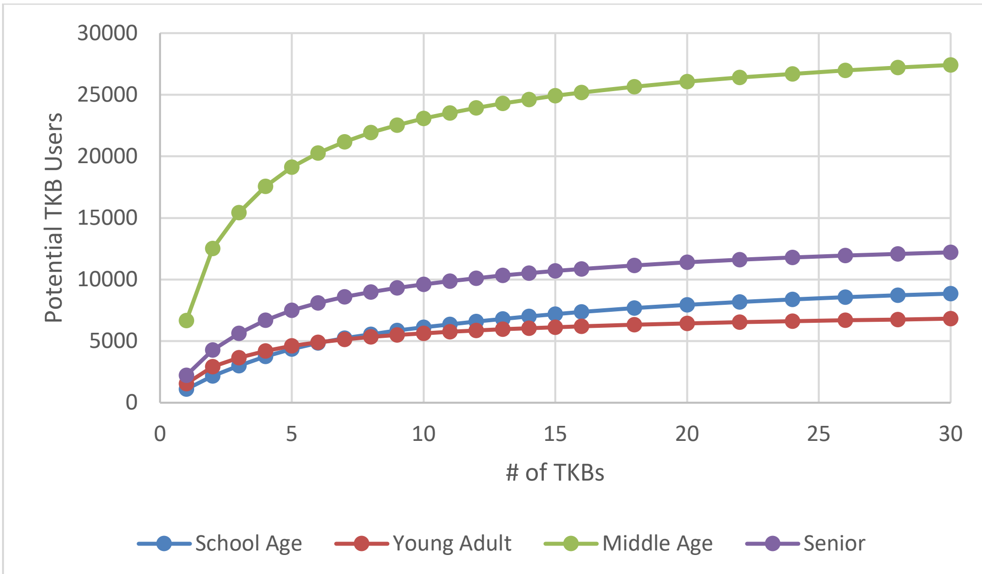


Figure 5.23 Total number of potential TKB users by age group for the Southern region.

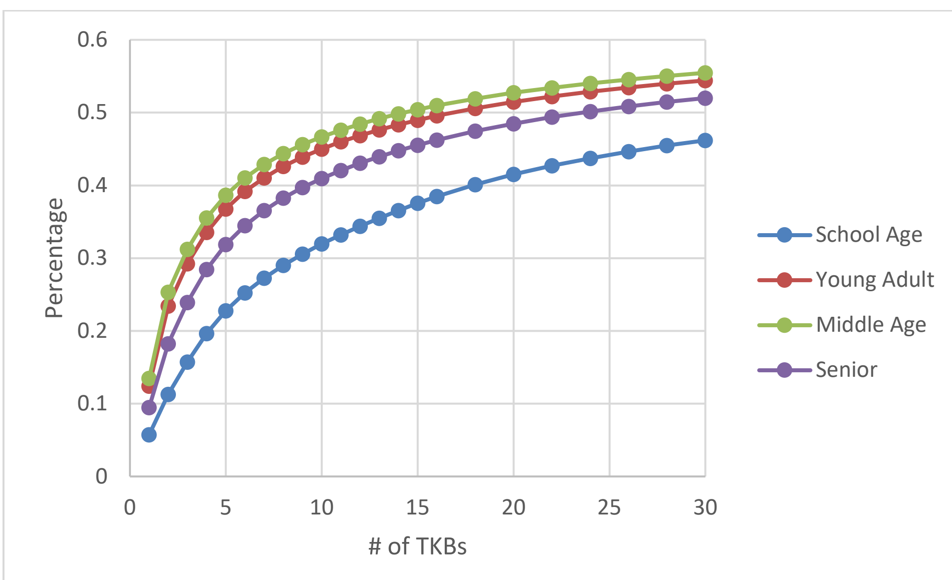


Figure 5.24 Population coverage by age group for the Southern region.

Figure 5.25 shows the number of potential TKB users per TKB by age group, which again reflects the dominance of the Middle-Aged group. These results reflect a large number of potential users per TKB when there are few TKBs (up to a total of 31.6 users per day with one TKB, assuming 365 days per year of operation), but if a TKB operates many hours each day, this demand would not be excessive. Figure 5.26 provides a related perspective showing the fraction of users per TKB by age group. This shows that the percentage of potential users per TKB in the Middle-Aged group declines as the number of TKBs increases but remains above 50%. The remaining users are split between Seniors (about 19-22%), Young Adults (12-13%) and School Age (increasing from about 9% to almost 17%).

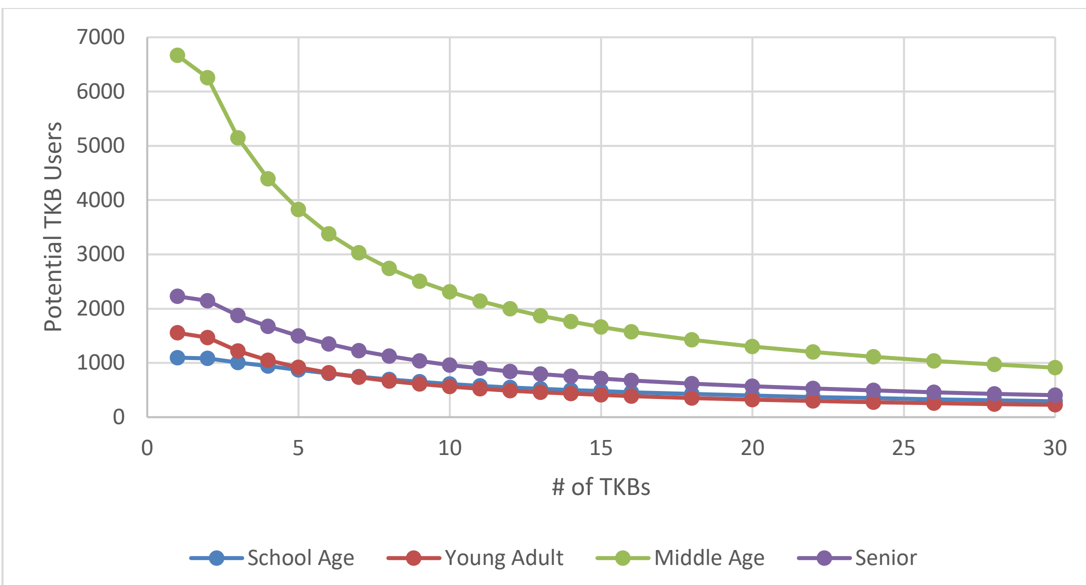


Figure 5.25 Number of potential TKB users per TKB by age group for the Southern region.

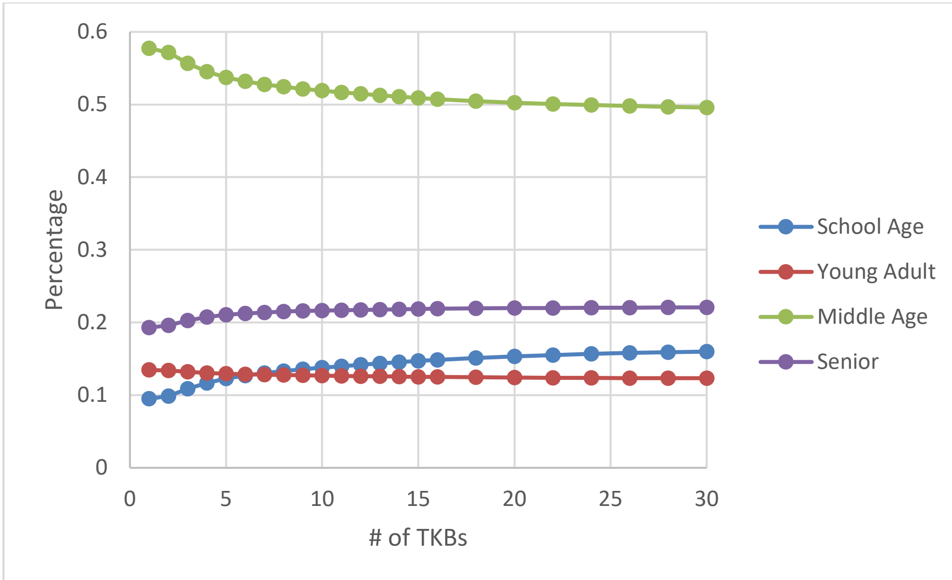


Figure 5.26 Fraction of potential TKB users per TKB by age group for the Southern region.

Figures 5.27-5.31 provide several other key performance measures. Figure 5.27 shows the average Accessibility Index (AI), which increases for all age groups as TKBs are added, and is consistently highest for Young Adults and lowest for Middle Age. This shows inequities that reflect the different population sizes. As there are relatively few in the Young Adult group and relatively many in the Middle-Aged group, and both groups have similar likelihoods to the use the TKB (see Figure 4.4), the AI by definition shows preference to the smaller population given the fixed number of TKBs, with the assumption that the "supply" at a TKB is the same for all age groups. Interestingly, the School Age group has a higher AI than the Senior group even though the Senior group is larger (21.2% vs. 17.3% of the population), because Seniors are much more likely than School-Aged potential users to visit a TKB (Figure 4.4).

Figure 5.28 shows the average round trip travel time by age group, which has interesting differences due to the shapes of the travel time decay functions. All average travel times are within two minutes once there are 11 or more TKBs, but with few TKBs the differences are more pronounced. The longest travel times are for the Young Adult and Middle-Aged groups, which have very similar travel time decay behavior (Figure 4.4). Because School Age has the strongest decay, the average travel time is smallest, as there are fewer patients willing to make long trips.

Figure 5.29 illustrates the total travel hours saved with TKBs compared to a single centrally located healthcare facility. The results closely mirror the chart of total potential TKB users (Figure 5.23), though Seniors and School-Aged groups contribute disproportionately to travel time savings when there are fewer TKBs. With a larger number of TKBs, the percentage of total hours saved by each age group aligns more closely with its share of total demand, as travel time decay curves become similar. For instance, with 30 TKBs, the average one-way travel time is 14.3 minutes, and the maximum is 21.4 minutes, making only the initial portion of the travel time decay curve relevant (for small travel times), where age groups exhibit similar behavior. Note that with additional TKBs the travel time savings increase at a decreasing rate, while the costs to establish and operate a network of TKBs may increase at a faster rate. For example, doubling the number of TKBs from seven (one per county) to 14 (a 100% increase), increases the travel time savings by only 37%.

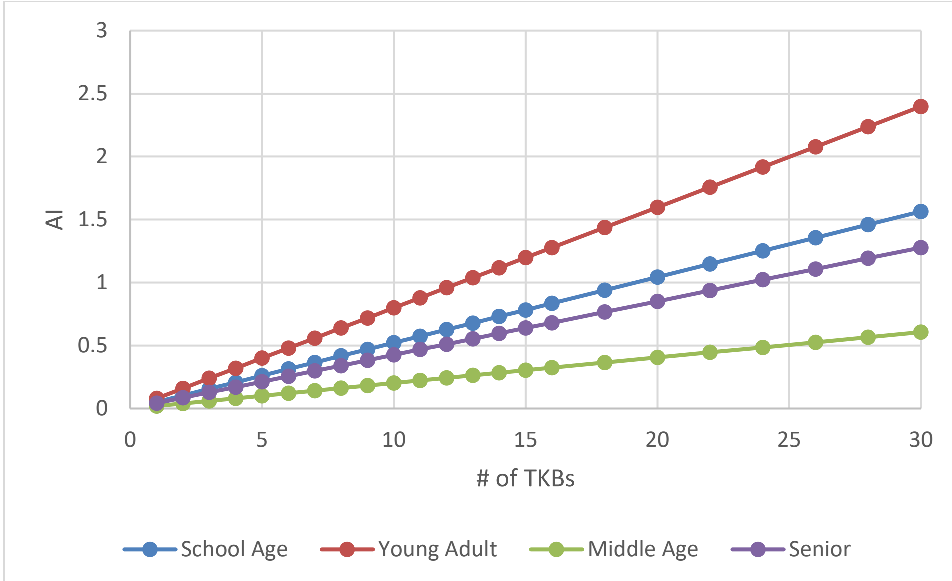


Figure 5.27 Accessibility index (AI) by age group for the Southern region.

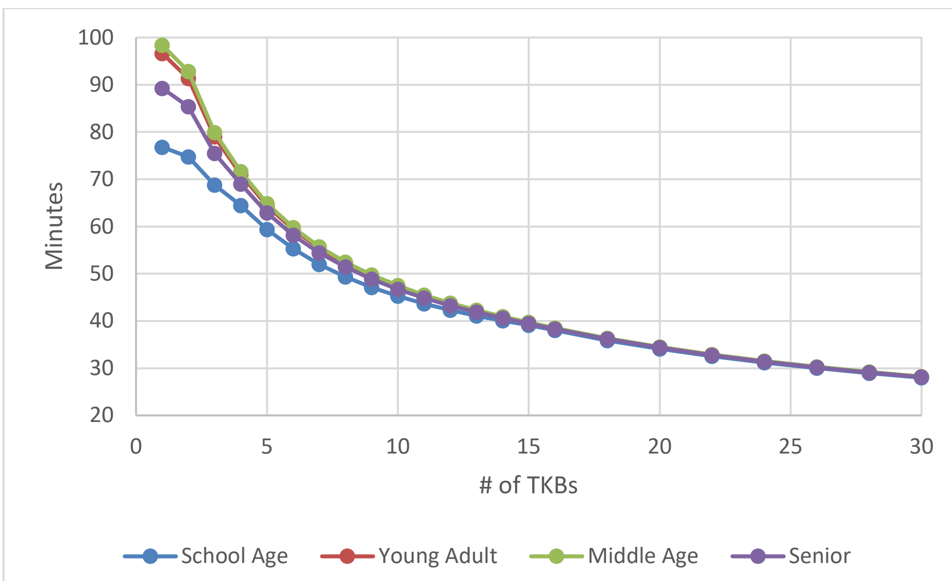


Figure 5.28 Average round trip travel time by age group for the Southern region.

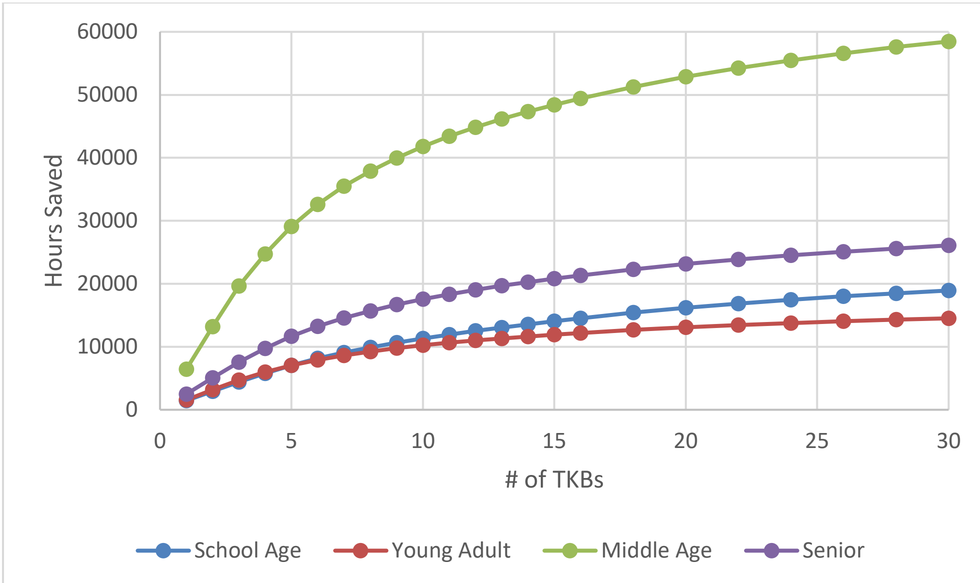


Figure 5.29 Total travel time savings compared to one existing healthcare facility for the Southern region.

