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The Impact of Expanded Tele-Mental Health on Quality-Of-Care Indicators: A Three-Pronged Regression Analysis at Los Angeles County's Department of Mental Health

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By

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby ___approves__ the manuscript of Ami Bhatt as fulfilling the scope and quality requirements for meriting the degree of Doctor of Public Health.

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Abstract

The Impact of Expanded Tele-Mental Health on Quality-of-Care Indicators: A Three-Pronged Regression Analysis at Los Angeles County's Department of Mental Health

By: Ami Bhatt

Claremont Graduate University: 2022

Background: The use of Tele-Mental Health (TMH) skyrocketed after the COVID-19 pandemic led to the announcement of a public health emergency in March 2020. This rise coincided with soaring rates of mental health issues and increasing demand for accessible and sustainable treatment, all while meeting physical distancing requirements. TMH use is theorized to improve timely access to care and provide opportunities to improve quality of care indicators in individuals and at the health systems level.

Research Question: How has the widespread adoption of Tele-Mental Health changed quality of care (QoC) indicators among patients of LA County Department of Mental Health's (LAC DMH) Directly Operated (DO) clinics?

Methods: The study design for this analysis is a multivariate quasi-experimental study with a pseudo-control. A three-pronged approach to the analysis was used to tackle the research question and two QoC indicators are defined as the binary "Timely" variable and the continuous "Appointment Adherence" variable. All the models adjusted for covariates (demographic variables and the ratio of patients to providers) and mediators (the Request Type, which determines the timely standards of care). A "Pandemic Time" variable referred to if the data

point took place before March 19, 2020, which referred to the date that the Safer-at-Home Order (SHO) was announced, or after. The first prong, approach A, used a logistic regression for the Timely variable and an OLS regression for Appointment Adherence; it compared users of TMH to those receiving in-person care and included the pandemic time variable. Approach B did the same but accounted for crowding effects over time by adding an offset variable for the ratio of appointment requests to providers. An ANOVA for the first two approaches determined the effect size of the variables and those that had an effect size over 0.01 were used to build a parsimonious model for Approach C. Approach C used Interrupted Time Series models to compare the actual changes in QoC indicators from March 2017 to February 2021 with the expansion of TMH taking place post-SHO (March 2020-February 2021) to a pseudo-control for the whole health system. Approach C transformed the “Timely” and “TMH” variables to be continuous by transforming them to the percent of the total patients that received timely care and the percent of services delivered via TMH.

Results: Approach A found that TMH use was significantly associated (p=0.00) with a 15% reduced probability of receiving a timely appointment compared to those that received in-person care, though the probability of receiving a timely appointment increased 10% post-SHO compared to pre-SHO (p=0.00). Approach A also found that TMH use was significantly associated with a 2.5% increase in Appointment Adherence (p=0.00) compared to those receiving in-person care, but that post-SHO there was a 4% decrease in Appointment Adherence as compared to pre-SHO (p=0.00). Approach B found that TMH use was significantly associated (p=0.00) with a 6% decrease in the probability to receive a timely appointment when accounting for the crowding effect; TMH use was not significantly associated with Appointment Adherence.

Approach C used Interrupted Time Series regression to find that there was no significant association between TMH use and receiving a timely appointment and that the fluctuations in timely care both exceeded and fell short of the pseudo-control. TMH adoption did however have a significant relationship at a 10% level (p=0.09) with appointment adherence, in which every additional percent of TMH adoption by DMH was associated with a 7% increase in appointment adherence compared to the pseudo-control.

Conclusion: TMH use, timely access to care, and Appointment Adherence all increased post-SHO. DMH's adoption to TMH is associated with an increased likelihood of Appointment Adherence compared to if DMH kept TMH use at pre-SHO levels. Request Types with shorter timely standards are more likely to receive a timely appointment and to adhere to appointment plans when the health system had adopted TMH. However, there was no significant association exists between the adoption of TMH and Timely care within the health system. Among individuals that used TMH, there was a decreased likelihood to receive Timely care as compared to those receiving in-person care, though the likelihood of receiving timely appointments increase post-SHO. Individuals that used TMH were more likely than those that received in-person care to adhere to their appointment schedules. Future research should examine the impact of TMH use on QoC indicators over a longer time-period. Additionally, TMH should be evaluated as a promising intervention to reduce disparities in care, especially when adjusting for language and racial concordance, and to improve cost-effectiveness through redistribution of resource.

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Introduction

The COVID-19 pandemic has increased the incidence of emotional and psychological distress and exacerbated pre-existing mental illness (Czeisler et al., 2020; Yao et al., 2020). As social distancing measures restrict mobility and disrupt non-urgent health services, the US has expanded tele-mental health (TMH) as an alternative form of care to prevent and manage the rising prevalence of mental illness (Zhou et al., 2020). The "Pandemic Paradox" refers to how public health measures intended to keep individuals safe from the virus during the pandemic has led to spikes in mental health disorders and violence (Racine et al., 2020). The uncertainty related to the pandemic, lockdown and physical distancing may lead to social isolation, loneliness, inactivity, decreased access to basic service and social support, lost income, and increased access to food, alcohol, and online gambling (Moreno et al., 2020). Further, the economic changes due to the pandemic has led to unemployment, financial insecurity, poverty, and loss of health insurance. This has coincided with increased alcohol sales and increased alcohol and substance use.

While most adverse mental health impacts due to physical distancing or quarantine resolve themselves, problems may persist in key populations. These populations may find difficulty acquiring care through traditional methods as psychiatric units have decreased capacity or are converted for use for patients infected with COVID-19 (Moreno et al., 2020). A Pew poll conducted on March 30th, 2020, indicated that Latinos and Black people experienced "high psychological distress" at a higher rate than their white peers (28%, 26%, and 22% respectively). People of color are also disproportionately likely to suffer job or income loss. One third of lower income Americans are now in the high distress group, as are 29% of households that have experienced job or income loss due to the outbreak (Keeter, 2020). About one in four Medicare beneficiaries have a mental illness (McGinty, 2020). During the initial case surge in April 2020, the prevalence of serious psychological distress among adults aged 55 and older was nearly double pre-COVID levels; among Hispanic and low-income adults, rates were more than triple. This is especially concerning given that mental illness is already more common among Medicare beneficiaries. The prevalence of mental illness is greatest among beneficiaries under age 65 who qualify for Medicare because of disability, as well as among low-income beneficiaries who are dually eligible for Medicare and Medicaid. Higher proportions of American Indian/Alaska Native and Hispanic beneficiaries have mental illness relative to other racial and ethnic groups.

Stigma and discrimination related to contracting the virus may lead to poor mental health outcomes and make the tracking, diagnosis, and treatment of the condition difficult (Los Angeles County Department of Mental Health. Quality, Outcomes and Training Division, 2020, p. 4). Discrimination goes hand in hand with stigma, but in the American context has been concentrated on Asian Americans during the COVID-19 pandemic. The FBI has found that there has been a spike in hate crimes and reported instances of racism against Asian Americans, specifically following the rhetoric of blaming China for the “Wuhan Virus” (Wen, Aston, Liu, & Ying, 2020). The potential health effects of racism, xenophobia, and discrimination may include paranoia, PTSD, generalized anxiety disorder, substance and alcohol abuse disorder and others (Rodriguez-Llanes, Vos, & Guha-Sapir, 2013; Wen, Aston, Liu, & Ying, 2020).

Historically, economic downturns are associated with increased mental health needs. However, a paradox arises: while larger portions of the population become eligible for safety net services, safety net services receive less funding due to a decrease in tax revenue. The dearth of funding and increased demand burdens an already overstretched safety net system. In the case of the COVID-19 pandemic, funding for health services have increased by State and Federal governments, however these resources are generally used for providing COVID-related expenses, with inpatient care reserved for pandemic related care. Additionally, stigma, discrimination, and general fear in times of public health crises reduces care seeking behavior (Los Angeles County Department of Mental Health. Quality, Outcomes and Training Division, 2020, p. 7). The result is that pre-existing health conditions worsen, and the incidence of preventable conditions increases leading to poor health outcomes and more expensive and intensive treatment.

Those with mental illness face heightened risk of their mental health conditions worsening, of contracting COVID-19, and having a severe case of COVID-19 if contracted. Yao, Chen and Xu listed four reasons why individuals with mental illness may experience heightened risk during the pandemic: first, patients may be less aware or less compliant to social distancing measures; second, they may be less able to recognize symptoms and be more affected by stigmatization; third, the collective panic and anxiety due to the pandemic may aggravate symptoms of underlying mental disease; and finally, there may be disruption of services due to existing undersupply of mental healthcare as well as the redistribution of resources to focus on managing the public health emergency (Yao, Chen, & Xu, 2020). Patients with a history of, or current medical (including psychiatric or substance use) disorder experienced worsened psychiatric symptomology (Vindegaard & Benros, 2020). One such study found that 37.5% of patients with eating disorders reported worsening eating disorder symptomatology and 56.2% reported additional anxiety symptoms during the public health emergency (Vindegaard & Benros, 2020).

Young people's increased risk for experiencing mental health disorders is associated with disruptions in schooling, which are aligned with socialization, health interventions, psychological interventions, managed physical activity and nutrition, preventive care, and a setting where staff and faculty can refer students for additional care have been some of the many services that have become unavailable. Additionally, mental health may worsen among children due to the changes in their family/caretaker dynamic. Increased alcohol sales and drug use has been reported, which is associated with increasing rates of domestic violence. Heightened family stress and turmoil can exacerbate child maltreatment (Racine et al., 2020). Economic strain and increased psychological stress among adults and caregiver coupled with the disruption of buffers such as childcare, schooling, and child healthcare have all led to poor mental health outcomes, violence, and maltreatment. Organizations providing child mental health care and trauma treatment have had to rapidly pivot to TMH to provide care within this context.

TMH has already been proven to be cost-effective, preserve continuity of care, and increase patient satisfaction (Appleton et al. 2021; Hubley et al. 2016). The effectiveness of TMH is limited by lack of access to the internet and technology, lack of a confidential or private space, and the severity and nature of the mental illness being treated (Stoll, Sadler, & Trachsel, 2020). There is limited literature on how TMH impacts a whole health system rather than just those that receive care via TMH, on how effective the introduction of TMH is for a range of severe requests and population groups, and how effective the use of TMH is for long-term appointment adherence. This paper explores the impact of TMH on individuals and a health system by using a multi-pronged approach with two comparator groups: those that receive care via in-person care and a pseudo-control of the DMH health system which represents the trends in quality of care (QoC) indicators had TMH not been adopted. Additionally, the analysis includes three request types, each with increasing urgency and shorter timely standards, to explore how TMH utilization by individuals and adoption by the health system may impact those requiring urgent care. Finally, the paper explores two QoC indicators, Timely Access to Care and Appointment Adherence. The first indicator uses the timely standards of each of the request types to determine if patients are receiving timely care and the latter calculates the ratio of appointment schedules within a 90-day period two which the patient adheres. The latter indicator acts as a proxy to how TMH use by individuals and the health system impacts the long-term adherence to treatment schedules.

Literature Review

The CDC reported that 40% of US adults reported struggling with mental health or substance use in June 2020; a spike in prevalence compared to levels pre-pandemic (Czeisler, et al., 2020). For August 2020 through February 2021, the CDC reported that the frequency of mental health symptoms increased, with the increases and decreases in the frequency of reported symptoms correlating with weekly numbers of new COVID-19 cases (Jia et al. 2021). The current public health emergency is unique from previous outbreaks due to the relative availability of TMH in the US and the global reach of the outbreak. This literature review gathers information on the implementation, feasibility, and success of TMH as a tool to manage and limit the mental health impacts of COVID-19. Key findings from the review share the reasons and prevalence of access, utilization, and acceptance of TMH by providers and patients; the changes in policy and allocation of funding for telehealth during the pandemic; and the benefits and limitations of TMH.

The pandemic has limited non-emergency care due to overwhelmed health systems, travel restrictions, facility closures, operational limitations, and risk of infection (Whaibeh, Mahmoud, & Naal, 2020). The disrupted service has been a contributing factor to widening health disparities and highlights the need for alternate methods to access and utilize treatment. In this context, TMH is the intuitive solution- it can effectively respond to the mental health needs of people in isolation, quarantine, or restricted mobility, thereby adhering to social distancing, promoting continuity of care, and optimizing public health in a way that fits existing strategies to prevent the spread of COVID (Stoll, Sadler, & Trachsel, 2020).

The definition of TMH is “the use of information and communications technologies, including videoconferencing, to deliver mental health care remotely, including evaluations, medication management, and psychotherapy” (Whaibeh, Mahmoud, & Naal, 2020). Well before the pandemic, the need for TMH was evident due to the shortage of the mental health workforce, poor coverage from insurers and health plans, and the general lack of access for rural, disabled, and poor individuals (Levin, 2017). Telepsychiatry consultations and follow up appointments were found to have clinical outcomes and patient satisfaction that was equivalent to those services delivered in-person, with an average 10% reduction in cost per person (O'Reilly, et al., 2007). TMH was found to be effective for continuity of care and patient evaluation in California, with significantly fewer no-shows and cancelled appointments than in-person appointment by cutting out the need for transportation, which limited accessibility for vulnerable groups (Eyllon et al., 2021; Leigh, Cruz, & Mallios, 2009). TMH has also been a tool recommended to limit the escalation of interpersonal violence through digital mental health resources for perpetrators and survivors alike to manage stressors and practice emotional regulation techniques and communication strategies (Carballea & Rivera, 2020). These tools may be used in lieu of hotline services as victims of violence may be unable to seek help when near their abusers. Further, because of the modalities of TMH including app-based, social media, and websites, these services are available to anyone that has internet access and an appropriate device.

Common limitations to providing TMH include technology such as the need for video, access to internet connection, the need for a private space as well as policy limitations on the ability to provide care across state lines and to have insurer coverage (Racine et al., 2020). Introducing safety plans and protocols to providing TMH outside of a clinically supervised setting may reduce limitations. While the policy limitations were removed due to temporary waivers passed after the announcement of a public health emergency, the permanence of those policies are still in discussion. To expand access to TMH, several policies to loosen regulatory barriers and expand coverage have been passed in the US. These include waiving restrictions on providing services digitally with simpler rules to ensure digital privacy; allowing providers to take on new patients through TMH; equal reimbursement regardless of mode of service (in-person vs. video, telephone, etc.); ability to prescribe controlled substances remotely; and the ability to see a health professional across state lines in certain states. The policies have indeed led to increased utility of TMH and acceptance of TMH as a modality of care.

The Universal Theory of Acceptance and Use of Technology (UTAUT) is a framework that identifies four primary constructs underlying the acceptance of a technology moderated by age, gender, and experience with technology: performance expectancy, effort expectancy, social influence, and facilitating conditions (Connolly et al., 2020). According to the UTAUT the strongest predictor of the intended utility of a technology is performance expectancy, which is defined as how strongly one believes the technology is useful and better than alternatives. Effort expectancy is the perceived ease of use of the technology; social influence is the perceptions of important people that may influence the individual; and facilitating conditions is if the necessary infrastructure is in place to use the technology. Effort expectancy held the most common concerns of the need for training to use the technology, solving technological problems, suboptimal audio and video quality, and malfunctions during treatment. This was compounded by the need for TMH-V equipment, funding, and ongoing technical support. The table below outlines the perceived benefits and limitations to the use and acceptance of TMH over in-person care from the perspective of providers compared to patients (Connolly et al., 2020; Racine et al., 2020).

Table 1: Provider and patient perspectives of the benefits and limitations of TMH.

	Provider Perspective	**Patient Perspective**
Benefits	Time and cost saving Increased flexibility for providers Increased check ins with high-risk patients Increased job opportunities and collaboration for providers Comparable to in-person care for short-term assessments Increased provider willingness to use TMH-V after the pandemic. Cognitive Behavior Therapy delivered through TMH was found to be effective in children and adult populations.	Increasing access to care by removing the need for travel Time and cost saving Increasing comfort and decreasing inhibition Providing care in a home vs. clinical setting which improved treatment adherence for avoidant patients Improved patient satisfaction Increased frequency of check ins with providers Patients were more open to TMH compared to providers prior to the pandemic
Limitations	Not preferred for child assessments or interventions Technical difficulties can be burdensome A minority of providers perceived TMH-V as impersonal and reinforced patient social isolation Perceived hassle associated with TMH-V Difficulties detecting nonverbal cues such as fidgeting, crying, poor hygiene, or intoxication Safety and legal concerns; providers were unsure of their liability in the case of a crisis and if they could see patients across state lines Inability to assess risk and coordinate patient transfers to inpatient care Need for training regarding cyber security and confidentiality Inability to conduct physical examinations	Technical difficulties: patients were less affected by this than providers, potentially because they were more used to service delays Access to necessary infrastructure and internet connectivity TMH-V would not be ideal for those with visual or hearing impairments TMH-V may not be ideal for elderly or youth populations Insufficient evidence regarding the effectiveness of TMH for children and adolescents facing maltreatment TMH-V may not be ideal for people experiencing homelessness or asylum-seeking populations. Perception of impersonal interactions may compound feelings of loneliness, neglect, or isolation Lack of private settings to receive TMH treatment

Providers have an overall positive attitude towards TMH through videoconferencing (or TMH-V) citing improving access to care for their patients, increasing efficiency, reducing costs, and improving treatment adherence; TMH-V was also well received by patients and organizational leadership despite needing to be supported by training and technical support systems (Connolly et al., 2020). Provider's positive attitudes and acceptance of TMH-V was determined by their prior experience with TMH-V, their time practicing since medical school, their age (generally younger), and their practice being in a rural location (Choi et al., 2019). Providers found TMH-V most useful for psychotherapy, medication management, and assessment services, usually to patients at their homes or at remote clinics (Connolly et al., 2020). Providers described technological problems, the need for additional training, and perceptions of impersonal service delivery as the most common drawbacks.

Global reports of TMH use suggest population interest and acceptance of TMH. The Chinese, Singaporean and Australian governments were among the first to recognize the psychological impacts of COVID-19 and released guidance to address their needs (Zhou, et al., 2020). Research in these countries showed that those in isolation actively sought online support through digital modes including email, text, video, telephone, and app-based allowing for prevention, management of mild psychological symptoms, identification of mental illness, and the opportunity to connect with a mental health provider if necessary. At the Veterans Administration (VA), the largest healthcare system in the US, TMH-V showed a 556% growth from March to April 2020, made possible when pre-existing telehealth infrastructure was met with policies that removed barriers to implementation (Connolly, et al., 2020). Over 77% of the patients and 35% of the providers using TMH-V were first time users.

In implementing TMH, clinic and health care administrators emphasize the need to investigate the most effective forms of TMH or hybridized service delivery and adapt workflows according to the needs of the patient population. Successful strategies to complete this include engaging in communities of practice, collaborating with willing organizations, learning of others experiences with delivering TMH via grey and peer-reviewed literature, and leveraging pathways to access resources for TMH (Racine et al., 2020). Additionally, trauma informed training, which includes a framework that acknowledges the impact of trauma and develops policy and practice based on core principles of transparency, safety, peer support, collaboration, empowerment/choice, and cultural, historical and gender issues, must be matched with technical training for service delivery in an electronic platform. All of this must be supported with ongoing technical and IT support and policy advocacy.

This paper explores if TMH has improved QoC indicators among Los Angeles County's (LAC) patient populations. The dataset for the analysis was provided by LAC Department of Mental Health (DMH), the largest county mental health department in the United States and was composed of Directly Operated (DO) clinics (Los Angeles County Department of Mental Health. Quality, Outcomes and Training Division 2020). DO clinics are clinics that DMH directly controls and operates, as opposed to contracted agencies and facilities. The reason for using DO clinics is that they have standardized data collection and reporting processes which are sent directly to DMH's informatics division whereas contracting agencies have unique data collection and reporting practices. The findings will assess TMH use, timely access to care, and appointment adherence before and after the Safer-at-Home Order (SHO) was announced across three service types. The research question of this project is: "How has the widespread adoption of Tele-Mental Health changed quality of care indicators among patients of LAC Department of Mental Health's DO clinics?". The primary objective is to examine if TMH use among each of the three service Request Types has a significant relationship with quality-of-care indicators when controlling for demographics and the workforce available. The findings will contribute to the evidence pool to inform TMH policy and developing guidance on optimizing health system workflows and TMH implementation.

This paper examines the impact of TMH to improve appointment adherence and timely access to care, which act as the two QoC indicators, among DMH's clientele. The majority of DMH clients are insured by Medi-Cal, are using emergency services and are uninsured, and/or are categorized as low-income. The Safer-at-Home Order (SHO) reduced barriers for providers to provide care and expanded capacity to rapidly transition to TMH by expanding scope of work laws, promoting reimbursement parity despite the modality used, and simplified the rules regarding digital privacy. DMH's transition to and adoption of TMH was massive; as the largest mental health system in the US, from March 19th, 2020 (when the SHO was announced) to the end of April 2020, DMH implemented TMH throughout the health system and transitioned at least 1.2 million residents to TMH. By the end of 2020, TMH improved timely access to care across California; LA County alone saw rates of cancellations and no-shows plummet for TMH-users (Connolly et al., 2020). Previous research confirms that TMH has the potential to improve adherence to follow up appointments as comfort with the modality increases (Connolly et al., 2020). Acceptance for the modality is already high within California due to removing transportation and scheduling barriers. Further, TMH has increased access to a broader workforce (again because providers wouldn't need to travel), especially those that are multilingual. Finding a provider that can speak the same language as the patient has dual benefits: lower wait times to access the provider speaking the preferred language (if the patient can't speak in English at all) and the ability for the patient to better communicate and potentially share a cultural background with the provider (this is especially the case for patients that may speak English, but it isn't their preferred language) (Hilty et al. 2019).

Since the start of the pandemic, telemedicine has gone from a promising but rarely used modality of health care (in 2016, approximately 15% of physicians used telemedicine in their practice) to a mainstay of care provision (by May 2020, 91% primary care physicians included telemedicine in their practice) (Kane 2018; North 2020). Even with the possibility of COVID-19 becoming endemic and routine in-person care returning, TMH has become the preferred modality for routine and preventive care and has a growing role in mental health screening. Previous research has explored the reach of TMH and its benefits before and during the pandemic. Many studies have shared findings about TMH increasing access, timely appointments, and reducing no-shows and cancellations despite limited resources and increased prevalence of mental health issues (Stoll, Sadler, & Trachsel, 2020; Whaibeh, Mahmoud, & Naal, 2020). Yet, the current body of literature does not disaggregate findings to examine the change in access to care and timely access by the urgency of the service request and the corresponding severity of the mental health need. Further, the pandemic has exposed pre-existing health disparities, but research examining the impact of TMH on health equity for racial/ethnic minorities, women, and child and elderly populations is severely lacking (North 2020; SPROUT 2022; Wood et al., 2020). Finally, many studies confirm that TMH improves timely access to care, but only for patients that utilize it; little information exists about how QoC indicators change for all patients in a health system that utilizes TMH (regardless of which modality the patient uses). Similarly, while no-shows and cancellations are indeed reduced when TMH is the modality of care, studies examining the adherence to follow-up appointments and scheduled treatment plans are limited.

This paper attempts to fill this gap in research by statistically examining QoC indicators for all patients within a health system rather than just for TMH patients. This is also the first study to my knowledge that examines adherence to follow-up appointments and/or a scheduled treatment plan. Additionally, the descriptive analyses and regressions disaggregate the data by service Request Type, race, age, gender, and employment status to explore disparities in the outcome measures. The study approach builds upon research that examines which populations are at elevated risk using relative risk and odds ratios, and research that illuminated health disparities and recommended TMH to resolve them (Cziesler et al. 2021; Wood 2020). Until recently, the ability to evaluate if TMH has indeed reduced disparities in care was not feasible. The findings will contribute to a pool of evidence to develop guidance on efficient workflows within hybridized modalities of care.