Figure 5.30 highlights per patient round trip travel time savings compared to a single existing healthcare facility. The school-age group benefits the most, with savings of 1.3 to 1.8 hours per patient for 1-10 TKBs, followed by seniors with savings of 1.1 to 1.8 hours per patient. These per-patient savings reflect one annual trip to a TKB per potential user.

For comparison, Figure 5.31 also presents results with three existing healthcare facilities. Here, per-patient travel time savings are significantly reduced and can even be negative with few TKBs. However, as the number of TKBs increases, savings grow to approximately 50% of the level observed with a single existing facility for all age groups.

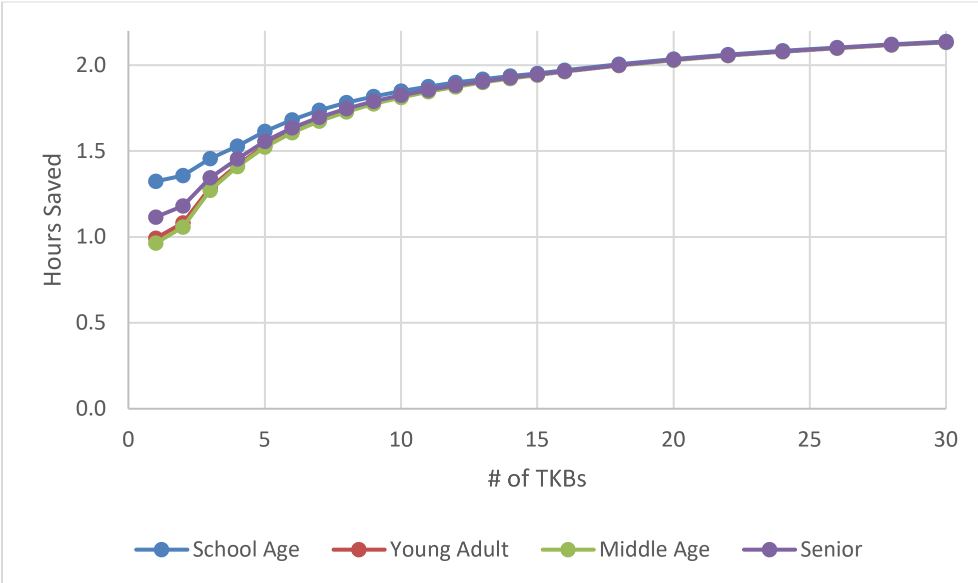


Figure 5.30 Per patient round trip travel time savings compared to one existing healthcare facility for the Southern region.

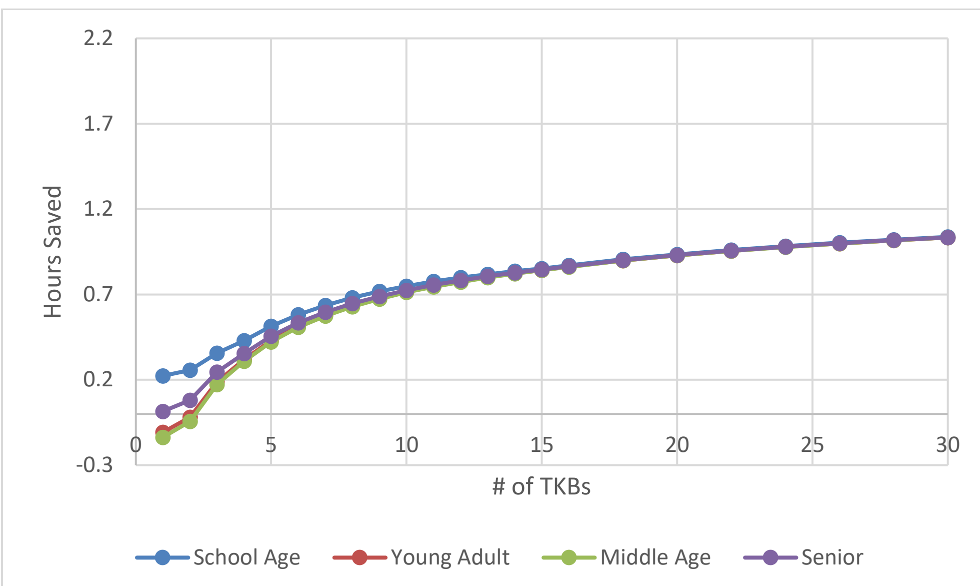


Figure 5.31 Per patient round trip travel time savings compared to three existing healthcare facilities for the Southern region.

The results for the West-Central case study region are similar to those for the Southern region, so only a selection of charts is included. Figure 5.32 shows the total number of potential

TKB users by age group, highlighting the dominance of Middle-Aged users, as seen in the Southern region. This dominance is due to Middle-Aged users being the largest fraction of the population and having the highest likelihood of visiting a TKB (see Figures 4.3 and 4.4). Unlike the Southern region, the other three age groups in the West-Central region contribute more evenly to the total.

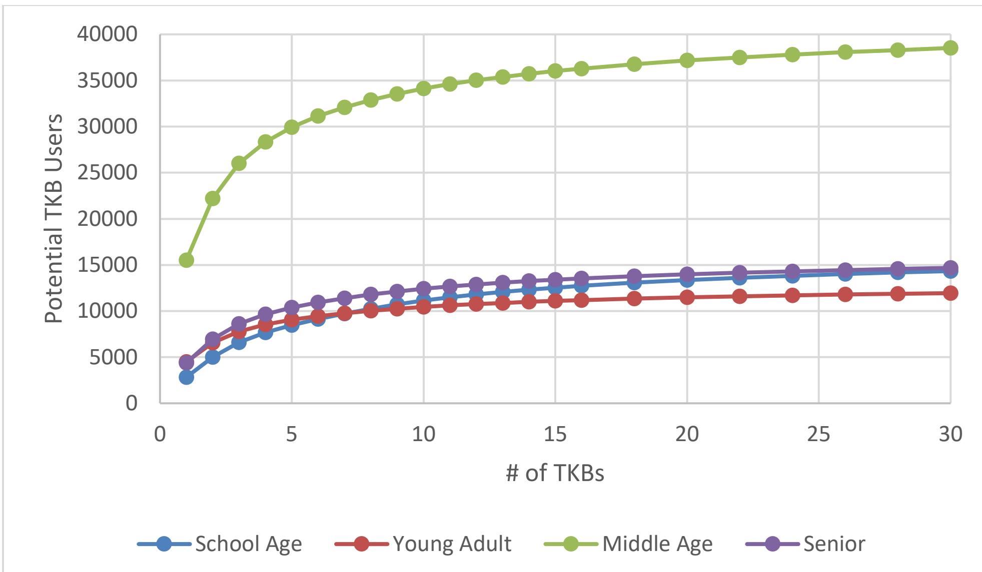


Figure 5.32 Total number of potential TKB users by age group for the West-Central region.

Figure 5.33 illustrates population coverage by age group, which follows a similar trend to the Southern region but at higher levels due to a greater proportion of Young Adult and Middle-Aged residents, who are more likely to use a TKB. Coverage is initially low with few TKBs but increases rapidly before leveling off. The maximum population coverage with 60 TKBs ranges between 56% and 62% for all age groups, reflecting the maximum likelihood of using a TKB of under 68% (see Table 4.4 or Figures 4.3 and 4.4).

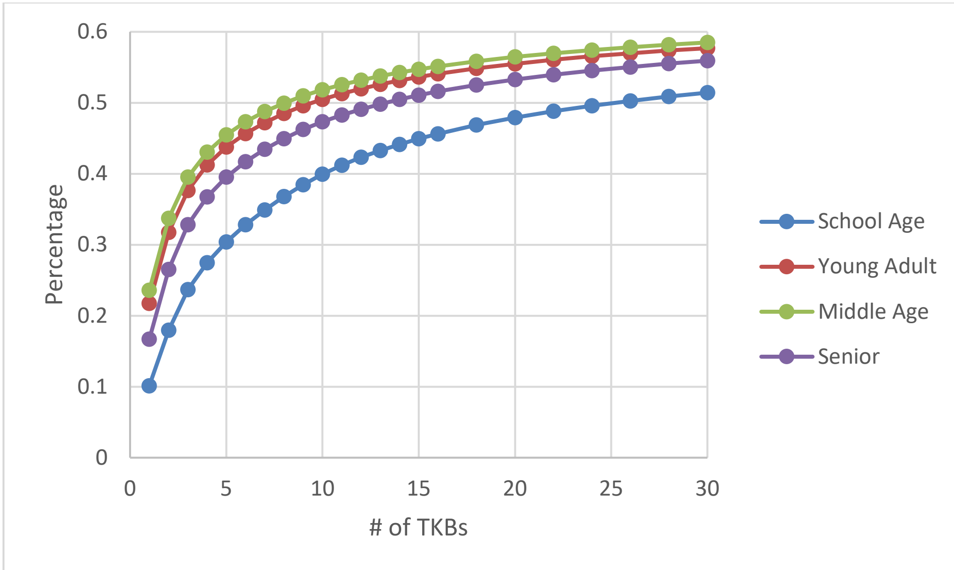


Figure 5.33 Population coverage by age group for the West-Central region.

Figure 5.34 shows the number of potential TKB users per TKB by age group, again reflecting the dominance of the Middle-Aged group and the much higher population density in the West-Central region compared to the Southern region (35.6 vs. 14.8 per square mile). In this chart, the other age groups contribute more evenly to potential patients at a TKB, unlike the Southern region.

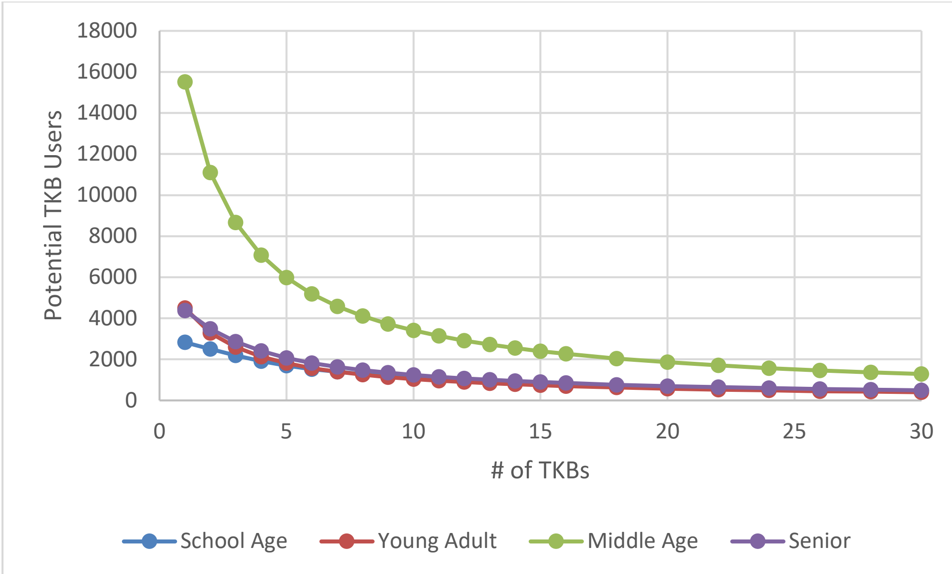


Figure 5.34 Number of potential TKB users per TKB by age group for the West-Central region.

Figure 5.35 complements this by showing the fraction of users per TKB by age group. Middle-Aged users account for approximately 50%, while the remaining three age groups share the other 50% more equally.

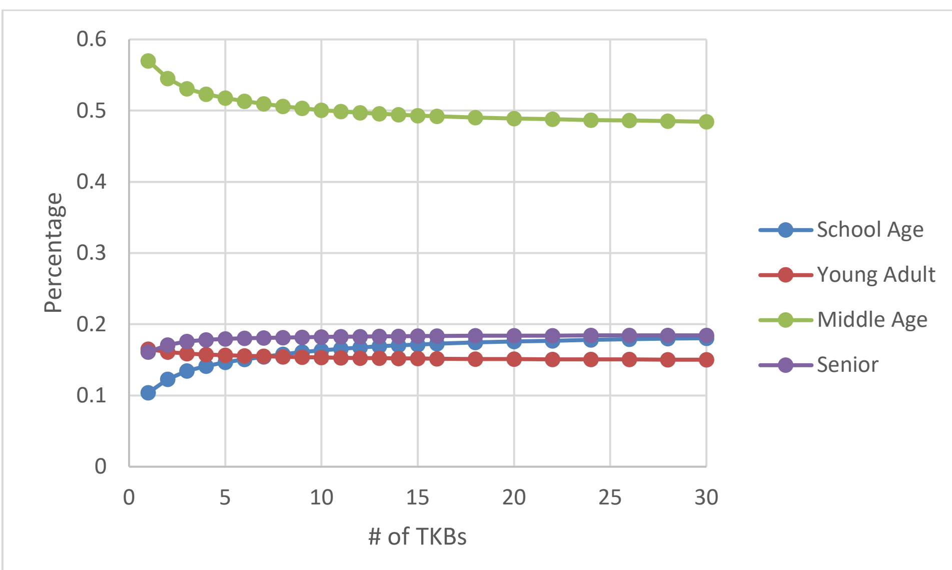


Figure 5.35 Fraction of potential TKB users per TKB by age group for the West-Central region.

Figures 5.36-5.40present key performance measures for the West-Central region. Figure 5.36 shows the average Accessibility Index (AI), which increases for all age groups as TKBs are added but is much lower than in the Southern region due to the greater population being served. Similar to the Southern region, this highlights inequities, with higher accessibility for Young Adults and lower accessibility for Middle-Aged residents.

Figure 5.37 illustrates the average round trip travel time by age group. While the trends are similar to those in the Southern region, the decline in travel time is steeper, and the travel times are shorter due to the smaller service area (4,212 square miles for the West-Central region compared to 7,487 square miles for the Southern region). For instance, with 10 TKBs, the average round trip travel time to a TKB is 46.7 minutes in the Southern region but only 36.4 minutes in the West-Central region, reflecting the benefits of a higher density of TKBs (from having a more compact service area).

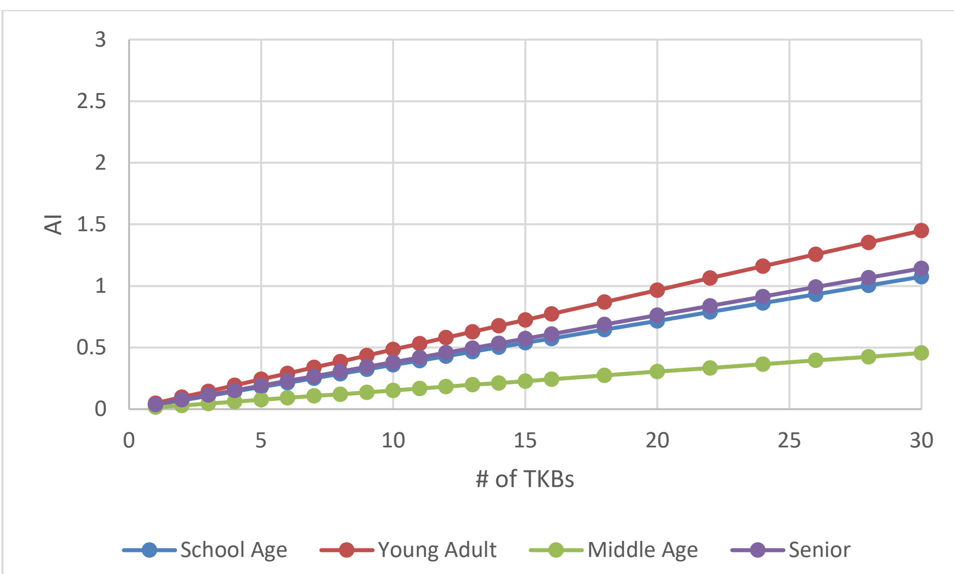


Figure 5.36 Accessibility index (AI) by age group for the West-Central region.

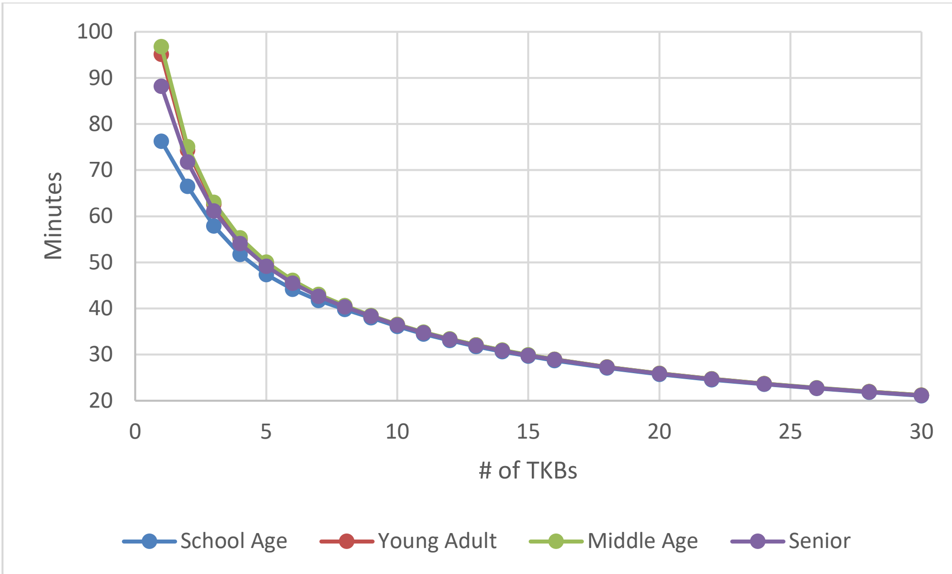


Figure 5.37 Average round trip travel time by age group for the West-Central region.

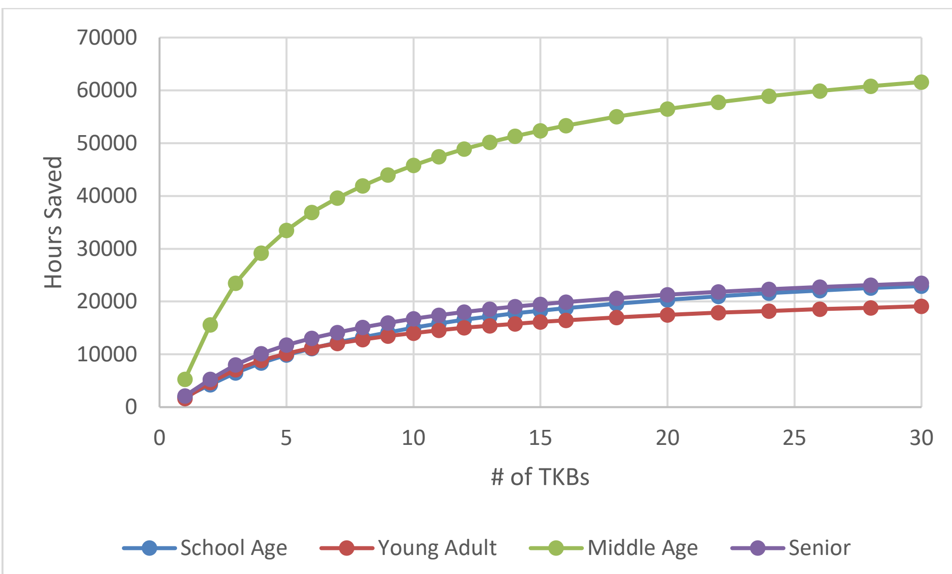


Figure 5.38 Total travel time savings compared to one existing healthcare facility for the West-Central region.

Figures 5.38-5.40present travel time savings results for the West-Central region, analogous to Figures 5.29-5.31for the Southern region. The Middle-Aged group dominates in contributing to total travel time savings, though the savings across age groups are similar when there are only a few TKBs.

Figure 5.39 highlights per patient travel time savings, ranging from 0.3 to 1.6 hours, which is lower than the Southern region's savings of 1-2 hours per patient. This reduction primarily reflects the smaller geographic area of the West-Central region, with age distribution differences playing a minor role. Among the age groups, School-Aged children benefit the most, followed by Seniors, though the differences are relatively modest.

Figure 5.40 shows results with three existing healthcare facilities, where the travel time savings are substantially reduced compared to Figure 5.39. With a larger number of TKBs, the savings level off at about 50% of the savings observed with one existing healthcare facility, reflecting the impact of having additional existing healthcare options in the region.

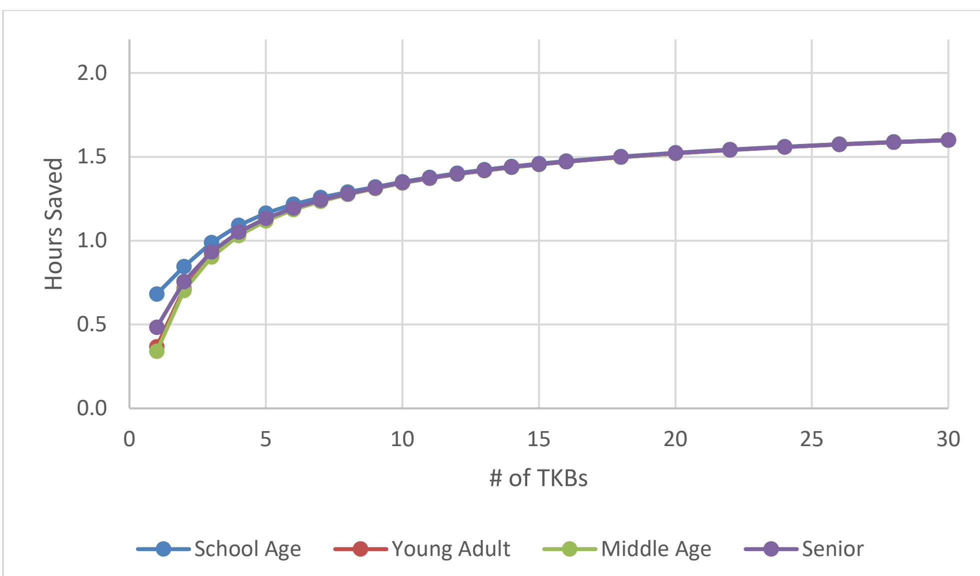


Figure 5.39 Per patient round trip travel time savings compared to one existing healthcare facility in West-Central region.

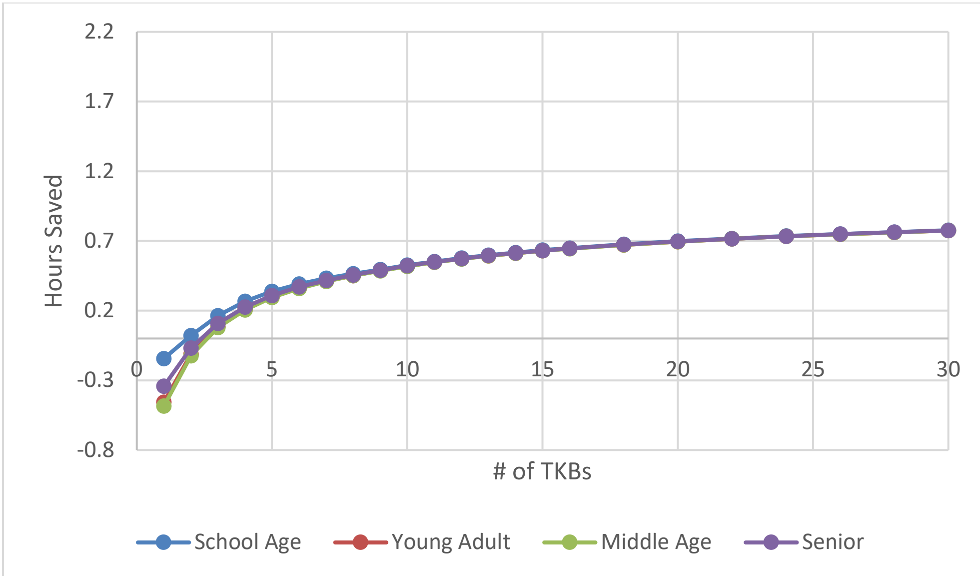


Figure 5.40 Per patient round trip travel time savings compared to three existing healthcare facilities for the West-Central region.

In summary, the findings from the two case study regions highlight the potential of TKBs to reduce travel times and enhance healthcare access, particularly in rural areas. The results demonstrate how different age groups can be incorporated into the modeling framework and how their distinct distributions and likelihood to utilize TKBs influence system performance. TKBs show significant promise in substantially reducing travel times for healthcare, particularly in larger rural areas with limited existing healthcare options. In contrast, smaller rural regions or those with a higher density of existing healthcare facilities may experience less pronounced benefits.

Nevertheless, TKBs offer unique advantages, including around-the-clock access to healthcare, expanded access to telehealth specialists, and the ability to provide services where patients may prefer not to engage in face-to-face interactions. These capabilities position TKBs as a valuable addition to rural healthcare delivery systems, addressing accessibility challenges and expanding service options.

5.4 Concluding Remarks

In this chapter, we developed continuous approximation (CA) models to evaluate the potential benefits of deploying telehealth kiosks/booths (TKBs) in rural regions, focusing on improving healthcare access and reducing travel times. A key element of the analysis was incorporating travel time decay functions to capture the decreasing likelihood of patients visiting a TKB as their travel time increases. Analytical results demonstrated how system performance metrics vary with the number of TKBs, different levels of travel time decay, and the availability of existing healthcare facilities. This chapter treated demand for service at a TKB as being continuously and evenly distributed over the service region to derive analytical expressions for system performance. This uniform distribution of demand is, of course, not true in reality. Nonetheless, the results for system performance as a function of the number of TKBs deployed can be insightful. Exact locations for TKBs (i.e., specific towns, addresses, etc.) requires more detailed modeling that better captures the demand variability over the service region, as from treating demand as occurring at discrete points (e.g., towns, census block groups, zip code centroids, etc.). Such modeling is the topic of the next chapter.

5.4.1 Key Findings

The results highlight the significant role of travel time decay in shaping system performance. While travel behavior strongly influences outcomes, accurate calibration of travel time decay models is essential to reflect real-world conditions. Simplified approaches, such as step functions or piecewise linear models, offer practical advantages when properly calibrated, providing comparable results while being easier to interpret and communicate.

Travel time savings were shown to increase proportionally with the density of potential TKB users. However, uneven distributions of users introduce trade-offs between accessibility and travel time performance measures. While the presence of existing healthcare facilities reduces the travel time savings from TKBs, the ongoing closure of rural hospitals underscores the importance of TKBs, particularly in large rural regions with limited healthcare options.

5.4.2 Case Studies

Two Missouri case studies demonstrated the practical implications of deploying TKBs:

- A network with one TKB per county in the Southern region could serve 40% of the population, saving nearly 81,000 travel hours annually compared to a single central hospital.
- A network with one TKB per county in the West-Central region could serve 56% of the population, saving approximately 67,000 travel hours compared to a single central hospital annually.

These results underscore the potential of TKBs to significantly reduce travel times and improve healthcare access. However, their effectiveness depends on local factors, including patient willingness to use TKBs, TKB functionalities, and the availability of alternative healthcare options.

5.4.3 Future Directions

While this research focused on patients' willingness to use TKBs, future studies should consider the intensity of use—how frequently potential patients visit TKBs. Factors such as population demographics, prevalent health conditions, and TKB capabilities will strongly influence usage rates. Customizing TKB designs to address specific regional healthcare needs or focusing on particular age groups or health conditions could enhance their effectiveness. Deploying different types of TKBs across rural regions may also optimize outcomes.

Another promising avenue for exploration is integrating drone operations with TKBs for rapid transport of medical supplies, test kits, and laboratory samples. Fully automated drone delivery systems could enable rapid delivery of critical items to TKBs, enhancing their functionality and utility. For further insights on drones in healthcare, see Enayati et al. (2023a, 2023b) and Steele (2022).

Periodic staffing of TKBs by healthcare professionals, such as clinicians or nurse practitioners, is another potential enhancement. Scheduled visits could expand the range of care offered, appeal to patients reluctant to rely solely on automated services, and strengthen the omnichannel healthcare approach. This hybrid strategy could complement existing clinics and hospitals while addressing gaps in rural healthcare access.

5.4.4 Implications for Omnichannel Healthcare

Omnichannel healthcare systems, which offer multiple avenues for care delivery, could be further optimized by examining the interactions between TKBs and other healthcare facilities. For example, TKB screenings might reduce clinic visits for routine care but could also drive follow-up appointments for issues requiring in-person attention. Understanding these cross-channel dynamics is essential for designing efficient, patient-centered systems. For more on omnichannel healthcare systems, see Moreira and Santos (2020) and Moreira et al. (2023).

Overall, this chapter demonstrates the potential of TKBs to improve healthcare access in underserved regions while providing a roadmap for future research and system enhancements. The next chapter explores a complementary modeling approach using discrete optimization for more specific and detailed planning of TKB deployment strategies.