The three-pronged approach used in this paper attempts to combine the strengths of papers evaluating timely access to care and follow up visits. Research on timely access to care has been ongoing but for research focusing on the post-SHO era, methods range from simple descriptive analysis to show changes in statistics of timely care (Connolly et al. 2021) to regressions that evaluate the associations between modality and no-shows and cancellation rates (Leigh 2009; Whaibeh, Mahmoud, & Naal, 2020). This analysis uses variables for timely standards as dictated by three request types to go beyond evaluating if the patient received care and if standards are being met.

As the pandemic continues, few papers have evaluated the long-term impact of TMH on QoC indicators, and those that have, have focused on follow up visits (Appleton et. al. 2021; Connolly et. al. 2020). Only one other study has evaluated visit adherence and has used Interrupted Time Series (ITS) to do so (Eyllon et al., 2022). The study used a similar data structure and method as the ITS used in this analysis, but this analysis precedes the ITS by conducting an ANOVA to find the effect size of each of the covariates to build a parsimonious model for the ITS. This approach is taken for both QoC indicators, that is to evaluate the impact on the timely access per each appointment and the long-term adherence to appointment plans.

Notably, this paper is among a growing body of health services papers that use ITS as their study design (Hategeka et al., 2020). As public health research leverages time-series data and can control for trends and seasonality, particularly studies related to quality improvement, guidance on the methods has also expanded and has recommended ITS to measure population-level health impacts, especially when randomization is not possible (Bernal et al., 2017). This study follows previous guidance in developing and testing ITS models and using forecasting to create a counterfactual; it also increases the model fit by developing a conceptual model and identifying mediators vs. covariates and using a three-pronged approach to estimate effect size, the latter of which determines which variables should be included in the ITS.

Methods

This paper explores if TMH has improved QoC indicators among LAC DMH's DO clinic patient population. DO clinics are clinics that DMH directly controls and operates, as opposed to contracted agencies and facilities. The reason for using DO clinics is that they have standardized data collection and reporting processes which are sent directly to DMH's informatics division whereas contracting agencies experience reporting lags due to unique data collection and reporting practice and subsequent lags for the DMH informatics team to standardize the data format. The dataset for the analysis was provided by the LAC DMH informatics team and is composed of over 160,000 unique patient observations from March 2017 to February 2021. The findings will assess TMH use, timely access to care, and appointment adherence pre- and post-SHO (with the SHO announcement taking place on March 19, 2020) across three service Request Types. The research question of this project is: *How has the widespread adoption of*

Tele-Mental Health changed quality of care indicators (appointment adherence and timely access to care) among patients of LAC DMH's DO clinics? The primary objective is to examine the relationship between TMH use within a health system and changes in quality-of-care indicators for the whole health system. The secondary objective is to examine this relationship for TMH users alone. The tertiary objective is to examine the relationship among the three service Request Types (Routine, Inpatient/Jail Discharge, and Urgent), each with increasing urgency. The final objective is to determine which of the predictor variables have the largest effect on the relationship prior to the SHO versus after the SHO. All the models created to answer the research question will control for demographics and workforce available; the announcement of the SHO (March 19th, 2020) will act as the point of TMH expansion.

This will be tested by conducting a quasi-experimental multivariate pre-post analysis with a pseudo-control. The reason for choosing a quasi-experimental design is due to the dataset being observational and retrospective; it is multivariate because it was necessary to account for multiple covariates (workforce available and demographics) and service Request Type, which had unique timely standards and acted as a mediator (see Conceptual Model); and a pseudo-control is used as the expansion of TMH within LA County happened immediately after the SHO. The pseudo-control was created by forecasting the two QoC indicators based on the data available from March 2017-March 2020 for the period of April 2020-February 2021. The actual observations for the same time-period of were compared to the pseudo-control to estimate the impact of TMH on the two QoC indicators. The findings will contribute to the evidence pool to inform TMH policy and developing guidance on optimizing health system workflows and TMH implementation.

Conceptual Model

Based on the research outlined in the literature review, it has been established that TMH improves timely access to care, has high acceptance by providers and patients, and may lead to increased adherence to treatment because of language/cultural concordance and reduced barriers to care. Building upon that foundation and accounting for potential confounders, a conceptual model is presented below. The confounders are included in the regression models as covariates, while an interrupted time series model is stratified to account for the confounders. The Request Type is a partial mediator. A causal mediation analysis in R was used to develop a conceptual model for each of the QoC. Additionally, the model is based on the practical elements of providing care via TMH including the standards for timely care, the length of the treatment (i.e., Routine requests generally have more follow up appointments compared to Urgent requests), and provider and patient preferences on care.

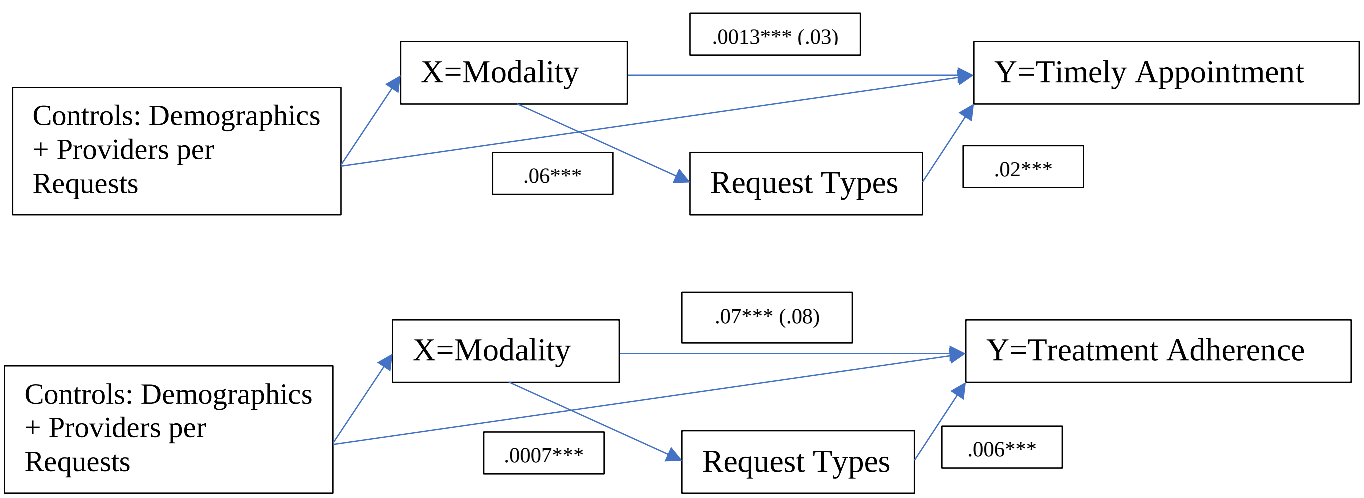


Figure 1: Conceptual models of how request types act as mediators between Modality and the two QoC Indicators

The dataset consists of observational data, and it is impossible to have perfect control; to account for this, an interrupted time series model is used to forecast QoC indicators had the SHO not expanded the use of TMH. This forecast acted as a pseudo-control. Additionally, since this is an observational dataset, the analysis is a pre-post quasi-experimental design with modeling that controls for confounding variables, offsets for a crowding effect, and creates a pseudo-control by forecasting. Extensive data cleaning, adjustments, and transformation were necessary to account for the realities of providing care at the scale and volume of the population.

Dataset & Variables of Interest

Los Angeles County's Department of Mental Health (LAC DMH) shared a dataset for Directly Operated (DO) clinics organized by service Request Type from March 2017 – February 2021. The data was cleaned to remove extreme observations, correct data entry errors, and create variables to disaggregate services provided in a timely manner according to the three service types and by service modality (either in-person or via TMH). TMH includes care delivered via telephone or through video. The dataset also included a variable to determine appointment adherence for treatment plans up to 90 days long. The following variables were provided, notes regarding the real-world circumstance of the data are provided and how they were transformed are described below:

Variable	Definitions	Notes & Considerations
Service Request IDs	Randomized, unique de-identified patient IDs	
Service Request Type	Inpatient/Jail Discharge, Routine, Urgent	This dataset is based on real-world data, with certain limitations. In this case, responders have subjective criteria for categorizing referrals based on the severity of the mental health disorder and the patient. This has led to responders categorizing requests as "Urgent" to prioritize a referral. This is also a reason some "Urgent" requests may be deemed eligible for TMH in some cases and need in-person care in other circumstances.

Modified Request Date, Modified Date of First Offered Appointments, Date of Accepted Appointments, and Assessment Date		“Modified” dates are to account for any date that fell on a weekend or holiday. The modification is that the date for the first business day following the original date.
Modality	In-person or TMH	TMH services use phones and video. LA county has a policy of providing a cell phone and limited data/minutes to those that otherwise could not access it. Given limited access to internet, lack of access to video, and other infrastructure limitations, most TMH services in LA county are provided via telephone. A concerted effort to move clients to video based TMH is underway.
Business days to First Offered appointment, Business Days to the First Accepted appointment, Business days to the Kept Appointment		A “kept” appointment indicated a claimed service. Some of the claimed services were independent of the request itself. Common occurrences include no-show patients returning as a walk-in after an initial request or a patient is referred to/moves to another clinic and upon returning to the original clinic receives care that is dated as a response to the original request. Any modified business days counts that were more than 90 days were removed during the regressions to account for said occurrences, because the analysis measures appointment adherence up to 90 days, and because the scheduled appointment variable provided by DMH only counted to 90 days.
Appointment Kept	A binary variable indicating if the patient fulfilled the appointment	
Timely Appointment	A binary variable indicating if the appointment was fulfilled according to the three timely standards.	The timely standards for fulfilling each of the service requests are: Urgent: 48 hours Routine: 10 business days Inpatient/Jail Discharge: 5 business days
Demographic information	Gender, Age, Employment Status, Patient	Patient language indicated the patient’s preferred language for service; this was fulfilled, when possible, via referrals. When not possible, a translator may be

	Language, Ethnicity, Race	requested, a family member may accompany the individual, or the individual may experience delays in service until a provider becomes available.
Appointment Adherence Percent	The percentage of the scheduled appointments that were fulfilled	N Appointments Over a 90-day Period and N Kept Appointments Over a 90-day Period (n_appts/n_kept) *100). For example, a treatment plan may have a scheduled 10 appointments, with 8 appointments having been fulfilled indicating an 80% appointment adherence rate for that individual. For the appointment adherence percent >100%, the n_appts were corrected for data entry errors in consultation with a DMH analyst. For n_appts that were within 3 appointments lower than the n_kept appointments, the percentage is revised to 100% to account for walk-ins.
N Patients	The number of patients requesting care per month.	
N Providers	The number of providers available per month.	Outliers for this variable were removed.
Per Request:	The number of patients per number of providers per month.	This variable was created to adjust for the changes in the volume of requests and workforce available.
Pandemic Time	A binary variable to indicate if the request date was before or after the Safer-At-Home Order (SHO). If the modified request date was prior to March 19th, 2020, it was coded as "Pre-SHO", any date	Contextually, March and April were a period of major transition for providers and patients alike. In March, DMH was still finalizing the mechanism for inputting new patients that used TMH.

	after was coded as "Post-SHO".	

Analysis

After cleaning and coding was completed, descriptive statistics of the requests, timely appointments, and appointment adherence were produced. The tables are presented in the "Results" section. The study design for this multivariate analysis was a quasi-experimental study with a pseudo control. A three-fold approach to the analysis is as follows. The purpose of each regression with the y variable used is outlined under the respective section.