Chapter 6 Discrete Optimization Modeling

Similar to Chapter 5, this chapter addresses the problem of designing an optimal deployment strategy for Telehealth Kiosks or Booths (TKBs) to maximize healthcare accessibility while ensuring equitable access across a diverse population. However, unlike the continuous approximation approach previously explored, this chapter introduces a discrete optimization framework that enables more precise and granular planning.

The problem involves a service area composed of multiple demand locations, each characterized by a specific population size and distribution across predefined subgroups. These demand locations vary in their geographic placement, presenting challenges in ensuring consistent access to healthcare services. TKBs, as a scalable and flexible solution, have the potential to bridge service delivery gaps if strategically deployed to balance accessibility, equity, and resource efficiency.

Each demand location's access to healthcare is influenced by proximity to TKBs, travel times, subgroup-specific preferences, and the capacity of TKBs to handle assigned populations. The goal is to develop a deployment strategy that maximizes overall access to healthcare services while addressing disparities and adhering to resource constraints such as the total number of deployable TKBs.

Deploying TKBs effectively in rural or underserved areas presents several challenges. First, balancing the trade-off between maximizing accessibility and ensuring equity is complex. Concentrating TKBs in high-demand areas can increase overall coverage but risks neglecting sparsely populated regions. Conversely, evenly distributing TKBs can reduce disparities but may dilute their overall impact by spreading resources thinly. Second, the diverse geographic and demographic characteristics of the service area complicate planning. Different subgroups exhibit varying travel tolerances and preferences for telehealth services, requiring the model to account for these heterogeneities. Finally, managing the capacity of TKBs is crucial to avoid overburdening some kiosks while leaving others underutilized.

This chapter formulates the problem as a discrete optimization model, incorporating the following key features:

1. **Demand and Subgroup-Specific Requirements**: Each demand location has a fixed population distributed across subgroups (e.g., age, socioeconomic status). These subgroups have varying preferences for utilizing TKBs, influenced by factors such as technology literacy, trust in telehealth services, and cultural acceptance. Preferences are modeled through geographic impedance functions (travel time decay function) that capture the likelihood of service utilization based on travel time.
2. **Candidate TKB Locations**: Deployment of TKBs is restricted to a predefined set of candidate locations, each characterized by attributes such as attractiveness, which reflects its suitability for serving demand. Demand is modeled as occurring at discrete points to represent the spatially distributed yet clustered nature of the population, ensuring that the analysis captures the realistic dynamics of healthcare access in the region.
3. **Travel Time and Catchment Areas**: Travel times between demand locations and candidate TKBs are precomputed. Accessibility is evaluated within specific catchment radii (e.g., 0–30 minutes, 30–60 minutes, 60–90 minutes), with diminishing likelihood to use TKBs as travel time increases.
4. **Provider Capacity**: Deployed TKBs have a finite capacity, modeled as a provider-population ratio, to ensure equitable service distribution within their catchment areas.

5. **Equity and Accessibility**: Accessibility is measured using the accessibility index (like Chapter 5) that integrates travel time, subgroup preferences, and provider capacity. Equity is assessed using the Gini coefficient, which quantifies disparities in access across demand locations.
6. **Resource Constraints**: The deployment strategy is constrained by a fixed budget, limiting the number of TKBs that can be deployed.

The discrete optimization model is developed under the following assumptions:

- *Demand Characteristics*: Each demand location has a fixed population size and subgroup distribution that remain constant during the planning horizon.
- *Catchment and Service Areas*: Accessibility is evaluated only within predefined catchment radii. Locations outside the largest catchment radius are considered underserved.
- *Candidate Location Attributes*: Candidate locations are a predefined, known, and fixed set.
- *Provider Capacity*: Each TKB can serve the population within its catchment area, constrained by its capacity.
- *All-or-Nothing Assignment*: Demand locations are either fully assigned to a TKB within a catchment or not at all.
- *Equity and Accessibility Metrics*: Accessibility indices are computed for each demand location, accounting for contributions from assigned TKBs and subgroup preferences.
- *Fixed Budget*: The budget for deploying TKBs is known and fixed.
- *Independent Catchments*: Assignments to overlapping catchments are treated independently.

By integrating these features and assumptions, the discrete optimization model offers a structured and practical approach for determining the optimal deployment strategy for TKBs. This chapter explores the application of this model to two case study regions in Missouri, building on the continuous approximation insights from Chapter 5, while offering a more detailed and specific framework for planning and implementation. The remainder of this chapter is structured as follows: Section 6.1 presents the modeling approach. Numerical Results are discussed in Section 6.2. Managerial insights and conclusions are included in Section 6.3.

6.1 Model Formulation

This section presents the formulation of the Optimal Deployment of Telehealth Kiosks (ODTKB) model, which aims to strategically place a limited number of TKBs in a service area. The objective is to maximize healthcare access, while ensuring equitable coverage across different population subgroups and minimizing travel distances to improve accessibility for all individuals. Suppose the service area is made up of various demand locations $\mathcal{I}$ (e.g., block groups), which represent areas where people need healthcare access. These demand locations are spread across the area, and each has a population that may have different healthcare needs. These populations are further divided into subgroups $\mathcal{K}$ based on factors such as age, chronic health conditions, and socio-economic status. The model aims to provide these populations with optimal access to healthcare services through the deployment of TKBs.

The potential locations for placing the TKBs are referred to as candidate locations $\mathcal{J}$. A TKB can only serve demand locations that are within a certain catchment radius $\mathcal{C}$ from the candidate location. The catchment radius defines how far a TKB can effectively serve people in nearby demand locations, which is crucial for maximizing accessibility and reducing travel times. The travel time t_{ij} between each demand location $i \in \mathcal{I}$ and each candidate TKB location $j \in \mathcal{J}$ is a key factor in determining how easily a population can access healthcare.

Each demand location has a population size P_{ki}, and the populations are classified into different subgroups. Each subgroup's healthcare needs are considered through a geographic impedance function $\mathcal{W}_{ck}(t_{ij})$, which models how travel time influences the likelihood of a person's willingness to seek healthcare services at a given TKB location. This function is specific to each subgroup, as different groups may experience different levels of difficulty when accessing healthcare based on factors like mobility or urgency.

The model's objective is to maximize healthcare access for the population. This is quantified by a measure of accessibility, $\mathcal{A}_i$, which is an index calculated for each demand location. The accessibility index considers the number of TKBs deployed, their proximity to demand locations, and the attractiveness S_j of each TKB candidate location. The attractiveness of a location reflects how well-suited it is to serve the population, considering factors such as population density and existing healthcare infrastructure.

In addition to maximizing access, the model also incorporates an equity constraint to ensure that healthcare is distributed fairly across the service area. The goal is to minimize disparities in healthcare access, ensuring that no demand location is significantly disadvantaged compared to others. This is achieved by limiting the inequity tolerance ϵ, which restricts the maximum allowable difference in the accessibility indices across all demand locations.

Decision variables include binary variables y_j and x_{ijc} to determine whether a TKB is deployed at a candidate location and whether a demand location is assigned to a specific TKB within a catchment radius, respectively. The number of TKBs to be deployed is constrained to a specified maximum, n, ensuring that resources are allocated efficiently. Table 6.1 summarizes all the notations.

Table 6.1 Summary of Notations

Sets	
$\mathcal{I}$	set of demand locations
$\mathcal{J}$	set of TKB candidate locations
$\mathcal{K}$	set of subgroups in the population
$\mathcal{C}$	set of catchment radii
$\mathcal{F}_{cj}$	subset of demand locations that are within catchment radius $c \in \mathcal{C}$ from TKB candidate location $j \in \mathcal{J}$
$\mathcal{Q}_{ci}$	subset of TKB candidate locations that are within catchment radius $c \in \mathcal{C}$ to cover demand location $i \in \mathcal{I}$
Parameters	
n	given number of TKBs to deploy in the service area
S_j	supply of TKB candidate location $j \in \mathcal{J}$
t_{ij}	travel time from demand location $i \in \mathcal{I}$ to TKB candidate location $j \in \mathcal{J}$
P_{ki}	population of the subgroup $k \in \mathcal{K}$ residing in demand location $i \in \mathcal{I}$
$\mathcal{W}_{ck}(t_{ij})$	geographic impedance function of travel time t_{ij} for subgroup $k \in \mathcal{K}$ within catchment $c \in \mathcal{C}$
$\mathcal{R}_j$	provider-population ratio of TKB candidate location $j \in \mathcal{J}$
$\mathcal{A}_i$	accessibility index for demand location $i \in \mathcal{I}$
α_c	Value of getting assigned to a TKB within catchment $c \in \mathcal{C}$
ϵ	inequity tolerance
Decision Variables	
y_j	binary variable, 1 if a TKB is deployed at candidate location $j \in \mathcal{J}$, 0 otherwise
x_{ijc}	binary variable, 1 if demand location $i \in \mathcal{I}$ is assigned to a TKB deployed at $j \in \mathcal{J}$ within catchment $c \in \mathcal{C}$, 0 otherwise

The model formulation for Optimal Deployment of TKBs (ODTKB) is then given by:

$$[ODTKB]\ maximize \sum_{c \in \mathcal{C}} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \alpha_c P_{ki} x_{ijc} \mathcal{W}_{ck}(t_{ij}) \tag{6.1}$$

Subject to:

$$\sum_{j \in \mathcal{J}} y_j \leq n \tag{6.2}$$

$$x_{ijc} \leq y_j, \qquad \forall i \in \mathcal{I}, c \in \mathcal{C}, j \in Q_{ci} \tag{6.3}$$

$$\sum_{j \in \mathcal{J} \setminus Q_{ci}} x_{ijc} = 0, \qquad \forall i \in \mathcal{I}, c \in \mathcal{C} \tag{6.4}$$

$$\sum_{c \in \mathcal{C}} \sum_{j \in Q_{ci}} x_{ijc} \leq 1, \qquad \forall i \in \mathcal{I} \tag{6.5}$$

$$\mathcal{A}_i = \sum_{c \in \mathcal{C}} \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{Q}_{ci}} \mathcal{R}_j \, \mathcal{W}_{ck}(t_{ij}) y_j, \qquad \forall i \in \mathcal{I} \tag{6.6}$$

$$GI(\mathcal{A}) \leq \epsilon \tag{6.7}$$

where,

$$\mathcal{R}_j = \frac{S_j}{\sum_{c \in \mathcal{C}} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{F}_{cj}} P_{ki} \, \mathcal{W}_{ck}(t_{ij})} \qquad \forall j \in \mathcal{J} \tag{6.8}$$

and

$$GI(\mathcal{A}) = \frac{\sum_{i \in \mathcal{I}} \sum_{i' \in \mathcal{I}} | \mathcal{A}_i - \mathcal{A}_{i'} |}{2|\mathcal{I}| \sum_{i \in \mathcal{I}} \mathcal{A}_i} \tag{6.9}$$

The objective function (6.1) aims to maximize the weighted healthcare access across all demand locations. It is calculated as the sum of the product of population size P_{ki}, subgroup-specific geographic impedance function $\mathcal{W}_{ck}(t_{ij})$, and the assignment of demand locations x_{ijc} to deployed TKBs. This term is further weighted by α_c, reflecting the importance of assigning demand locations to closer TKBs. That is, the access for each demand location is influenced by the number of TKBs deployed, their proximity, and how well they serve the population in each subgroup. Constraint (6.2) ensures that the total number of TKBs deployed does not exceed the maximum number, n, specified in the problem. Constraints (6.3) ensure that a demand location can only be assigned to a TKB if that TKB is already deployed. In constraints (6.4), a demand location must be assigned to a TKB within its allowed catchment area; if no TKBs are within the catchment, the assignment is not made. Constraints (6.5) ensure that each demand location is assigned to at most one TKB. The objective function incentivizes assignments to the closest possible TKB, aligning with the goal of maximizing access efficiency. Constraints (6.6) define the accessibility index, for each demand location, quantifying healthcare access by considering the deployment of TKBs and their ability to meet healthcare needs. This index is weighted by the population and the effectiveness of TKBs. A critical element in this calculation is the provider-population ratio $\mathcal{R}_j$ at each TKB candidate location $j \in \mathcal{J}$, as defined in equation (6.8). This ratio measures the availability of TKBs relative to a demand location, with demand weighted by population size and the geographic impedance that accounts for willingness to travel to a TKB for healthcare services. A higher ratio indicates better service capacity relative to demand, enhancing healthcare access in nearby demand locations. Therefore, the accessibility index reflects both the capacity of the TKBs and the distance or difficulty of access for each demand location, ensuring that locations with higher population needs and better provider-population ratios are prioritized. Constraint (6.7) then quantifies the inequity in accessibility across all demand locations. This constraint limits the Gini index to a specified tolerance, ϵ, ensuring that access to healthcare is distributed as equitably as possible. Gini Index is given by (6.9) that calculates the relative disparity in accessibility indices across demand locations, with a higher value indicating greater inequity. The Gini index can take a value between 0 and 1; 0 indicates perfect equality, meaning all demand locations have equal access to healthcare, while a Gini index of 1 indicates maximum inequality, meaning that access is highly concentrated in just a few locations, with others having little or no access. By constraining the Gini index, the model ensures that healthcare access is as evenly distributed as possible within the given parameters.

6.2 Numerical Results

This section presents the numerical results of the analysis for the deployment of TKBs, ranging from 1 to 30 units, in the West-Central region case study. The findings provide a detailed examination of the trade-offs and relationships between key metrics—coverage, equity, travel time, and accessibility—highlighting the challenges and opportunities in designing equitable and efficient rural healthcare systems. Results for the Southern region are summarized separately in Appendix A to avoid redundancy, as the policy implications align with those of the West-Central region.

The analysis begins by evaluating the trade-offs between maximizing service coverage and ensuring equitable access. By varying inequity tolerance, measured by the Gini index, the results demonstrate how different allocation strategies affect the total population served and the fairness of resource distribution. The impact of resource sufficiency is also assessed by examining how the number of deployed TKBs influences the maximum expected covered demand, revealing the balance between equity and efficiency as resources increase.

Travel time and accessibility are then analyzed, with results for both average and maximum round-trip travel times to the nearest TKB. These metrics illustrate how stricter equity constraints prioritize underserved populations but may slightly compromise efficiency. The analysis further explores demographic disparities in accessibility, focusing on the unique barriers faced by Seniors, Middle-Aged individuals, Young Adults, and Children, and how these groups benefit from TKB deployment.

Lastly, the geographic placement of TKBs under varying equity constraints is presented, with maps visually demonstrating how resource allocation prioritizes underserved areas as equity constraints tighten. These results emphasize the need to balance equity and efficiency, particularly in resource-limited scenarios, while highlighting the diminishing returns of additional TKB deployments as coverage approaches saturation.