A. **Ordinary Least Squared (OLS) and Logistic (Logit) regressions relative to SHO**. In this case, each regression was run with a variable for the SHO to understand how the indicators were impacted relative to the SHO. The purpose of the models was to provide a cross-sectional estimate of the likelihood of each of the service request types to receive the desired quality of care indicators relative to SHO in patient populations receiving TMH vs. those receiving In-Person care. The regressions will determine an odds ratio (OR), the average marginal effects (AME), and regression coefficients for the indicators before and after the SHO; and to estimate the differences in the effect size.

Logit: Y_{Timely}=Timely Access (binary, yes=1 or no=0)

$$\hat{Y}_{Timely} = \hat{\beta}_0 + \hat{\beta}_1 * Modality + \hat{\beta}_2 * Request\ Type + \hat{\beta}_3 * Pandemic\ Time + \hat{\beta}_4 * Age + \hat{\beta}_5 * Race + \hat{\beta}_6 * Employment + \hat{\beta}_7 * Gender + \hat{\beta}_8 * Language + \hat{\beta}_9 * Per\ Request + e$$

OLS: $Y_{Adherence}$: Percent Appointment Adherence

$$\hat{Y}_{Adherence} = \hat{\beta}_0 + \hat{\beta}_1 {*Modality} + \hat{\beta}_2 {*Request\ Type} + \hat{\beta}_3 {*\ Pandemic\ Time} + \hat{\beta}_4 {*\ Age} + \hat{\beta}_5 {*\ Race} + \hat{\beta}_6 {*\ Employment} + \hat{\beta}_7 {*\ Gender} + \hat{\beta}_8 {*\ Language} + \hat{\beta}_9 {*\ Per\ Request} + e$$

B. The Offset models included both logit and OLS regressions for the whole time-period (March 2017-February 2021). This approach builds upon the previous by finding the effect size of the variables in a pooled dataset. The logit regression had binary timely access to care variable whilst the OLS regressions had continuous versions of both. The purpose of the logit regressions was to provide the odds ratio for the indicators when adding an offsetting variable to account for the crowding effect (in this case providers per request).

Logit: $Y_{TimelyO}$=Timely Access (binary, yes or no)

Offset: s_i= Providers per Request

$$\hat{Y}_{TimelyO} = \hat{\beta}_0 + \hat{\beta}_1 {*Modality} + \hat{\beta}_2 {*Request\ Type} + \hat{\beta}_3 {*Per\ Request} + \hat{\beta}_4 {*\ Age} + \hat{\beta}_5 {*\ Race} + \hat{\beta}_6 {*\ Employment} + \hat{\beta}_7 {*\ Gender} + \hat{\beta}_8 {*\ Language} + s_i + e$$

The OLS regressions that included an offset used continuous 'Y' variables. In these models, the purpose was to provide a coefficient for the indicators when controlling for the crowding effect. And to estimate the effect size of each of the predictor variables and covariates when the Y is a grouped continuous variable accounting for monthly outcomes (Y in this case is a the average percent of appointment adherence).

OLS: $Y_{AdherenceO}$=Percent of Appointment Adherence

Offset: s_i= Providers Per Request

$$\hat{Y}_{AdherenceO} = \hat{\beta}_0 + \hat{\beta}_1 *Modality + \hat{\beta}_2 *Request\ Type + \hat{\beta}_3 *Per\ Request + \hat{\beta}_4 * Age + \hat{\beta}_5 * Race + \hat{\beta}_6 * Employment + \hat{\beta}_7 * Gender + \hat{\beta}_8 * Language + s_i + e$$

C. The Interrupted Time Series models compared the actual changes in timely access to care and appointment adherence from March 2017 to February 2021 with the expansion of TMH taking place in March 2020 to the forecasts of both variables based on the historical trends of both variables (the latter serving as the pseudo-control). The variables selected in this model were selected based on which of the covariates and predictor variables were found to have an effect greater than 0.00 in the OLS and Logit model before and after the pandemic, and those that had an effect greater than 0.00 in the offsetting model. This analysis was done for the whole dataset with all data averaged per month. The models were stratified by demographics and controlled for trend and seasonality.

Y_{Timely}= Percent Timely

$Y_{Adherence}$= Percent Appointment Adherence

Actual; T = March 2017-February 2021 :

$$\hat{Y}_{t\ \text{Timely | Adherence}} = \hat{\beta}_0 + \hat{\beta}_1 T + \hat{\beta}_2 *Percent\ TMH + \hat{\beta}_3 *Request\ Type + \hat{\beta}_4 *Age + \hat{\beta}_5 * Race + \hat{\beta}_6 * Employment + Trend + e_t$$

Pseudo-Control; T = March 2020-February 2021:

$$\hat{Y}_{t\ Timely\ |\ Adherence} = \beta_0 + \beta_1 T + \beta_2 {*} Percent\ TMH + \beta_3 {*} Request\ Type + \beta_4 {*}\ Age + \beta_5 {*}\ Race + \beta_6 {*}\ Employment + Trend + e_t$$

Each of the three approaches build upon one another to answer the research question and address the objectives of this project. The objectives that each of the approaches fulfills is summarized below.

Approach A: Disaggregated by time relative to SHO (pre-SHO = March 2017-March 19th, 2020; post-SHO = March 20th 2020-February 2021)	Determine the effect size of variables in the model to determine how the effect of the variables changed after the onset of the pandemic. The effect size will be used to determine which of the variables to use to construct the pseudo-control keep in the Approach C model. Investigate the association between the modality of care and QoC indicators relative to SHO for the individuals receiving care in that modality. Provide a cross-sectional estimate of the likelihood of each of the service Request Types to receive the desired QoC indicators relative to SHO in patient populations receiving TMH vs. In-Person care. Output: Effect Size (pre-/post-SHO), Average Marginal Effect (AME) and OR, and Coefficient. Objective: Identify which variables should be used to create a parsimonious model for Approach C and note changes in effect size pre-/post-SHO.
Approach B: Pooled data for the total time-period (March 2017-February 2021)	Determine the effect size of the variables for the pooled time-period. Investigate the association between the modality of care and QoC indicators pre- and post- SHO for the individuals receiving care in that modality for the total time-period (March 2017-February 2021) Provide a cross-sectional estimate of the likelihood of each of the service Request Types to receive the desired QoC indicators for the total time-period in patient populations receiving TMH vs. In-Person care. Output: Effect Size, AME and OR, and Coefficients Objective: how TMH use impacts QoC indicators for each service Request Type among the patients that use it.

Approach C: Interrupted Time Series indexed by month	Develop a parsimonious model based on the effect size of variables identified in approaches A and B. Investigate the association between the proportion of TMH use and quality-of-care indicators over time compared to if there was no expansion of TMH (the latter acting as a pseudo-control). Output: Coefficients Objective: Investigate the relationship between modality and quality-of-care indicators for the whole health system regardless of the modality of care used (i.e., how did the quality-of-care indicators change for the health system, regardless of which modality individuals within the system used). Investigate how TMH use within a health system impacts QoC indicators for each service Request Type over the time-period when controlling for covariates and mediators.

*Note: AME, OR, and Coefficients found in approaches A and B will be cross-sectional estimates whereas ITS will be over time indexed by month. The comparison group for Approach A and B is in-person care, the comparison group for Approach C is a pseudo-control.

Each model was designed after multiple attempts of finding the best model fit and ensuring all the assumptions of running regressions were met. The rationale behind each of the model designs are as follows.

The VIF was determined for each model run to identify multicollinearity; if VIF exceeded 5, the reason for the multicollinearity was identified and removed. Adding an interaction term results in multicollinearity and has no impact on the coefficients, significance or model fit. This is likely because the two interaction terms that could exist (Request Types and Modality) are categorical, and the interaction makes the VIF huge. This aligns with the conceptual model which sees the Request Type as a mediator rather than a moderator (a moderator would need to be added as an interaction term). Thus, all models removed interaction terms.

The models presented have up to nine predictors and covariates, which may reduce model fit. To ensure that the appropriate covariates and independent variables were selected, effect sizes were estimated for each model (for models in approach A and B). This was completed through an ANOVA for the OLS regressions and by adding each variable and running the model in a stepwise fashion for the Logit models. The covariates with effect size greater than 0.00 for the models were kept in the ITS model while the other variables (<0.00 in model sets A and B) were removed.

For the offset model, the offset acts as the level of exposure on the outcomes, in this case, providers per requests. While this produced a better model fit and accounted for crowding effects in the OLS models. The models yielded better model fits by avoiding an offset and including the providers per request variable as a covariate. The results of the logit models are included in the results section.

The dataset from DMH is observational data, so there is no way to have a perfect control since the widespread implementation of TMH was only after the SHO. Thus, the pseudo-control was created by forecasting in the ITS.

Results

Both the QoC indicators increased post-SHO across all Request Types and demographics. Additionally, the disparities in the two indicators decreased across all the variables, though measuring the significance of changes in disparities was beyond the scope of this project. The ITS models indicated that the roll-out of TMH enabled by the SHO is significantly associated with appointment adherence up to 90 days, but there was no statistically significant association between TMH and timely appointments.

Variables with missing values and data entry errors were dropped for the regression analysis. Due to its small sample size, the Urgent Request Type was grouped with Inpatient

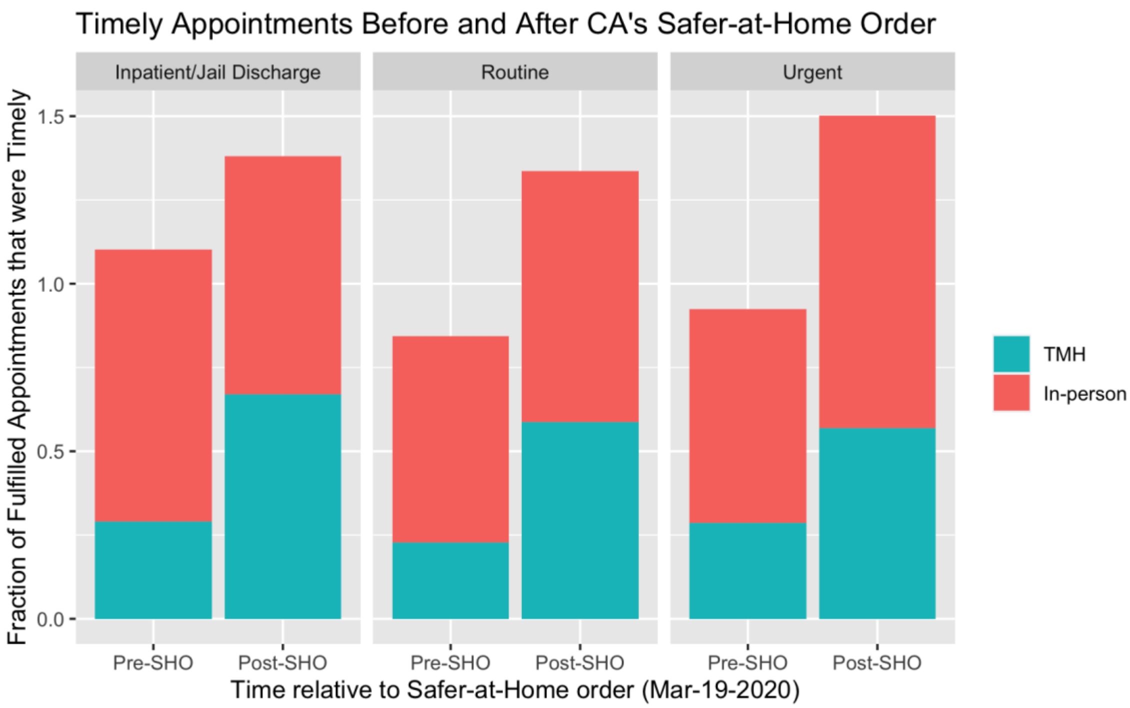
Care/Jail Discharge for the purposes of the regression analysis. Both had shorter timely standards and were more likely to use inpatient care but reported separately for the descriptive analysis.