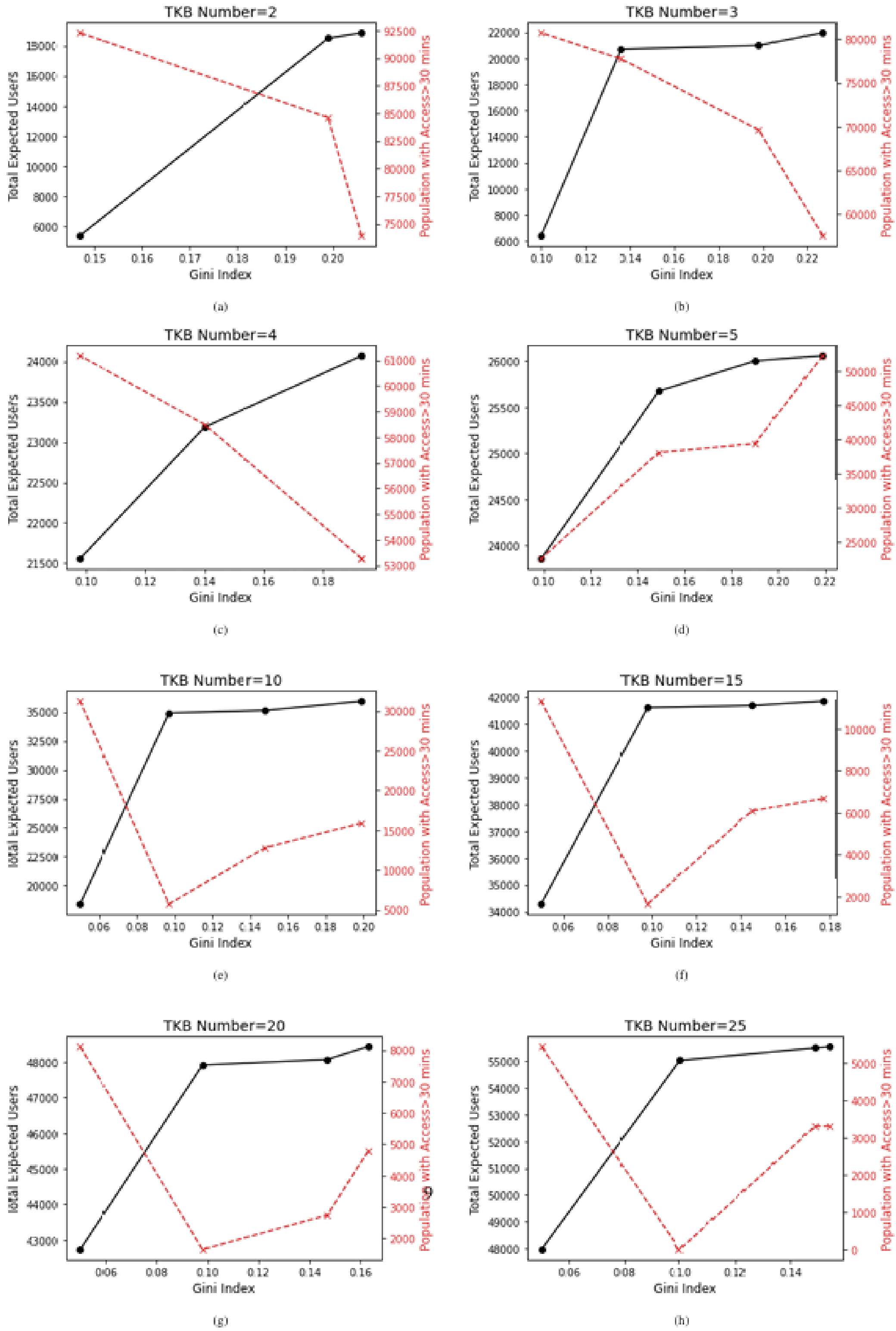


Figure 6.1 Total Expected Users and Population with Long Travel Times. The left axis illustrates the maximum expected covered population for different levels versus various inequity tolerance ϵ. The secondary axis shows the population that experiences travel times longer than 30 minutes to the nearest TKB.

Figure 6.1 illustrates the trade-off between equity, accessibility, and resource allocation efficiency as measured by the total expected users and the Gini index for varying numbers of TKBs. They highlight the intricate balancing act required in designing equitable yet efficient rural healthcare systems. Each panel corresponds to a different number of deployed TKBs, ranging from 2 to 25, and presents two key metrics as the Gini index varies: the total expected users (black solid line) and the population with access greater than 30 minutes to the nearest TKB (red dashed line). These metrics highlight how healthcare accessibility and service coverage evolve as equity shifts. The Gini index, represented on the x-axis, measures inequality, with lower values indicating more equitable access to healthcare. The total expected users (black line) reflect the total population served by the deployed TKBs, accounting for travel willingness. Meanwhile, the population with access > 30 minutes (red dashed line) represents the segment of the population that faces significant travel barriers, serving as a proxy for inequity in access. As the Gini index increases, reflecting a greater tolerance for inequity in the distribution of resources, the total expected users tend to rise. This trend indicates that relaxing equity constraints often allows resources to be concentrated in areas with higher demand, thereby maximizing usage efficiency. Conversely, when inequity tolerance is low, resources are distributed more evenly to reduce disparities. However, this egalitarian approach can lead to an overall reduction in service coverage, as observed in the graphs. For cases where resources are extremely limited (TKB ≤ 4), enforcing strict equity considerations appears to have unintended consequences. Figures (a) through (c) illustrate that the population experiencing access times longer than 30 minutes (red dashed lines) is higher under lower Gini index values. This result underscores that in resource-scarce scenarios, prioritizing equity too rigorously can detract from overall accessibility and efficiency. For instance, scarce resources spread thinly to achieve equity may leave many users with suboptimal access, illustrating a potential inefficiency in the system.

The situation improves with a moderate increase in resources (TKB $\geq$ 5 in Figures (d) through (h)). In these cases, while the population with longer access times still increases as inequity tolerance grows, the trade-offs are more manageable. The general trend suggests that allowing some flexibility in equity constraints enables a better balance between access and efficiency. Notably, when the Gini index is set too low, even with a sufficient number of TKBs, accessibility suffers. For instance, a Gini index of 0.05 or lower may result in increased population segments facing long access times, highlighting the risks of overly stringent equity considerations. An important turning point is evident with TKB = 25, where sufficient resources are available to achieve both equity and efficiency goals effectively. At this level, when the inequity tolerance ϵ is set to 0.1, the population with access times longer than 30 minutes drops to zero. This result demonstrates the potential for synergistic outcomes when resource availability aligns with carefully calibrated equity constraints. These findings emphasize the need for nuanced policy design. In resource-limited scenarios, imposing rigid equity constraints may unintentionally harm overall accessibility, leaving vulnerable populations underserved. Conversely, in resource-rich environments, equity considerations can be more stringently enforced without compromising efficiency. Policymakers should therefore adopt a context-sensitive approach, adjusting equity thresholds dynamically based on resource availability and population needs. Moreover, these results highlight the importance of understanding the interplay between equity and efficiency in resource allocation. While equity is a vital goal in healthcare delivery, it must be balanced against practical considerations of coverage and accessibility. This analysis provides a framework for designing resource allocation policies that are both equitable and effective, paving the way for more resilient and inclusive healthcare systems.

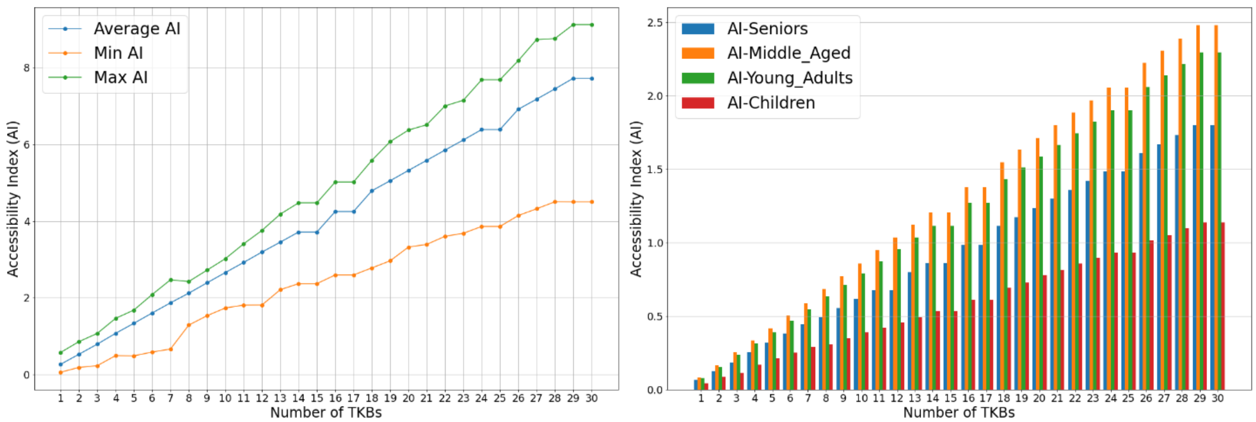


Figure 6.2 Analysis of the Accessibility Index (AI) for TKB Deployment: The left panel presents the overall AI trend, showing the minimum, maximum, and average accessibility indices as the number of deployed TKBs increases. The right panel illustrates the distribution of AI across different age groups (Seniors, Middle-Aged, Young Adults, and Children) for various numbers of deployed TKBs, highlighting the varying accessibility levels for each demographic.

Figure 6.2 illustrates the relationship between the number of TKBs and the Accessibility Index (AI). In the left panel, the Average AI represents the overall level of accessibility achieved across the population, while the Max AI reflects the highest levels of access attained in the best-served regions. The Min AI, in contrast, tracks accessibility in the least-served areas, shedding light on disparities and the degree to which underserved populations benefit from additional TKBs. Together, these metrics reveal the trade-offs between equity and efficiency in resource allocation. The right panel provides a demographic breakdown, capturing how different age groups experience changes in accessibility as the number of TKBs increases. The Accessibility Index for each group measures the extent to which members of that demographic can benefit from the deployed resources. The comparison across age groups reveals the relative prioritization and unique challenges faced by each demographic segment in accessing telehealth services.

From the left plot in Figure 6.2, the Max AI (green line) shows a sharp increase early on, followed by a plateau after approximately 25 TKBs, suggests diminishing returns in areas that are already well-covered. Adding more TKBs beyond this point does not significantly improve accessibility for the most served regions, emphasizing the need to focus on underserved areas instead of continuing to saturate already accessible regions. The Min AI (orange line) starts at zero when TKBs are scarce. Although it rises as more TKBs are deployed, its growth is slower compared to the Max AI. This disparity highlights persistent inequities, as underserved regions take longer to see meaningful benefits even when resources are added. The Average AI (blue line) steadily increases across all scenarios, indicating that the general population consistently benefits from additional TKBs. However, the widening gap between the Min AI and Max AI demonstrates trade-offs between equity and efficiency. While overall accessibility improves, underserved regions may still lag significantly behind, emphasizing the need for a balance between maximizing total accessibility and reducing disparities.

From the right plot in Figure 6.2, we can observe that Children (red) consistently exhibit the lowest AI, likely due to reliance on caregivers and unique barriers, while Seniors (blue) also face slower improvements, potentially due to mobility challenges or difficulties adopting telehealth technologies. In contrast, Middle-Aged individuals (yellow) and Young Adults (green) benefit the most, reflecting fewer barriers and prioritization in resource allocation.

Although all groups experience improvements as the number of TKBs increases, diminishing returns are evident beyond 25 TKBs, indicating that simply adding more resources is insufficient to address persistent inequities. These findings suggest that the Gini index constraint could consider both demographic and geographic locations as subgroups in the future research rather than focusing solely on geographic location, enabling a more nuanced approach to equitable access in telehealth systems.

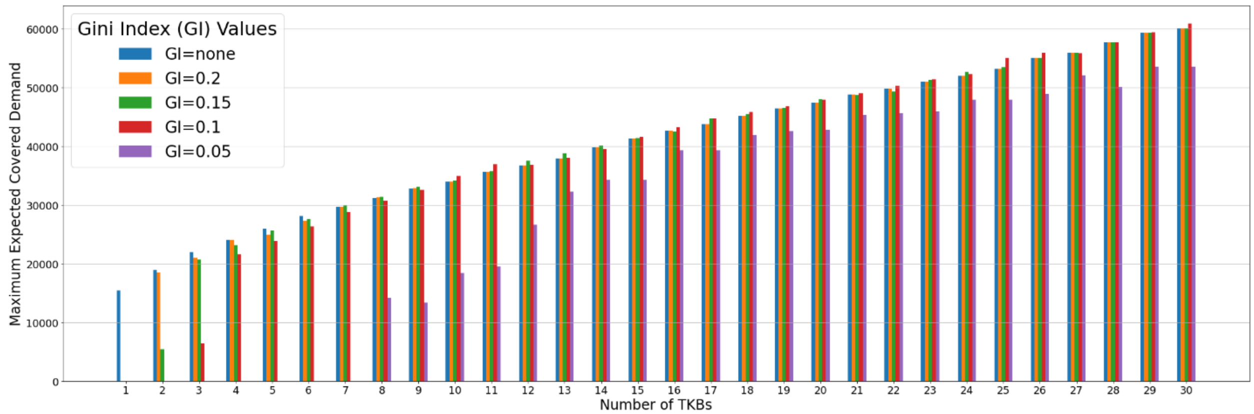


Figure 6.3 Maximum expected covered demand versus the number of deployed TKBs, with varying Gini index values indicating different levels of equity in healthcare access distribution.

Figure 6.3 demonstrates the maximum expected total users served as the number of TKBs increases under different levels of inequity tolerance, represented by the Gini Index (GI). The Gini Index values indicate varying degrees of tolerance for inequity, with lower values (e.g., GI = 0.05) reflecting stricter equity constraints and higher values (e.g., GI = 0.2 or "none") representing more relaxed equity considerations. The main observation is that the total number of users served increases consistently as the number of TKBs grows. This trend holds true for all levels of inequity tolerance, demonstrating that deploying additional TKBs improves service coverage across the board as expected. When no equity constraint is applied (GI = none, blue bars), the maximum expected covered demand is consistently the highest across all TKB scenarios. This indicates that prioritizing efficiency without considering equity results in the greatest overall service coverage. However, as the Gini Index constraint becomes stricter (e.g., GI = 0.05, purple bars), the maximum expected covered demand decreases. This suggests that enforcing stricter equity constraints sacrifices some efficiency in favor of a more equitable distribution of resources. For lower numbers of TKBs (e.g., TKBs ≤ 10), the difference in total users served between relaxed (GI = none) and strict (GI = 0.05) constraints is more pronounced. This reflects that in resource-scarce scenarios, imposing strict equity constraints can significantly limit overall efficiency. As the number of TKBs increases, the differences between Gini Index levels become less pronounced. For instance, at around 25–30 TKBs, the total covered demand converges for all Gini Index values. This suggests that with sufficient resources, it becomes possible to achieve both equity and efficiency goals. When resources are limited, relaxing equity constraints may allow for maximizing total service coverage but at the cost of inequitable access. Stricter equity constraints are more impactful in resource-scarce environments, where balancing fairness and efficiency becomes challenging. With higher numbers of TKBs, the diminishing marginal returns in efficiency highlight the potential to prioritize equitable distribution without significantly sacrificing total coverage.