The logit regressions were run for the binary "Timely" variable; the OLS regressions were run for the continuous "Appointment Adherence" variable. Average Marginal Effects (AME) were reported for each of the logistic regressions and an ANOVA was completed for each of the OLS regressions to find the effect size of each of the variables.

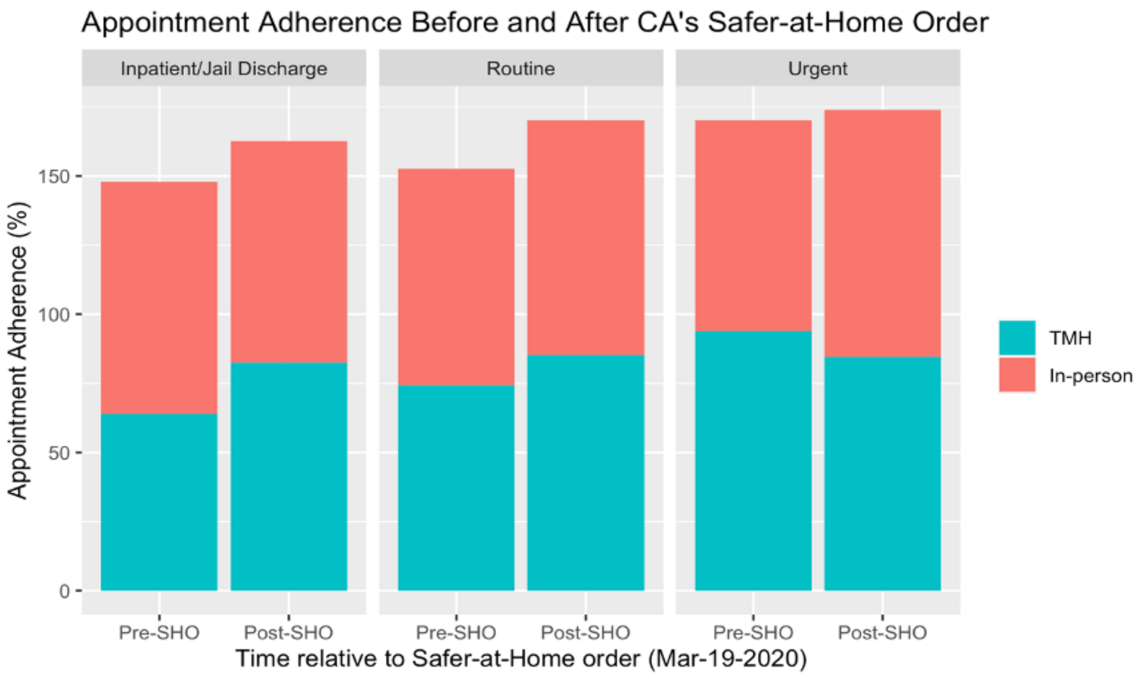
The effect sizes were determined based on ANOVAs run for approaches A and B. These determined that of the demographic variables, Age, Race, and Employment status had an effect size>0.01 prior to the SHO and across the whole time-period. The effect size determined how much of the total effect of the modality, moderated by the Request Type, was determined by the other variables in the model (demographics and the ratio of providers to requests).

Descriptive Statistics

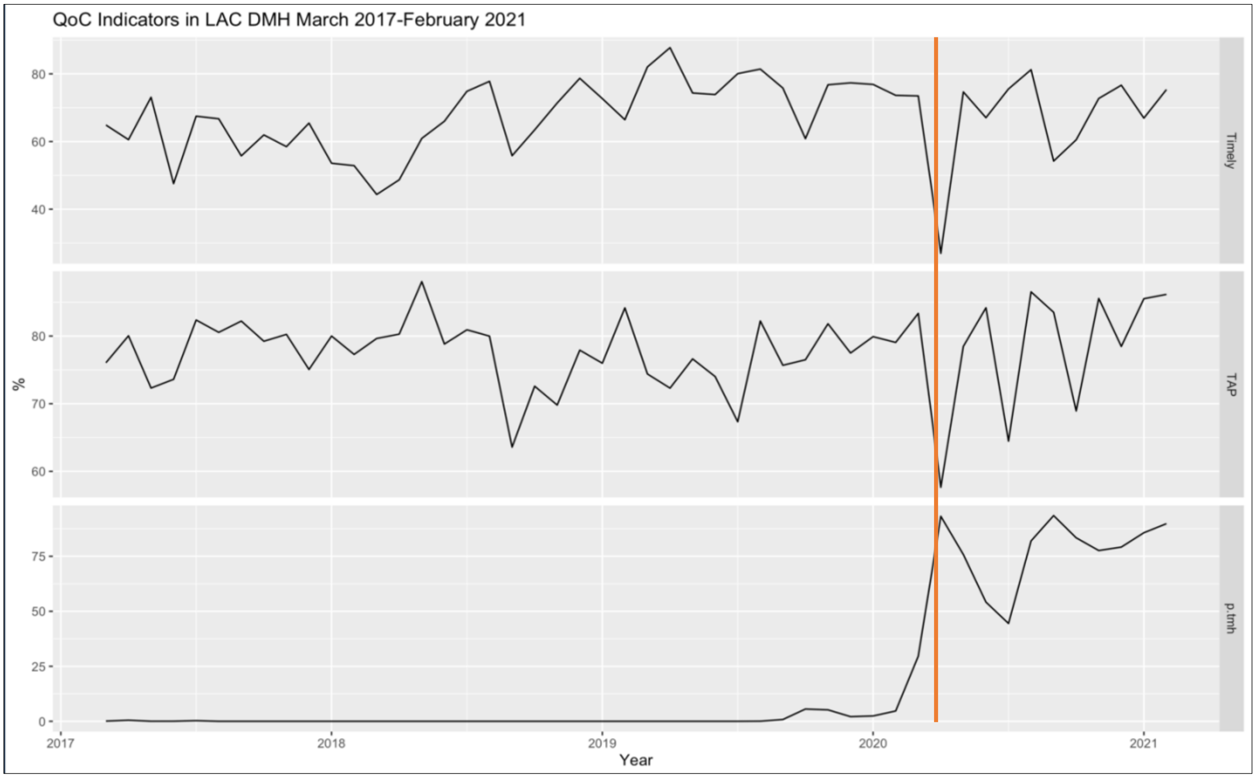
On average, appointments based on all Request Types and modalities saw an overall increase in the percent of timely appointments. Additionally, there was a reduction in the disparities of timely appointments across the demographic groups, though the statistical significance of the change of disparities was beyond the scope of this project and not measured (see Appendix).



The mean changes in appointment adherence saw a more definitive increase across all modalities and Request Types (see Appendix). As in the case of timely appointments, appointment adherence also saw a decrease in disparities, though this was met with overall increases in the mean adherence percentage across all demographics.



The average monthly change over time in Timely appointments, appointment adherence (TAP), and percent TMH adoption (p.tmh) is plotted below. The adoption of TMH coincided in an initial decrease in timely appointments and appointment adherence, though there was a quick rebound in April 2020. This was because in March 2020 through early April 2020, DMH was still setting up their workflows and claims protocols to accept requests via TMH. Additionally, in June and July of 2020, many DMH employees (and LA County employees) were reassigned to emergency pandemic response due to rising case rates. In turn, this reduced the number of providers available. The first graph from the top, “Timely”, refers to the percent of timely appointments over time; the second, “TAP”, refers to the appointment adherence over time; and the final graph, “p.tmh” refers to the percent of appointments that used the TMH modality over time. The red line indicates March 2020, when the SHO was announced.



To complete the ITS, the data was indexed by month and analyzed to find if the data was stationary or if it did include seasonality or trends; the data was found to have trends but no seasonality. Because of this, no seasonal adjustments were necessary for the time series regressions.

Regressions

The regressions took a three-fold approach (see: Methods) to test the models. The first, approach A, separated the dataset relative to the SHO; the second, Approach B, pooled the dataset and offset for the ratio of providers to requests to account for any crowding effect; and the final, Approach C, was an Interrupted Time Series (ITS) that created a parsimonious model based on the findings of Approaches A and B. An ANOVA was run for Approaches A and B to determine which of the demographic covariates had an effect size>.01; this in turn determined which demographic variables should be included in the ITS model in Approach C. For Approaches A and B, the comparator was the in-person modality of care; the statistical model was logistic regressions for the binary "Timely" variable and an OLS regression for the continuous "Appointment Adherence" variable; and provided cross-sectional estimates of the impact of the modality of care when moderated by the Request Type. For the OLS models for Approaches A and B, all categorical variables were coded as factors. Approach C, the ITS model, developed a parsimonious model that also controlled for trends; constructed a counterfactual based on the pre-SHO forecast; and gave an estimate of the impact of the modality of care, when moderated by Request Type, on the QoC indicators. A summary of the models, the goodness of fit, and the regression coefficients of Modality and Request Type are reported in the table below.

Model	**Model Fit**	**Modality**	**Request Type**
Y = Timely Appointments (Binary); Logistic Regression			
Approach A:	χ^2 (18) = 1820.71, p = 0.00 Pseudo-R^2 (Cragg-Uhler)= 0.06, Pseudo-R^2 (McFadden) = 0.03, AIC = 53870.18, BIC = 54034.86	TMH (AME): -0.15*** TMH (OR): 0.51***	Urgent or Inpatient/Jail Discharge (AME): 0.07*** Urgent or Inpatient/Jail Discharge (OR): 1.43***
Approach B: Offset	χ^2 (15) = 51450.66, p = 0.00, Pseudo-R^2 (Cragg-Uhler) = 0.76, Pseudo-R^2 (McFadden) = 0.49, AIC = 53929.99, BIC = 54068.66	TMH (AME): -0.06*** TMH (OR): 0.77***	Urgent or Inpatient/Jail Discharge (AME): .10*** Urgent or Inpatient/Jail Discharge (OR): 1.62***
Y = Appointment Adherence (Continuous); OLS Regression			
Approach A:	F(18,40225) = 88.11, p = 0.00 R^2 = 0.04	TMH: 2.48***	Urgent or Inpatient/Jail

	Adj. $R^2 = 0.04$		Discharge: No significant association
Approach B: Offset	F (14,40229) = 306.09, p = 0.00, $R^2 = 0.10$, Adj. $R^2 = 0.10$	TMH: No significant association	Urgent or Inpatient/Jail Discharge: No significant association
Interrupted Time Series (Multivariate adjusted, Time Series Linear Model (TSLM))			
Approach C: Timely	Multiple R-squared: 0.725, Adjusted R-squared: 0.6219, F-statistic: 7.032 on 6 and 16 DF, p-value: 0.00	TMH: No significant association	Urgent or Inpatient/Jail Discharge: No significant association
Approach C: Appointment Adherence	Multiple R-squared: 0.6157, Adjusted R-squared: 0.3915, F-statistic: 2.746 on 7 and 12 DF, p-value: 0.05972	TMH: 0.07.	Urgent or Inpatient/Jail Discharge: 6.24.

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

A. Logit Regression and OLS Relative to SHO Pre- and Post-SHO

Approach A completed a logistic regression to determine the relationship between Modality and Request Types, and Timely appointments. The OLS regression did the same to ascertain the relationship with Appointment Adherence. Both were completed with an additional variable that was relative to SHO. The relationships between Modality and Request Types, and Timely appointments or Appointment Adherence were all significant. The Average Marginal Effect (AME) and Odds Ratios (OR) were used to describe the relationship and an ANOVA was run to describe the effect size. Individuals that received TMH care saw a 15% decreased probability in receiving a timely appointment, but the probability of receiving a timely appointment increased 10% post-SHO. TMH users also saw a 3.5% increase in appointment adherence for every additional appointment received via TMH as compared to those that used in-person care. Post-SHO, appointment adherence decreased 4% for every additional appointment compared to pre-SHO appointments. For both QoC indicators shorter and more urgent timely standards saw increases in both the QoC indicators.

Logistic Regression

The greatest changes in effect size were for Age (.01), Race (.01), and Employment (.01). Language, that is, if the patient speaks English, had a negligible effect size (.01). Gender had no effect to the model. Due to this finding, the variables of Age, Race, and Employment were included in the ITS model in model C.

The Modality in which the care was delivered was significantly associated with receiving a Timely appointment when adjusting for covariates. The OR for receiving a timely appointment relative to SHO when the service was delivered via TMH was .51 as compared in-person care (p=0.00***). Using TMH had a reduced probability of receiving a timely appointment by 15% (OR=.51, AME= -.15 ;p=0.00***). The likelihood of receiving a timely appointment via TMH increased post-SHO, but the likelihood of receiving a timely appointment via in-person care remained higher during both time periods.

The regressions found that there was a significant relationship between Timely appointments and Request Types when adjusting for covariates. Request Types with shorter timely standards (Urgent and Inpatient/Jail Discharges) were more likely to receive a timely appointment (OR=1.43, AME =7%; p=0.00***) compared to Routine requests. The covariates of Age, Race, Employment, and Gender all had significant relationships with receiving timely appointment.

Being an adult over 26 made an individual slightly more likely (OR=1.3, AME=6%; p=0.00***) to receive a timely appointment compared to a person over 55 years, whilst being under 19 years old reduced the likelihood of receiving a timely appointment (OR=.57, AME=-13%; p=0.00***). Compared those that were White, Asian individuals were more likely (OR=1.93, AME=13%; p=0.00***), Multiracial individuals were less likely (OR=.76, AME=-6%; p=0.00***) to receive a timely appointment, and Black individuals had comparable probabilities (OR = 1.07, AME =1%; p=0.00***). Being unemployed (OR=.6, AME = -10%; p=0.00***), employed part-time (OR=0.36, AME = -22%; p=0.00***), being a part of a welfare work program (OR=0.26, AME = -42%; p=0.00***), or not in the labor force (OR=0.61, AME = -10%; p=0.00***) was associated with a decreased likelihood of receiving a timely appointment. Women were mildly less likely (OR=.93, AME= -2%; p=0.00***) of receiving a timely appointment as compared to those that identified as men. The relationships between language and Timely appointment were not significant.

Approach A: Timely Appointments

	AME	Odds Ratio	Estimate	Std. Error	z value	p-value
Intercept		2.98	1.09	0.08	13.38	0.00***
Pandemic Time						
Pre-SHO						
Post-SHO	0.10	1.64	0.49	0.06	7.80	0.00***
Request Type						
Routine						
Urgent; Inpatient/Jail Discharge	0.07	1.43	0.36	0.04	9.41	0.00***
Modality						
In-Person						
TMH	-0.15	0.51	-0.66	0.07	-9.90	0.00***
Requests Per Providers						
Per Request (High Average,0-1)						
Per Request (Low Average, 1-2)	-0.01	0.97	-0.03	0.03	-0.93	0.35
Per Request (High, 3-4)	-0.01	0.94	-0.06	0.03	-2.06	0.04*
Per Request (Low, >5)	0.00	1.00	0.00	0.03	0.02	0.99
Age Group						
Elderly (>55yrs)						
Adult (26-55yrs)	0.06	1.33	0.28	0.03	10.75	0.00***
Young Adult (19-25yrs)	-0.01	0.96	-0.04	0.04	-1.24	0.22
Youth (<19yrs)	-0.13	0.57	-0.56	0.05	-10.32	0.00***
Race						
White						
Black	0.01	1.07	0.07	0.03	2.65	0.01***
Asian	0.13	1.93	0.66	0.06	11.26	0.00***
Multiracial	-0.06	0.76	-0.28	0.03	-9.15	0.00***
Employment Status						
Full-Time						
Part Time	-0.22	0.36	-1.01	0.09	-11.77	0.00***
Welfare Work	-0.42	0.16	-1.85	0.09	-20.93	0.00***
Not in Labor Force	-0.10	0.61	-0.50	0.07	-6.78	0.00***
Unemployed	-0.10	0.60	-0.51	0.08	-6.43	0.00***
Gender						
Male						
Female	-0.02	0.93	-0.07	0.02	-3.44	0.00***
Language						
English						
Non-English	-0.01	0.98	-0.02	0.05	-0.52	0.60

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

OLS Regression

Both Modality and Request Type had a significant relationship with Appointment Adherence. For every additional service that was delivered via TMH, the likelihood of adhering to appointments increased by 2.5% (p=0.00**) as compared to in-person care. The likelihood of appointment adherence for Request Types with shorter timely standards (Urgent and Inpatient/Jail Discharge) increased by 0.66% (p=0.00***) as compared to Routine request types. No significant relationship was found between the ratios of Requests per Providers and appointment adherence, though this is likely due to missing data on the number of providers available.

As compared to elderly adults aged above 55 years, all the age groups had significant and negative relationships with appointment adherence. For each additional individual of the respective age group, appointment adherence decreased by 4.2% for adults aged 26-55 (p=0.00***), 2.1% (p=0.00***) for young adults between 19-25 years, and nearly 13% (p=0.00***) for youth under 19 years old.

Compared to those that self-identified as white, Black individuals were likely to experience a -2.3% reduction in appointment adherence (p=0.00***) while Multiracial individuals were likely to experience a 6% increase for every additional patient that self-identified in the respective racial group. For every additional individual that self-identified as part of the respective racial group, Asians were likely to experience a -2% (p=0.00***) decrease,

As compared to those that were employed full-time, all employment types had significant and positive relationships. Those that were employed part-time (19%, p=0.00***) or were unemployed (12%, p=0.00***) were likely to see the greatest increases in appointment adherence; those that were categorized as employed under Welfare Work programs (5%, p=0.00***) or were not in the labor force (10%, p=0.00***) were likely to see smaller increases in appointment adherence.

Being female had a significant but negative relationship with appointment adherence pre- (-4%, p=0.00***). Non-English speakers had a significant relationship, though this increased from an estimated increase of 2.9% (p=0.00***) in appointment adherence.

Approach A: Appointment Adherence

	Estimate	Std. Error	t value	p-value
Intercept	71.84	1.02	70.76	0.00***
Pandemic Time				
Pre-SHO				
Post-SHO	-3.93	0.78	-5.03	0.00***
Request Type				
Routine				
Urgent; Inpatient/Jail Discharge	0.66	0.51	1.3	0.19
Modality				
In-Person				
TMH	2.48	0.86	2.89	0.00***
Requests Per Providers				
Per Request (High Average,0-1)				
Per Request (Low Average, 1-2)	0.14	0.36	0.39	0.70
Per Request (High, 3-4)	-0.65	0.37	-1.75	0.08.
Per Request (Low, >5)	-0.19	0.40	-0.47	0.63
Age Group				
Elderly (>55yrs)				
Adult (26-55yrs)	-4.24	0.35	-12.13	0.00***
Young Adult (19-25yrs)	-2.10	0.49	-4.30	0.00***
Youth (<19yrs)	-12.54	0.77	-16.24	0.00***
Race				
White				
Black	-2.30	0.34	-6.84	0.00***
Asian	-2.06	0.68	-3.02	0.00***
Multiracial	6.13	0.41	15.07	0.00***
Employment Status				
Full-Time				
Part Time	19.37	1.08	17.93	0.00***
Welfare Work	4.56	1.12	4.06	0.00***
Not in Labor Force	9.87	0.90	10.92	0.00***
Unemployed	12.43	0.99	12.56	0.00***
Gender				
Male				
Female	-3.84	0.28	-13.65	0.00***
Language				
English				
Non-English	2.87	0.61	4.74	0.00***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

B. Offsetting Model: Logistic and OLS Regression

The three demographic values that had an effect size at or greater than .01 were Age, Race, and Employment (all at 0.01). The variables of Gender and Language had a negligible effect size of 0.00. Because the variable Requests per Provider acted as an offset, an ANOVA estimate was not possible for that variable.

When offsetting for Requests per Providers to account for any crowding that occurred as patients were transitioned to using TMH, both Modality and Request Types had a significant relationship with receiving a timely appointment. TMH use reduced the probability of receiving a timely appointment by 6% (OR=.77, p=0.00***) as compared to in-person appointments. Requests with shorter timely standards (Urgent, Inpatient/Jail Discharge) increased the probability of receiving a timely appointment by 10% (OR=1.62, p=0.00***). All covariates except for Language had a significant relationship with timely appointments.

As compared to elderly adults aged above 55 years, adults aged 26-55 years had an increased probability of receiving a timely appointment by 5% (OR=1.27, p=0.00***), whereas youth under the age of 19 years had a reduced probability of receiving a timely appointment by 13% (OR=0.58, p=0.00***). As compared to their White counterparts, Black and Asian individuals had an increased probability of 3% (OR=1.12) and 11% (OR=1.65) respectively receiving a timely appointment whereas those that self-identified as Multiracial had a decreased probability of -6% (OR= 0.77; all at p=0.00***).

As compared to their full-time employed counterparts, all the employment groups had a decreased probability of receiving a timely appointment; those that were part of a welfare work program had a decreased probability of 43% (OR=0.15), part-time employees had a decreased probability of 22% (OR=0.36), those not in the labor force had a decreased probability of 14% (OR=0.52), and those that were unemployed had a decreased probability of 10% (OR=0.60; all at a significance level of p=0.00***). Women experienced similar likelihoods of receiving a timely appointment, albeit a mildly negative relationship (-2%, OR=0.91; p=0.00***).

Conversely, there was no significant relationship between Request Type, modality, and appointment adherence. All covariates had a significant relationship with appointment adherence. Identifying as Multiracial, all employment types, and speaking a language other than English had an increased likelihood of appointment adherence.

As compared to elderly adults aged above 55 years, all the age groups had significant and negative relationships with appointment adherence. Appointment adherence decreased by 3.7% for adults aged 26-55 (p=0.00***), 1.8% (p=0.00***) for young adults between 19-25 years, and nearly 12% (p=0.00***) for youth under 19 years old. Compared to those that self-identified as white, Black individuals were likely to experience a 2.4% reduction in appointment adherence (p=0.00***) while Multiracial individuals were likely to experience a 6% (p=0.00***) increase.

As compared to those that were employed full-time, all employment types had significant and positive relationships. Those that were employed part-time (21%, p=0.00***) or were unemployed (13%, p=0.00***) were likely to see the greatest increases in appointment adherence; those that were categorized as employed under Welfare Work programs (6%, p=0.00***) or were not in the labor force (11%, p=0.00***) were also likely to see increases in appointment adherence though these were smaller.

Being female had a significant but negative relationship with appointment adherence both (-3.4%, p=0.00***). Non-English speakers had a significant relationship and positive relationship with appointment adherence and saw a 3% (p=0.00***) increase in appointment adherence.