Figure 6.4 shows the relationship between the number of TKBs and round-trip travel times to the nearest TKB under different levels of inequity tolerance, represented by Gini Index (GI) values. The left panel displays the average round-trip travel time in the line plot capturing how the average round-trip travel time decreases as more TKBs are deployed. Each line represents a different GI value, ranging from no equity constraint (GI=none) to increasingly stricter equity constraints (GI=0.05). The right panel displays the maximum round-trip travel time in a grouped bar plot for the worst-case locations (those farthest from a TKB) under different GI values. The bars for each TKB configuration are grouped by GI levels, illustrating the impact of inequity tolerance on accessibility for the most underserved regions.

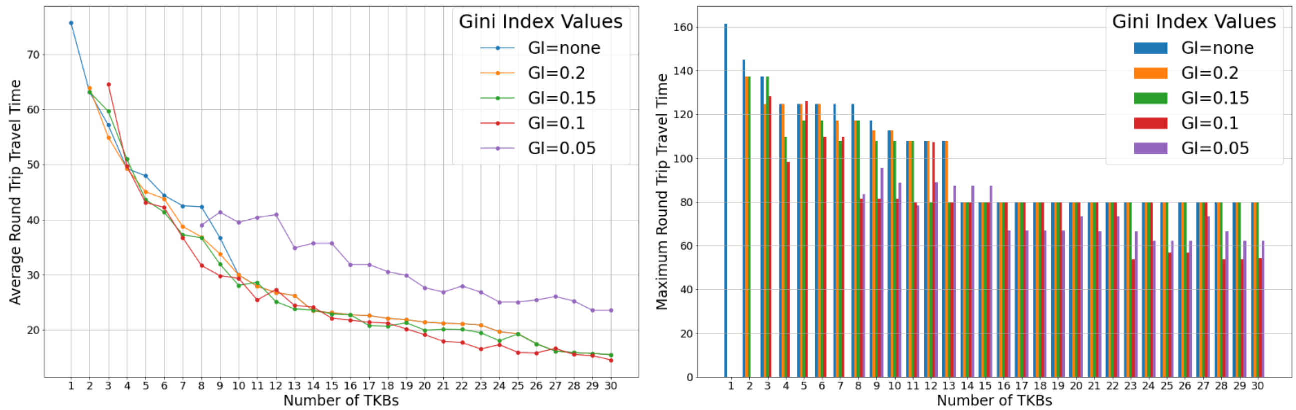


Figure 6.4 Impact of the Number of Telehealth Kiosks/Booths (TKBs) and Gini Index (GI) Constraints on Average and Maximum Round-Trip Travel Times: The left panel shows how average travel times decrease with increasing TKBs, with stricter GI constraints slightly increasing travel times due to prioritization of equity. The right panel illustrates the maximum travel times for the farthest locations, highlighting the trade-off between equity (stricter GI constraints) and efficiency (lower travel times) and the diminishing returns as TKB numbers increase.

From the left plot in Figure 6.4, it is observed that the average round-trip travel time decreases consistently as the number of TKBs increases, regardless of the GI value. This trend indicates that adding more TKBs improves overall accessibility for the population, as expected. Stricter GI constraints (e.g., GI=0.05, purple line) result in slightly higher average travel times compared to more relaxed constraints (e.g., GI=none, blue line). This suggests that enforcing equity may slightly compromise efficiency by spreading resources to prioritize underserved areas rather than optimizing for overall demand. As the number of TKBs approaches 25–30, the average travel times for all GI levels converge, indicating that with sufficient resources, the differences caused by inequity constraints diminish.

From the right plot in Figure 6.4, it is observed that stricter GI levels (e.g., GI=0.05, purple bars) consistently result in higher maximum round-trip travel times compared to more relaxed constraints. This reflects that enforcing equity spreads TKBs to prioritize underserved areas, which may leave certain regions farther from their nearest TKB. Furthermore, the maximum travel time decreases significantly as more TKBs are deployed, regardless of GI levels. However, the rate of improvement is slower for stricter GI constraints, as equitable distribution sacrifices some efficiency in reducing maximum travel times. Similarly, beyond 20–25 TKBs, the reduction in maximum travel time becomes less pronounced, indicating diminishing returns in adding more TKBs. This trend highlights that improving the placement strategy may be more effective than simply increasing the number of TKBs.

This analysis highlights several key implications for the deployment of TKBs under varying levels of inequity tolerance. Stricter Gini Index (GI) constraints prioritize equity by focusing on underserved areas, but this comes at the cost of slightly higher average and maximum travel times. However, with sufficient resources—around 25 to 30 TKBs—the trade-offs between equity and efficiency diminish, making it possible to achieve both goals simultaneously.

In resource-limited scenarios, the strategic deployment of TKBs becomes critical. Optimizing their placement can balance equity and efficiency, ensuring underserved regions are prioritized without significantly increasing travel times for others. Stricter GI constraints also lead to higher maximum travel times, highlighting the need for innovative solutions such as mobile TKBs or targeted support to reduce travel burdens for the farthest locations.

Finally, the diminishing returns observed beyond 25 TKBs suggest that simply increasing the number of kiosks is not always the most effective approach. Instead, smarter placement strategies and addressing specific barriers faced by remote regions will yield greater benefits in improving healthcare access.

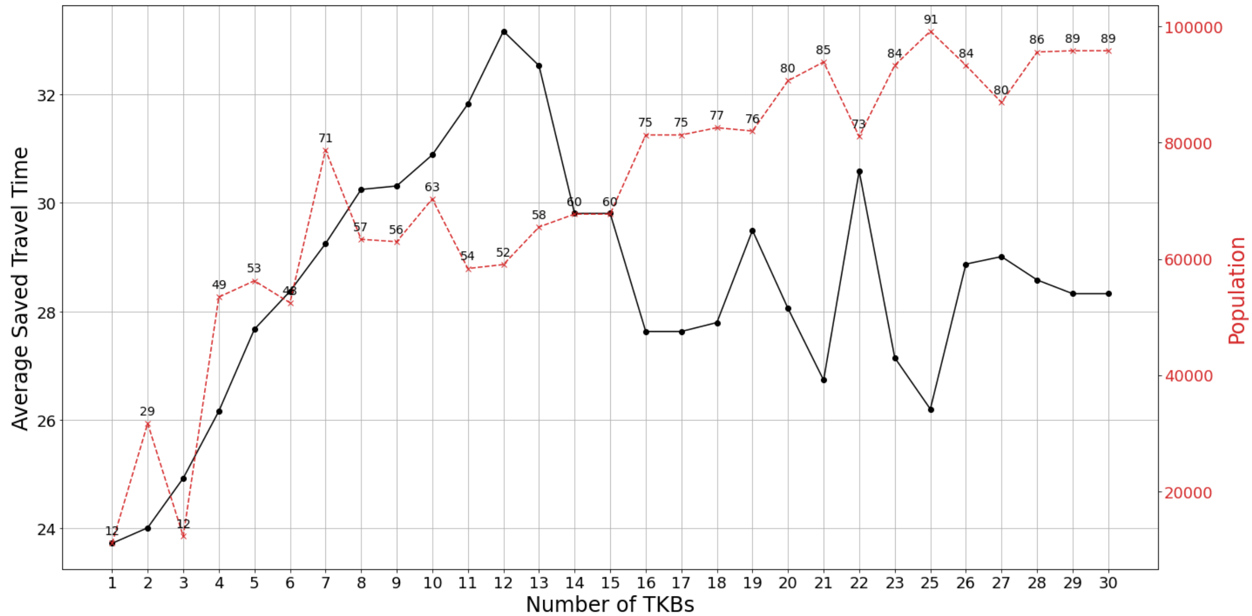
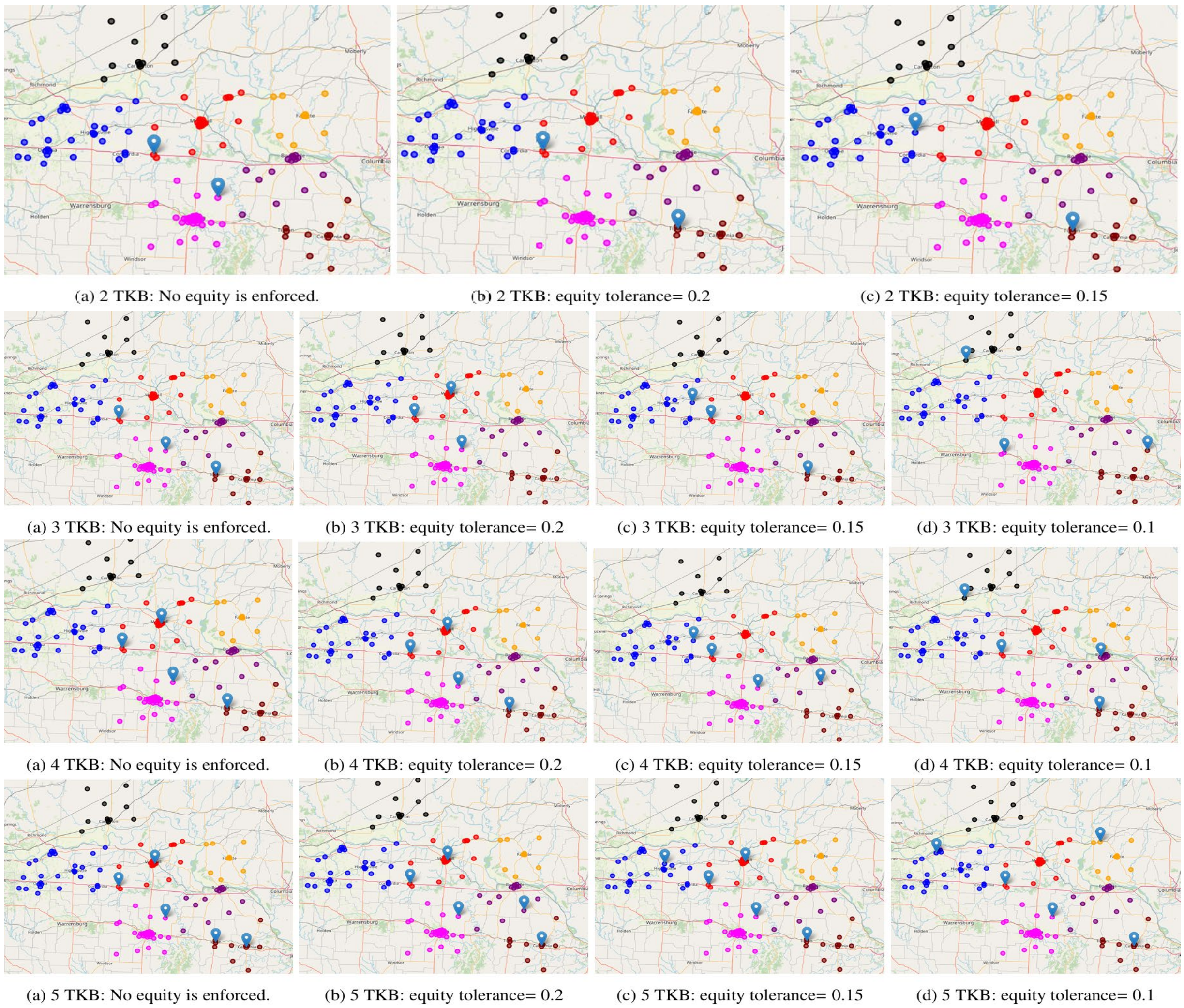


Figure 6.5 Average saved travel time (left axis) and total population benefiting from closer proximity to Telehealth Kiosks/Booths (TKBs) than the nearest hospital (right axis) under the most equitable deployment strategy for 1–30 TKBs. Numbers on the red line indicate the number of block groups benefiting from closer access.

Figure 6.5 displays the impact of deploying TKBs equitably across 1 to 30 deployment scenarios. It shows two key metrics; the black line, measured on the left vertical axis, represents the average travel time saved for individuals whose nearest TKB is closer than the nearest hospital. This metric reflects how much travel time is reduced, on average, for these individuals. The red dashed line, measured on the right vertical axis, represents the total population living in areas where TKBs are closer than hospitals. The numbers displayed along this red line indicate the number of block groups benefiting in each deployment scenario. A block group is a small geographic area, and the metric demonstrates how many such areas have improved access as more TKBs are deployed. It is observed that the average travel time saved generally falls within the range of 20 to 32 minutes, indicating a significant reduction in travel distance for individuals accessing healthcare services at TKBs. Early deployments (e.g., 1- 12 TKBs) lead to rapid improvements in travel time saved, rising from approximately 24 minutes with one TKB to over 33 minutes with 12 TKBs. This suggests that initial deployments are highly effective in reducing travel times for those who previously faced long distances to the nearest hospital. After 12 TKBs, the average travel time saved begins to fluctuate, reflecting the challenges of equitably deploying kiosks to cover underserved areas while maintaining efficiency. These fluctuations suggest that equitable placement may prioritize populations with varying needs, leading to uneven but targeted reductions in travel time. From TKB 20 onward, the average travel time saved stabilizes at around 25–28 minutes, highlighting diminishing returns in travel time improvements as the system approaches saturation in coverage. Observing the trend in the red dashed line, it is shown that the total population benefiting from the closest TKB access increases steadily with the deployment of additional kiosks, reaching approximately 90,000 by TKB 25 and stabilizing thereafter. This indicates that most of the population that can benefit from equitable TKB deployment has been reached by this point. The number of block groups benefiting follows a similar trend, rising sharply from 12 block groups with one TKB to 71 block groups by seven TKBs. Beyond this point, the increase slows, with the number of block groups plateauing at approximately 85–89 by 25-30 TKBs. This stabilization reflects that the deployment has effectively addressed previously underserved areas.

These findings suggest that the largest gains in both average travel time saved and population coverage occur in the first 10–15 TKBs. These initial deployments target the most underserved areas, yielding substantial improvements in access. Beyond 20 TKBs, the benefits of additional deployments diminish. The average travel time saved stabilizes, and the population benefiting from closer TKBs grows only marginally. This suggests that most block groups have already been reached, and further deployments have limited incremental impact. The fluctuations in saved travel time after 10 TKBs suggest that equitable placement prioritizes populations with varying needs. While this ensures underserved areas are reached, it may result in less consistent efficiency improvements. In this case, policymakers should consider the diminishing returns when expanding the network beyond 20–25 TKBs. At this stage, additional investments may be better directed toward improving service quality or addressing barriers to healthcare access within already-covered areas.

Finally, Figure 6.6 presents the geographic placement of TKBs for different deployment scenarios (2, 3, 4, and 5 TKBs) under varying levels of equity constraints, from "No equity enforced" to an equity tolerance of 0.1 (the strictest lower tolerance values of 0.05 results in infeasibility for seven or less TKBs). "No equity is enforced" focuses solely on maximizing efficiency, placing TKBs in areas with the highest demand or shortest travel distances without considering equity. Increasingly stricter equity tolerances (e.g., 0.2, 0.15, and 0.1) introduce constraints to ensure that underserved areas receive higher priority, often redistributing TKBs to achieve a more balanced geographic coverage. Each row in Figure 6.6 corresponds to a different number of TKBs (2 through 5), showing the evolution of geographic allocation as more resources are deployed. Each column represents a specific equity tolerance level, illustrating how stricter equity constraints affect the placement of TKBs. Points on the map represent different block groups. Points with the same color belong to the same block group. The TKBs (markers) are positioned to meet deployment and equity goals.



(a) 2 TKB: No equity is enforced. (b) 2 TKB: equity tolerance= 0.2 (c) 2 TKB: equity tolerance= 0.15

(a) 3 TKB: No equity is enforced. (b) 3 TKB: equity tolerance= 0.2 (c) 3 TKB: equity tolerance= 0.15 (d) 3 TKB: equity tolerance= 0.1

(a) 4 TKB: No equity is enforced. (b) 4 TKB: equity tolerance= 0.2 (c) 4 TKB: equity tolerance= 0.15 (d) 4 TKB: equity tolerance= 0.1

(a) 5 TKB: No equity is enforced. (b) 5 TKB: equity tolerance= 0.2 (c) 5 TKB: equity tolerance= 0.15 (d) 5 TKB: equity tolerance= 0.1

Figure 6.6 Geographic distribution of TKBs under varying equity levels (no equity enforced to strict equity tolerance of 0.1) for deployments of 2, 3, 4, and 5 TKBs. The maps highlight the impact of equity constraints on the spatial allocation of TKBs, prioritizing underserved areas as equity tolerance becomes stricter.

When equity is not considered, TKBs are concentrated in regions with the highest demand or efficiency (e.g., densely populated areas). As equity constraints tighten, TKB placement shifts to prioritize underserved areas. For example, with an equity tolerance set to 0.1, TKBs are more evenly distributed across the region, prioritizing access for underserved populations that might otherwise be overlooked if the sole objective were to maximize total coverage. It is observed that strict equity constraints (e.g., 0.1) ensure underserved areas receive access but may leave some high-demand areas underserved, potentially limiting system efficiency. Relaxed equity constraints (e.g., 0.2 or none) maximize efficiency but exacerbate disparities, leaving remote populations at a disadvantage. The maps underscore the importance of balancing equity and efficiency in healthcare planning. For limited resources, striking a balance between equity and efficiency is crucial, as overly strict equity constraints can reduce system-wide benefits. With more TKBs, stricter equity constraints can be enforced without significantly sacrificing efficiency.

6.3 Managerial Insights and Conclusion

This chapter provides a decision-aid tool for policy makers to design an equitable and efficient rural TKB network. The findings of this chapter provide actionable insights for policymakers, healthcare administrators, and planners involved in deploying TKBs in underserved regions. The results emphasize the importance of balancing equity and efficiency, tailoring deployment strategies to resource availability, and considering the unique needs of different populations. The key takeaways and conclusions are categorized below:

6.3.1 Trade-offs Between Equity and Efficiency

Relaxing equity constraints allows for resource concentration in high-demand areas, maximizing the total population served. However, strict equity constraints distribute resources more evenly, prioritizing underserved areas at the cost of efficiency. In resource-limited scenarios, however, overly strict equity constraints can reduce overall service coverage, as resources are spread thinly across regions. A moderate approach to equity constraints ensures that underserved populations receive access while minimizing efficiency losses. Policymakers should dynamically adjust equity thresholds based on the availability of resources and the specific characteristics of the target population.

6.3.2 Resource Sufficiency and Diminishing Returns

As the number of deployed TKBs increases, the trade-offs between equity and efficiency diminish, with accessibility improving across all demographics. However, diminishing returns become evident after enough TKBs (e.g., 25 TKB in West-Central case study) are deployed, with marginal gains in coverage and accessibility. For resource-rich scenarios, stricter equity constraints can be applied without significantly compromising efficiency, enabling equitable access across underserved areas. Further investments in additional kiosks yield limited benefits. Instead, resources could be redirected toward improving service quality or addressing specific barriers in already-served regions.

6.3.3 Accessibility and Travel Time

The deployment of additional TKBs consistently reduces average and maximum round-trip travel times, enhancing accessibility. However, stricter equity constraints result in slightly higher travel times as resources are distributed to underserved areas. Equitable placement of TKBs can address long-standing accessibility gaps for remote populations, but careful planning is needed to avoid increasing travel burdens for others. Strategies such as mobile TKBs or supplementary services can mitigate the impact of stricter equity constraints, ensuring accessibility for the farthest locations.

6.3.4 Demographic Disparities in Accessibility

Children and Seniors consistently experience the lowest Accessibility Index (AI) compared to Middle-Aged individuals and Young Adults, reflecting unique barriers such as reliance on caregivers and mobility challenges. Tailored interventions are required to address the specific needs of vulnerable groups, such as family-centered healthcare for children and technology training or transportation support for Seniors. Future equity metrics could incorporate demographic subgroups alongside geographic considerations to create more inclusive resource allocation frameworks.

6.3.5 Geographic Allocation of TKBs

Stricter equity constraints lead to a more balanced geographic distribution of TKBs, prioritizing underserved areas. However, this may leave high-demand regions underserved when resources are scarce. Geographic equity constraints should be carefully calibrated to ensure that underserved areas receive access without neglecting regions with high service demand. Resource allocation policies should incorporate both geographic and demographic considerations to optimize outcomes.

In summary, this chapter provides a comprehensive optimization framework for designing equitable and efficient TKB deployment strategies in rural healthcare systems. The findings highlight the importance of balancing equity and efficiency, dynamically adjusting resource allocation policies based on resource availability, and tailoring solutions to the needs of specific populations. By incorporating equity thresholds, accessibility goals, and demographic insights, policymakers can ensure that telehealth systems maximize their impact while addressing longstanding disparities in healthcare access.

Ultimately, this study underscores the need for context-sensitive strategies that align resource allocation with the dual goals of equity and efficiency. These insights can serve as a foundation for developing resilient and inclusive healthcare systems that meet the needs of diverse populations, paving the way for improved access to care in underserved regions.

Future research can explore alternative objective functions to examine how competing goals of equity and efficiency could be balanced and further refine deployment strategies for TKBs. For instance, objectives such as minimizing total travel times or minimizing total inequity could be considered. Furthermore, alternative ways of quantifying inequity beyond the Gini index—such as range, variance, or coefficient of variation—could be incorporated. Researchers could also explore the impact of setting equity or access-based goals as constraints while optimizing other measures of efficiency, such as minimizing average travel times. This direction would offer deeper insights into how different objective functions and equity definitions influence deployment outcomes.

Additionally, future work could incorporate more intricate dynamics of existing healthcare facilities and their interactions with TKBs. For example, integrating detailed demand patterns and facility-specific constraints, such as capacity limits or existing geographic service coverage, could yield more robust decision-making tools. Such models could examine how TKBs complement or compete with traditional facilities, particularly in regions where healthcare systems are already strained. This would enable a more granular understanding of how TKBs can alleviate pressure on existing systems while ensuring equitable access.

Moreover, expanding the scope of analysis to include temporal dynamics, such as peak usage periods or seasonal demand variations, could provide actionable insights into optimizing TKB deployments over time. Incorporating uncertainties, such as fluctuating demand or operational disruptions (e.g., weather conditions or staffing shortages), could further enhance the applicability of these decision-support tools.

Finally, future research could investigate the integration of emerging technologies, such as mobile TKBs, drones for last-mile delivery, or advanced data analytics to dynamically monitor and adjust deployment plans. These advancements could provide more adaptive, resilient, and scalable solutions to address disparities in healthcare access. By broadening the focus to include these additional factors, researchers can develop more comprehensive frameworks that better align with the complexities of real-world healthcare systems.

Chapter 7 Summary and Conclusion

This chapter synthesizes the key findings and insights from the preceding analyses, emphasizing the strategic deployment of Telehealth Kiosks/Booths (TKBs) to enhance healthcare access and equity in rural regions. The research integrates empirical data, advanced modeling techniques, and practical applications to address the unique challenges of healthcare delivery in underserved areas.

7.1 Key Findings and Contributions

This study makes several important contributions to the understanding and optimization of Telehealth Kiosk/Booth (TKB) deployment to improve healthcare access in rural areas. The findings bridge gaps between empirical evidence, advanced modeling, and practical applications, offering actionable insights for policymakers and healthcare administrators. Below are the primary findings and contributions from the analysis:

1. The study highlights significant disparities in healthcare accessibility in rural areas, where long travel times and sparse facilities limit access. TKBs show promise as a solution to reduce these disparities, especially for underserved populations, by offering localized and convenient healthcare options.
2. This study has empirically derived travel time decay functions to provide a realistic basis for understanding patients' willingness to travel for healthcare services. These functions account for demographic and geographic differences, enabling more accurate and targeted placement of TKBs.
3. The continuous approximation modeling approach implemented in this research highlights the critical influence of travel time decay in shaping system performance and demonstrates that simplified, well-calibrated travel behavior models can effectively

inform TKB deployment strategies. Case studies reveal that a network of TKBs can significantly reduce travel times and serve large portions of the rural population, with effectiveness depending on local factors such as user density, existing healthcare facilities, and patient willingness to adopt TKBs. These findings emphasize the transformative potential of TKBs in addressing rural healthcare access challenges, particularly in regions with limited healthcare options.

4. The proposed discrete optimization model and the analysis underscore the trade-offs between equity and efficiency, showing that strict equity constraints ensure underserved populations are prioritized, albeit at the cost of system-wide efficiency. Conversely, relaxed constraints maximize overall coverage but risk neglecting vulnerable regions. The results also highlight diminishing returns beyond a certain number of TKBs, suggesting that additional resources are better allocated toward improving service quality or addressing barriers in already-served areas. Equitable placement strategies, when complemented with targeted solutions like mobile TKBs, can effectively balance accessibility and efficiency across demographic and geographic disparities.
5. Data-driven analysis suggests that strict equity constraints prioritize underserved areas but may reduce system-wide efficiency. Relaxed equity constraints maximize total population coverage but can exacerbate disparities, underscoring the need for balanced approaches.

7.2 Practical Implications for Policymakers

The findings of this study offer actionable guidance for policymakers and healthcare administrators seeking to enhance access and equity in rural healthcare systems through the strategic deployment of Telehealth Kiosks/Booths (TKBs). These implications emphasize the importance of targeted resource allocation, flexibility in deployment strategies, and evidence-based decision-making to ensure the effective and equitable delivery of healthcare services.

7.2.1 Strategic Deployment

Policymakers should prioritize the placement of TKBs in areas with the greatest need, particularly in regions where long travel times to existing healthcare facilities serve as a significant barrier. Identifying high-priority areas requires a thorough understanding of local demographic and geographic characteristics, including the distribution of underserved populations, existing healthcare infrastructure, and travel patterns. By focusing on regions with high travel burdens, TKB deployment can have the greatest immediate impact, addressing disparities in access and improving healthcare equity.

7.2.2 Dynamic Equity Targets

Equity considerations must be tailored to the specific context and resource availability of each deployment scenario. Policymakers should adopt dynamic equity thresholds that balance the need to prioritize underserved populations with the goal of maintaining overall system accessibility and efficiency. In resource-limited scenarios, overly strict equity constraints may spread resources too thinly, reducing overall coverage. Conversely, in resource-rich environments, stricter equity targets can be enforced without significantly compromising efficiency, ensuring that vulnerable populations are adequately served. This flexible approach allows for the optimization of healthcare delivery in diverse rural settings.

7.2.3 Scalable and Flexible Solutions

Investments in scalable and flexible solutions, such as mobile or modular TKBs, can address dynamic population needs and evolving healthcare demands. Mobile TKBs can serve as a bridge for regions with temporary or seasonal population shifts, ensuring continuous access to care. Similarly, modular TKBs can be deployed in phases, allowing for incremental scaling based on changes in population density, demand, or healthcare priorities. These adaptable solutions provide policymakers with tools to respond effectively to shifting needs and optimize resource allocation.

7.2.4 Data-Driven Decision-Making

Leveraging empirical data and advanced modeling techniques is critical to designing effective TKB deployment strategies. Data-driven approaches ensure that decisions are informed by realistic assessments of healthcare demand, patient behavior, and accessibility barriers. The use of travel time decay models, equity metrics, and optimization algorithms provides a robust foundation for evaluating the trade-offs between equity and efficiency. By incorporating real-world insights and predictive analytics, policymakers can make informed choices that maximize the impact of TKB deployments while addressing systemic disparities.

7.3 Future Research Directions

This study provides a robust foundation for optimizing the deployment of Telehealth Kiosks/Booths (TKBs) in rural areas, but it also highlights several avenues for future exploration to further enhance the effectiveness and equity of healthcare delivery systems. Advancing this research will require innovative approaches that integrate emerging technologies, examine long-term impacts, and refine metrics for equity and resource allocation.

7.3.1 Integration of Emerging Technologies

The integration of cutting-edge technologies such as Artificial Intelligence (AI) and drones with TKB systems presents significant opportunities to transform healthcare delivery. AI can enhance service delivery by optimizing real-time resource allocation, personalizing patient care, and predicting healthcare needs based on demographic and geographic data. For instance, AI-driven analytics can help identify regions most in need of TKBs or suggest adaptive deployment strategies in response to shifting demand.

Drones, on the other hand, can complement TKBs by addressing logistical challenges in rural areas. They can be used for delivering medical supplies, such as medications, vaccines, or diagnostic samples, to remote locations where access is limited. The integration of TKBs and drones offers a promising avenue for creating resilient and adaptive healthcare systems capable of responding to emergencies, seasonal healthcare demands, and chronic care needs.

7.3.2 Longitudinal Studies

While this study focuses on the immediate and short-term impacts of TKB deployment, longitudinal studies are essential for assessing the sustained effects on healthcare access and equity over time. These studies could explore how the adoption of TKBs evolves as populations become more familiar with their use, and as healthcare needs and demographic profiles change. Long-term data would also provide insights into the durability and adaptability of TKB systems in addressing healthcare disparities and the extent to which they mitigate barriers like travel time and resource scarcity. Moreover, longitudinal research could evaluate the broader socio-economic impacts of TKB deployments, such as improved health outcomes, increased patient satisfaction, and potential cost savings for healthcare systems. These studies would provide valuable evidence for scaling TKB networks and integrating them more deeply into healthcare infrastructure.