Offset Model: Timely Appointments

	AME	Odds Ratio	Estimate	Std. Error	z value	p-value
Intercept		2.92	1.07	0.08	13.45	0.00***
Request Type						
Routine						
Urgent; Inpatient/Jail Discharge	0.10	1.62	0.48	0.04	12.76	0.00***
Modality						
In-Person						
TMH	-0.06	0.77	-0.26	0.03	-7.68	0.00***
Age Group						
Elderly (>55yrs)						
Adult (26-55yrs)	0.05	1.27	0.24	0.02	9.61	0.00***
Young Adult (19-25yrs)	0.02	1.07	0.07	0.04	1.88	0.06
Youth (<19yrs)	-0.13	0.58	-0.54	0.05	-10.22	0.00***
Race						
White						
Black	0.03	1.12	0.12	0.02	4.79	0.00***
Asian	0.11	1.65	0.50	0.05	9.56	0.00***
Multiracial	-0.06	0.77	-0.26	0.03	-9.11	0.00***
Employment Status						
Full-Time						
Part Time	-0.22	0.36	-1.01	0.09	-11.78	0.00***
Welfare Work	-0.43	0.15	-1.92	0.09	-21.82	0.00***
Not in Labor Force	-0.14	0.52	-0.66	0.07	-9.04	0.00***
Unemployed	-0.10	0.60	-0.50	0.08	-6.33	0.00***
Gender						
Male						
Female	-0.02	0.91	-0.09	0.02	-4.57	0.00***
Language						
English						
Non-English	0.01	1.04	0.04	0.04	0.97	0.33

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Offset Model: Appointment Adherence

	Estimate	Std. Error	t value	p-value
Intercept	66.30	1.03	64.43	0.00***
Request Type				
Routine				
Urgent; Inpatient/Jail Discharge	-0.14	0.53	-0.26	0.79
Modality				
In-Person				
TMH	0.51	0.48	1.06	0.29
Age Group				
Elderly (>55yrs)				
Adult (26-55yrs)	-3.67	0.35	-10.45	0.00***
Young Adult (19-25yrs)	-1.84	0.50	-3.65	0.00***
Youth (<19yrs)	-12.07	0.80	-15.09	0.00***
Race				
White				
Black	-2.40	0.34	-7.06	0.00***
Asian	-0.06	0.68	-0.09	0.93
Multiracial	6.05	0.41	14.73	0.00***
Employment Status				
Full-Time				
Part Time	20.62	1.12	18.38	0.00***
Welfare Work	6.17	1.16	5.34	0.00***
Not in Labor Force	10.84	0.94	11.57	0.00***
Unemployed	12.96	1.03	12.60	0.00***
Gender				
Male				
Female	-3.45	0.29	-12.08	0.00***
Language				
English				
Non-English	2.92	0.62	4.74	0.00***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

C. Interrupted Time Series (ITS)

The ITS began with determining if the dataset had any trends or seasonality. The percentage of monthly appointments that were timely had no seasonality or trends during 2017-2021, and the autocorrelation was found to be white noise. The monthly appointment adherence percentage did have a trend but no seasonality for the period of 2017-2021. Following the initial analysis, a dynamic regression was completed. There was no significant association between the percentage of timely appointments and TMH utility, though there was a significant at 10% (p<0.09) relationship between TMH use at appointment adherence when adjusting for covariates.

A forecast of the timely appointments for the period of March 2020-February 2021 indicated that the average percentage of appointments would be between approximately 70-80% (though the forecast interval was broader than this). The actual percent of timely appointments stayed somewhat within the forecasted time, though there was a large dip in the weeks of March 2020 due to a period of rapid transition.

The regression results found no significant relationship between the percent of services delivered via TMH and the percent of timely appointments[1]. However, every additional Routine appointment in a health system was associated with 5.3% (p=0.02*) increase in timely appointments, Requests per Providers was an often missing variable though each additional request per provider (with a cap of 4) increased the percent of timely appointments by 3.89% (p=0.00***). Younger clients were associated with a 2.33% (p=0.02*) increase in timely appointments. There was a marginally significant relationship between Race, Employment, and percent of Timely appointments. Clients that are non-white and not fully employed had a lower monthly likelihood of receiving a timely appointment.

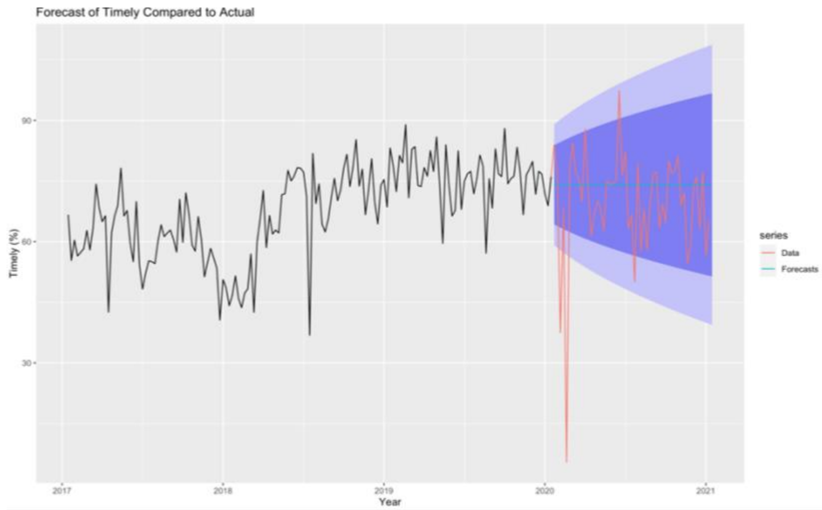
[1] Categorical variables were recoded as dummy variables when transformed to a time series object in R. The recoded data was as follows. Request Type- Routine=0, Inpatient/Jail Discharge=1; Race- White=0, Black =1, Asian=2, Multiracial =3; Employment- 0=Fulltime, 1=Part time, 2= Welfare Work, 3=Not in labor force, 4= Unemployed; Age- 0=Elderly (>55), 1=Adult (26-55), 2=Young Adult (19-25), 3=Youth (<19). The variables "%TMH" and "Requests per Providers" are both continuous.

Table 2: ITS dynamic regression results to measure the percentage of timely appointments indexed by month.

Y = % Timely Appointments

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	50.57	6.75	7.5	0.00***
% TMH	0.03	0.06	0.55	0.59
Request Type	5.39	2.01	2.69	0.02*
Race	-4.05	1.99	-2.04	0.06.
Employment	-1.15	0.65	-1.78	0.09.
Age	2.33	0.87	2.68	0.02*
Requests per Providers	3.89	0.93	4.18	0.00***

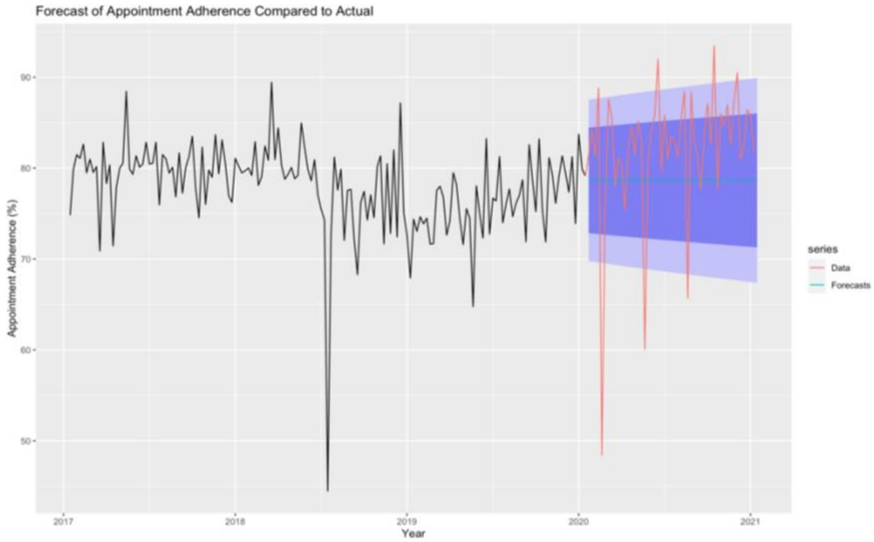
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1



Appointment adherence increased after the pandemic and the appointment adherence increased above the forecasts for March 2020-February 2021. When adjusting for the covariates, there was a marginally significant and positive relationship between the percent of TMH use and the monthly average of the percent of appointment adherence; for every additional percentage point of services delivered via TMH, there is a 7% (0.09.) increase in Appointment Adherence. Appointment Adherence had an overall positive trend. Being younger was negatively associated with appointment adherence; being non-white, having a Routine appointment were positively associated with timely appointments. The ratio of requests per provider and. employment status had no significant relationship with percent TMH.

Y= % Appointment Adherence				
	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	69.24	6.83	10.13	0.00***
% TMH	0.07	0.04	1.83	0.09 .
Trend	0.32	0.11	3.02	0.01*
Request Type	6.24	2.94	2.13	0.06 .
Race	3.27	1.08	3.02	0.01*
Employment	-1.44	0.86	-1.68	0.12
Age	-6.11	1.81	-3.38	0.01 **
Requests per Providers	0.18	0.87	0.21	0.84

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1



Discussion

The objectives of the three approaches were to: identify which variables should be included to create a parsimonious model for ITS by determining the effect size relative to SHO [approach A and B]; determine how TMH use impacted QoC indicators for each Request Type among the patients that received care via TMH versus those that received in-person care [Approach B]; analyze the relationship between modality and QoC indicators for the whole health system, i.e., how increasing TMH adoption may lead to improved indicators for the patients of the health system regardless of their modality of treatment as compared to if TMH adoption remained at the same rates pre-SHO [approach C]; and how TMH use within a health system impacted QoC indicators for each of the Request Types as compared to if TMH adoption remained at the same rates pre-SHO [approach C].

While each of these objectives are discussed in detail in the rest of this section, the findings suggested that TMH use was not associated with changes in timely care in the health system [see: Approach C Results], though cross-sectional estimates indicated that there was a significant and comparable relationship between those that received care via TMH and timeliness compared to those that received in-person care. Post-SHO, this relationship became changed so that the likelihood of receiving timely access to care was similar among those that received care via TMH and those that used in-patient care [see: Approach A and B Results]. This is consistent with comparisons of the actual changes in rates of timely access to care over-time versus the counterfactual for March 2020-February 2021. Appointment Adherence had a marginally significant (p=0.09) and positive relationship with TMH adoption for the health system post-SHO. The actual rates of appointment adherence were far greater than the pseudo-control of if TMH adoption stayed at the pre-SHO rates [see: Approach C Results]. Cross-sectional estimates of TMH adoption and Appointment Adherence pre- and post-SHO indicated that TMH use was associated with reductions in adherence rates pre-SHO, but this flipped post-SHO to show a near 6% increase in Appointment Adherence for patients that received care via TMH vs. those that received care in-person [see: Approach A Results].

As expected, use of TMH with LA County DMH skyrocketed post-SHO, reflecting trends across the nation (Chen et al., 2020; Whaibeh, Mahmoud, & Naal, 2020; Zhou et al. 2020). Timely access to care and appointment adherence increased relative to SHO for both care delivered via TMH and in-person. Widespread TMH adoption post-SHO correlated with decreased disparities in care across all demographics, though measuring change in disparities of care was beyond the scope of this analysis and the demographics of providers were not available within this dataset. Nevertheless, this statistic is especially relevant given the aims of DMH to enhance cultural competency by improving the effectiveness of treatment. In addition to language concordance, racial concordance offers a viable avenue to improve effectiveness of treatment. The reduced disparities in QoC indicators across the demographic variables points to the possibility that TMH may increase racial concordance, which in turn is associated with improved effectiveness of care (Shen et al. 2018; Saha et al. 1999).

All the demographic variables had small effect sizes (<5%) on both QoC indicators. Of those variables, only age, race, and employment status had effect sizes greater than 1%, though these changes increased post-SHO compared to pre-SHO. For the age variable, the youngest patients (<19 years old) were least likely to adhere to their appointments and had almost the same likelihood as elderly patients (>55 years) to receive a timely appointment. Research on mental health service delivery theorizes that the barriers to TMH-use are heightened for older populations, due to steeper learning curves with the modality. Likewise, children experience increased challenges with TMH-use due to poor emotional regulation and shorter attention spans (Racine et al. 2020; Connolly, et al., 2020; Wood et al., 2020). Surprisingly, though the effect size of language increased slightly post-SHO (from 0% pre-SHO), it remained under 1%. Hilty, et al. theorizes that TMH use would increase the availability of non-English speaking mental health providers and reduce barriers for non-English speaking patients (Hilty et al. 2019). While data on provider's native/fluent languages were not available in this dataset, controlling for the language concordance may result in increased effect size.