7.3.3 Exploration of Alternative Equity Measures

The study primarily uses the Gini index to evaluate equity in healthcare access, but future research could explore alternative measures and their implications for resource allocation. Metrics such as range, variance, or coefficient of variation could provide different perspectives on disparities and may be better suited to certain contexts. Additionally, equity measures that incorporate demographic factors, such as age, income, or health status, could enable more nuanced and inclusive resource allocation frameworks. Investigating the use of multi-criteria equity metrics that balance geographic and demographic disparities could offer policymakers more comprehensive tools for designing equitable healthcare systems. For instance, combining geographic access metrics with demographic vulnerability indices could help prioritize areas with the highest healthcare needs, ensuring that resource allocation strategies are both equitable and efficient.

7.3.4 Impact of Evolving Healthcare Models

Future research could also examine the role of TKBs within evolving healthcare delivery models, such as omnichannel systems that integrate virtual care, mobile units, and traditional healthcare facilities. Understanding how TKBs fit into these broader systems and how they interact with other healthcare channels could inform strategies for creating cohesive and efficient networks that maximize patient access and satisfaction.

7.4 Concluding Remarks

This report demonstrates the transformative potential of Telehealth Kiosks/Booths (TKBs) in addressing healthcare disparities in rural areas. By strategically balancing equity and efficiency, TKB deployments can significantly enhance access for underserved populations while optimizing resource allocation. The integration of advanced modeling techniques and empirical data provides actionable insights for policymakers, emphasizing the importance of tailoring deployment strategies to local needs and leveraging innovative solutions like mobile units and emerging technologies.

Looking ahead, the findings serve as a foundation for advancing healthcare delivery systems that are equitable, efficient, and adaptable. By building on these insights, future research and policy efforts can ensure that TKB networks continue to evolve to meet the diverse healthcare needs of rural populations. With strategic investments and collaboration among stakeholders, TKBs can play a central role in creating more inclusive and resilient healthcare systems.

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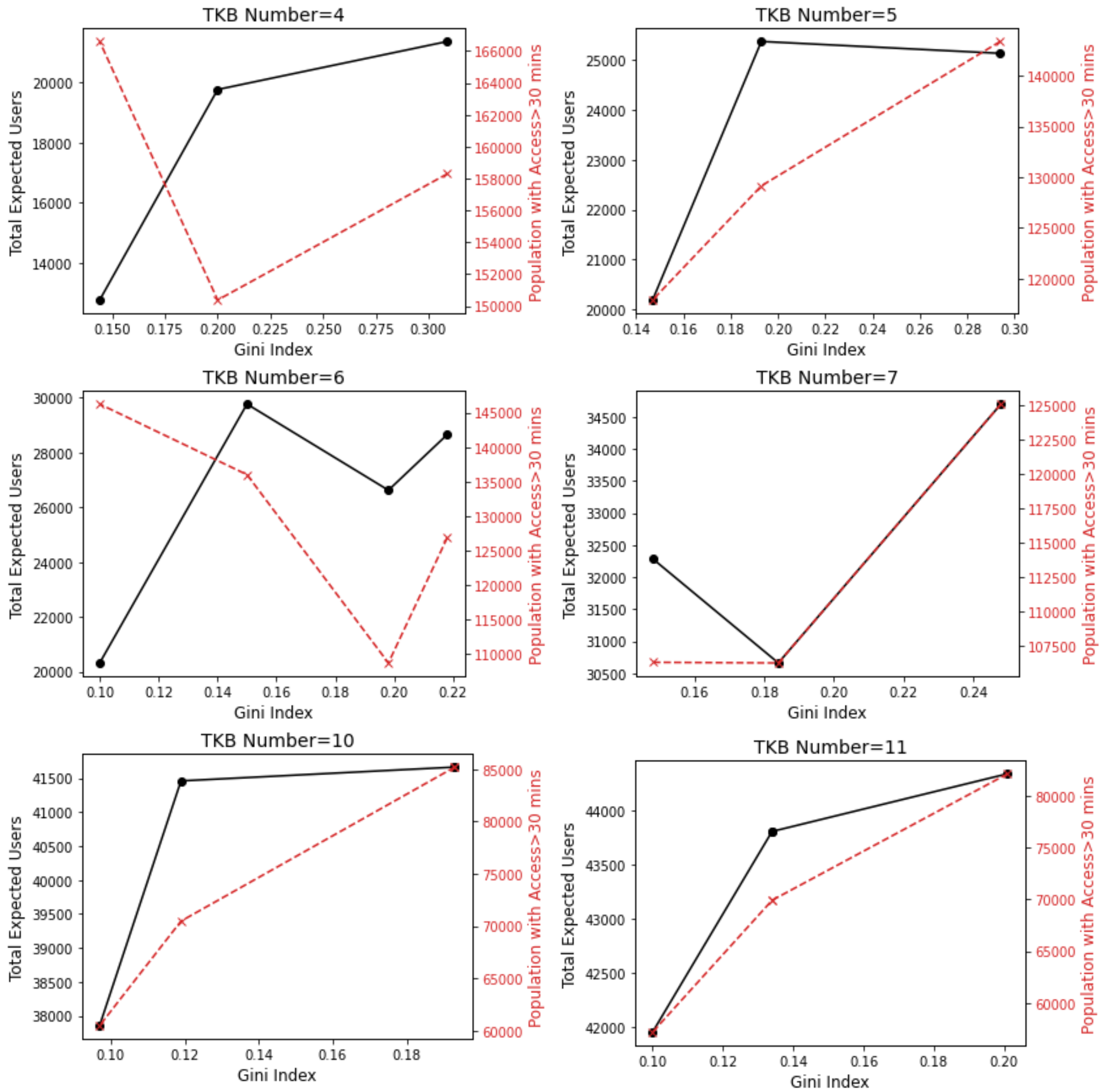

Figure A.1 Total Expected Users and Population with Long Travel Times in Southern region. The left axis illustrates the maximum expected covered population for different levels versus various inequity tolerance ϵ. The secondary axis shows the population that experiences travel times longer than 30 minutes to the nearest TKB.

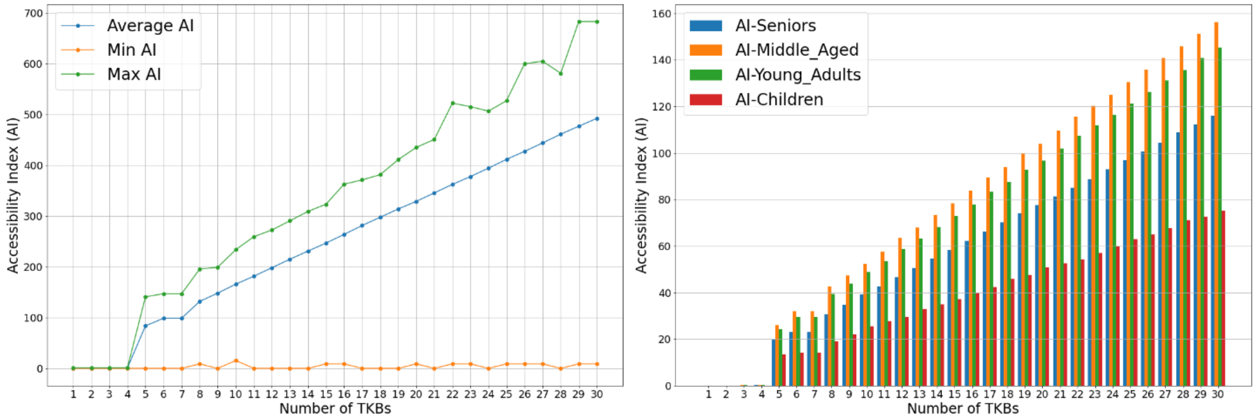

Figure A.2 Analysis of the Accessibility Index (AI) for TKB Deployment in Southern region: The left panel presents the overall AI trend, showing the minimum, maximum, and average accessibility indices as the number of deployed TKBs increases. The right panel illustrates the distribution of AI across different age groups (Seniors, Middle-Aged, Young Adults, and Children) for various numbers of deployed TKBs, highlighting the varying accessibility levels for each demographic.

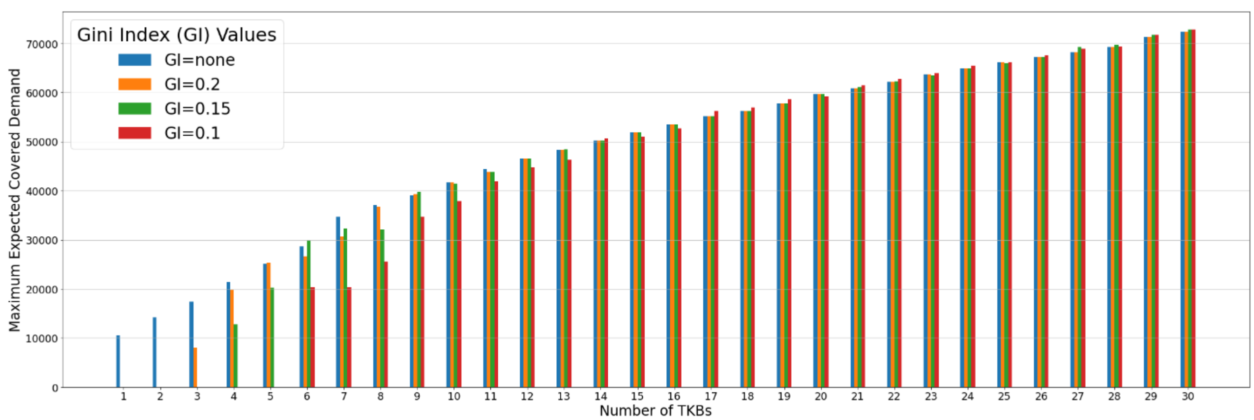

Figure A.3 Maximum expected covered demand in Southern region versus the number of deployed TKBs, with varying Gini index values indicating different levels of equity in healthcare access distribution.

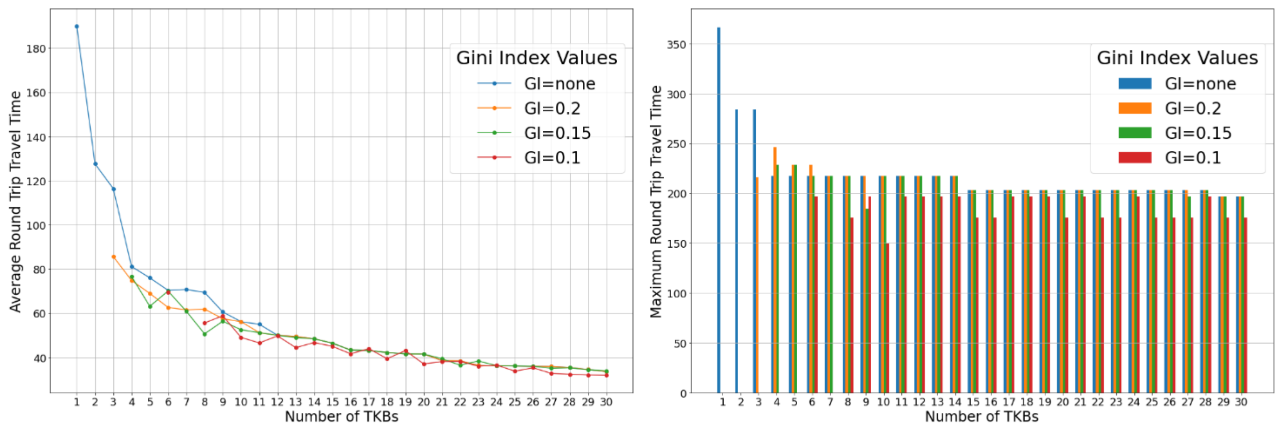

Figure A.4 Impact of the Number of Telehealth Kiosks/Booths (TKBs) and Gini Index (GI) Constraints in Southern region on Average and Maximum Round-Trip Travel Times: The left panel shows how average travel times decrease with increasing TKBs, with stricter GI constraints slightly increasing travel times due to prioritization of equity. The right panel illustrates the maximum travel times for the farthest locations, highlighting the trade-off between equity (stricter GI constraints) and efficiency (lower travel times) and the diminishing returns as TKB numbers increase.

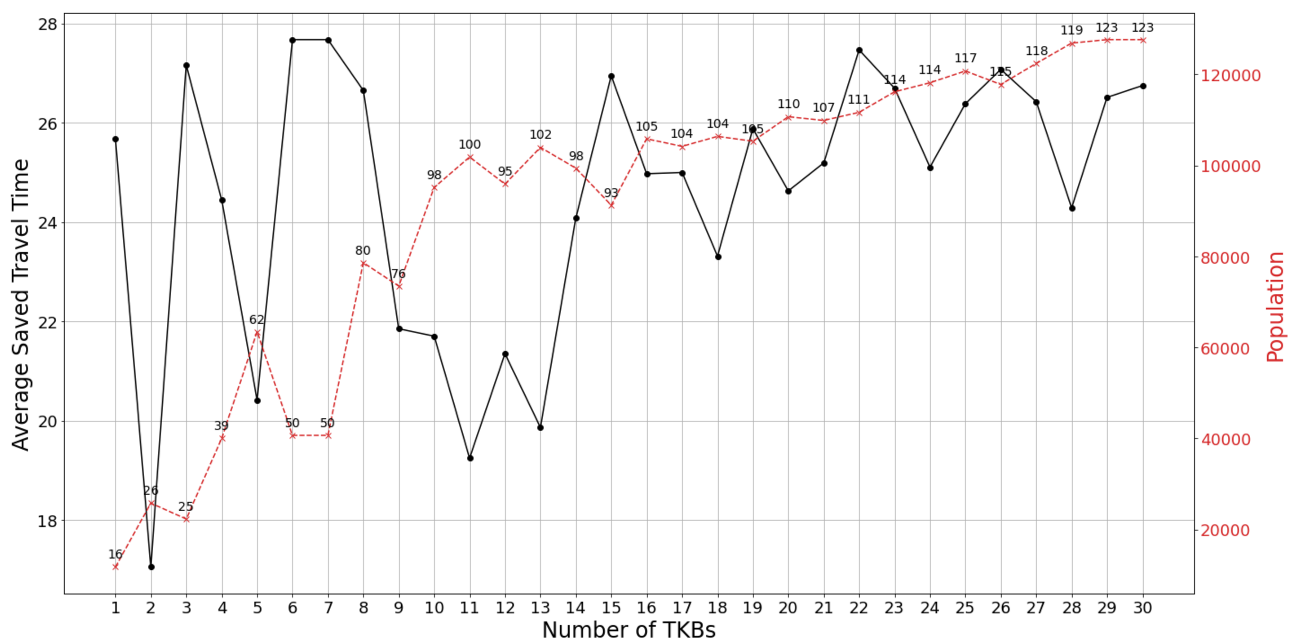

Figure A.5 Average saved travel time (left axis) and total population benefiting from closer proximity to Telehealth Kiosks/Booths (TKBs) than the nearest hospital (right axis) under the most equitable deployment strategy for 1–30 TKBs in Southern region. Numbers on the red line indicate the number of block groups benefiting from closer access.