DMH's goals to improve cultural competency has a focus on addressing the county's epidemic of peoples experiencing houselessness, and a disproportionate number of youth experiencing homelessness are also part of the LGBTQ+ community (Keuroghlian 2014). Individuals at the intersection between these three communities (youth, those that are queer-identifying, and those experiencing homelessness) puts them at an elevated risk for experiencing serious mental health issues. While the analysis completed in this paper does include results that highlights that a system-wide adoption of TMH could improve QoC indicators for youth, they remain less likely than their older counterparts to receive optimal quality of care. The data on if patients were experiencing homelessness or if they were queer-identifying was often missing and were dropped for this analysis.

Timely Access to Care

There was no significant association between TMH use within a health system and timely appointments over time when adjusting for providers available, demographic variables, and Request Type. Being younger and having fewer requests per provider was significantly associated with timely access to care ($p<.05$), while being non-white and not having full-time employment status was associated with decreased likelihood of receiving timely access to care (though the latter two had weaker associations at $p<0.10$). Cross-sectional estimates (approach B) found that there was a significant association, albeit mildly negative, between TMH use and timely appointments as compared to in-person appointments. Meanwhile, when running the regression for pre-SHO and post-SHO (approach A), the use of TMH had increased likelihood of timely appointment post-SHO (though still negative). Timely access to care did increase post-SHO, indicating that extraneous factors, beyond what was included in the models lead to the increased timely access (this is supported by the R^2 of all the models). A potential explanation for this is that the number of requests decreased substantially when the pandemic began, which could have led to more provider availability. Additionally, Inpatient/Jail Discharge and Urgent Request Types were consistently (i.e., within all three approaches) associated with an increased likelihood of receiving timely appointments, despite having shorter timely standards (48 hours and 5 business days respectively) and being more likely to need inpatient care. This may be due to the expedited release of incarcerated persons serving a sentence for non-violent offenses in April and July 2020; within LA county, persons being released from incarceration must have a mental health consultation when discharged. Additional exploration of trends in TMH adoption and timely access to care for longer periods of time post-SHO is needed to illuminate this relationship.

The findings do contradict other research about TMH being linked to timely access to care. As discussed in the literature review, TMH is associated with timely access to primary care and to mental healthcare (Chen et al. 2020; Connolly et al., 2020; Graetz et al. 2021; Racine et al., 2020; Zhou, et al., 2020). In the case of Graetz et al.'s findings, the study adjusted for more variables that this study did not have available, including transportation costs, travel time, paid parking, cost-sharing, technology access, etc. and excluded visits that occurred within 7 days of other clinical encounters. Given that the adjusted R^2 for the ITS model indicated that the variables accounted for 62% of the changes in the timely appointments, additional adjustments and optimizing the model may be necessary. Most studies that evaluated TMH effectiveness also accounted for reimbursement and diagnosis, both of which were not available in this dataset (Connolly et al., 2020; Racine et al., 2020; Zhou, et al., 2020). Finally, this study reported cross-sectional estimates via logistic and OLS regressions followed by an ITS to account for trends in timely access to care for three years prior to SHO as compared to 11 months post-SHO. Previous studies reported on cross-sectional estimates directly before and after TMH adoption which could account for the different conclusions (Chen et al. 2020).

Appointment Adherence

TMH use within a health system did have a marginally significant (p=.06) and positive relationship (7%) with appointment adherence. Cross-sectional estimates (as determined by approaches A and B) found that TMH use also improved the likelihood of appointment adherence in individuals using TMH compared to those that did not, though this was not the case pre-SHO (approach A). Moreover, while timely access to care was predominately within the forecasted levels in March 2020-February 2021, appointment adherence trended upwards and began surpassing the forecasted intervals. This may be because, despite the initial appointment not being timely, using TMH removed enough barriers to encourage users to sustain their scheduled treatment. Most importantly, TMH use within the health system increased appointment adherence for all modalities, which may be because delivering care using TMH uses fewer resources and less time for providers, which in turn allows for those resources to be redistributed to providing inpatient care for more urgent Request Types.

The results of the regressions aligned with findings that found TMH use in LA county and California had the potential to improve adherence to follow up appointments as comfort with the TMH modality increased (Connolly et al., 2020). The changes in ratios of requests to providers (which acts as a proxy for the number of providers available to accept and treat patients) had no impact on association with appointment adherence. This may be due to evidence that suggests that TMH can increase access and sustain treatment for new patients despite increased prevalence of mental health issues and limited resources (Stoll, Sadler, & Trachsel, 2020; Whaibeh, Mahmoud, & Naal, 2020). The information on provider licensing and scope of work was not available though recent research suggests that the provider type could lead to greater incidence of new treatment plans and may influence adequate treatment (Kniesner et al. 2005).

Finally, this study builds upon research that TMH-use improves appointment adherence; though while previous research compared adherence to scheduled appointments for those that used TMH versus in-person care, this study found that appointment adherence was associated with TMH-use for *all patients* within that health system and for a 90-day treatment plan (North 2020; SPROUT 2022; Wood et al., 2020).

Limitations

This study comes with several limitations. The dataset itself was only for patients of DMH's DO clinics, while most of DMH's clinics are contracted with independent clinics. The majority of DMH DO clinic patients were insured through MediCal or uninsured, experiencing poverty, or many housing insecure. This limited the generalizability of the findings. The data cleaning phase resulted in lost power. This included removing variables with treatment plans above 90 days, removing outliers, correcting any appointment adherence rates over 100% (approximately 2000 observations out of the over 200,000), and removing two variables that were majority missing values (smoking status and homelessness). The data cleaning phase also involved removing observations that had a "No Entry", "Prefer not to answer", or "Other" response from each of the demographic variables for the regression. Likewise, the gender variable had to drop the trans-identifying individuals due to small sample size.

Trans-identifying and LGBTQ+ persons have disproportionately high rates of serious mental illness and experiencing homelessness but are less likely to receive care. Research on effective strategies to reach these individuals is severely lacking, and this study was unfortunately unable to help fill that gap. Given that LA County has one of the largest population of people experiencing homelessness in the country, understanding if individuals that need complex care are getting it, especially by working collaboratively with county-wide projects is vital to strengthening programs or interventions that could resolve the crisis.

Finally, data on providers was limited to the ratio of providers to requests. Data on the demographic background, geography, the type of provider (i.e., the license, scope of work, and/or specialty), and the languages available were not available. This removed the possibility for evaluating and controlling for language and racial concordance, which has been shown to improve the effectiveness of treatment (Shen et al. 2018; Khurana 2021; Hilty et al. 2019). Further, the provider type would provide information on the types of treatment and the populations that the provider would be able to serve.

Implications for Practice & Best Practices

Telehealth adoption is associated with timely access to care for primary care appointments post-SHO and reduced no-shows for both primary and specialized care (Blackstone et al. 2022; Connolly et al. 2020). Primary care appointments allow for a unique opportunity for depression screenings through communication with patients that may otherwise avoid seeking mental healthcare, educating them about mental health, and encouraging care utilization. This study found that the use of TMH had significant and positive relationships with appointment adherence, which in turn indicates that TMH could be an effective tool for long-term psychotherapy and patient retention. This study also found that TMH-use within a health system (approach C) allows for improved appointment adherence and was associated with increased QoC indicators for patients that need inpatient or urgent care. The results indicate that TMH use within a health system is associated with a redistribution of resources that could improve QoC indicators for all patients regardless of modality, prevent exacerbation of mental health conditions, and maintain treatment.

The rise of long-COVID, complicated grief, PTSS, PTSD, and prevalence of mental health disorders among the general population emphasizes the need for continuous and accessible mental health care. TMH use may improve appointment adherence by reducing barriers to care for patients, but it must be matched with other best practices to maximize the effectiveness of care. Given that racial minorities are disproportionately likely to experience negative health outcomes, care teams must be representative, include peer-support, and be culturally competent to increase care utility. One avenue for this is increasing language and racial concordance by improving access to providers that share the background of the patient (Shen et al. 2018). Language concordance is associated with cultural competency, which in turn leads to increase patient satisfaction, patient involvement in self-care, communication with providers, and adherence to both pharmaceutical and non-pharmaceutical treatment plans (Moreno et. al 2020; Saha et al. 1999; Shen et al. 2018). Racial concordance is associated with decreased emergency department visits, hospitalizations, and decreased healthcare expenditure (Khurana 2021). Diversifying how mental health is accessed (flexibly and in diverse settings) which can include integrating a patient-led approach, with collaboration from a community-led organization, and peer-support services leads to improved care utility and treatment adherence as well (Moreno et. al 2020). These recommendations should supplement clinical mental health services to expand access and improve cost-effectiveness.

Mental health concerns addressed during the pandemic include a patchwork of preventive measures (self-help apps and coping mechanisms), modifying access to treatment and ensuring continuity of care via the transition to TMH and the loosening of regulatory barriers (Moreno et al., 2020). This must be supported by screening and identification of new cases of mental health disorders (Blackstone et al. 2022).

Even among communities that have transitioned to TMH, evaluation of health and service outcomes must be continuous to define practices that should be developed versus those to discontinue (often this will depend on the population). The Associated Press found that 62% of people aged over 50 are using Telehealth (The AP-NORC Center for Public Affairs Research 2021). Older people of color preferred using telehealth, especially to avoid exposure to COVID and improved timely access to care, but they also stated concerns regarding quality of care. These concerns included not having a personal relationship with their provider, receiving less effective care, facing technical issues, and concerns about confidentiality. Given that elderly populations rapidly transitioned to TMH and according to this study were, along with youth aged under 19 years, receiving less favorable QoC indicators compared to adults and young adults, these considerations may lead to improved timely care and appointment adherence.

The availability of IT staff for ongoing technical support and training for providers and patients is integral. Policy to enable widespread access to internet, private spaces, equipment, and reduction of regulatory barriers should all be part of a systematic approach to strengthen the provision of TMH and as a key funding consideration. Providers will need to be trained for technological proficiency, trauma informed care, and improved "webside manner". All these recommendations and tools are vital to implement TMH, keeping in mind that that modality of service provision will go together with in-person and hybrid care models (Blackstone et al. 2022; Moreno et al., 2020).

As evident from the findings of this study, TMH alone cannot lead to improved QoC indicators, but does provide an opportunity for more efficient workflows (North 2020). This may involve brief and more frequent patient interactions, including training and testing for video-based calls, experimenting with modalities within TMH (including telephone or texting), and connecting with the patients support network and other clinical care providers if/when it is possible.

Conclusion

TMH use within a health system was associated with an increased likelihood of appointment adherence. Urgent and Inpatient/Jail Discharge Request Types were more likely to receive a timely appointment and to adhere to appointment plans when the health system adopted TMH. No significant association existed between TMH use and timely access to care within the health system, but individuals that used TMH were slightly less likely to receive timely care as compared to those receiving in-person care. Descriptive statistics found reduced disparities in care across race, gender, age, and employment type after TMH was adopted post-SHO.

Future research should examine the impact of TMH use on QoC indicators over a longer time-period post-SHO to further understand the relationship. Additionally, TMH should be evaluated as a promising intervention to reduce disparities in care, especially when adjusting for language and racial concordance. Future research should also evaluate workflows for TMH and hybridized care to pinpoint which populations and diagnoses should avoid versus utilize TMH as a modality of care, which provider or scope of practice should leverage TMH, and compare specific outcomes as related to specific conditions. Other QoC indicators associated with increased effectiveness of care, such as patient engagement, patient satisfaction, medication adherence, among others should be evaluated in relation to TMH use. Rigorous primary data collection is needed among groups disproportionately impacted by serious mental illness, namely those experiencing homelessness, those that identify as LGBTQ+, immigrants, single parents, and other socioeconomic minorities. Future research could use claims data to evaluate the cost-effectiveness of TMH-use in different populations.

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Appendix A: Descriptive Statistics

Number of Fulfilled Appointments that were or were not Timely

Request Type		Pre-SHO In-person Timely N (%)	Pre-SHO In-person Not-Timely N (%)	Pre-SHO TMH Timely N (%)	Pre-SHO TMH Not-Timely N (%)	Post-SHO In-person Timely N (%)	Post-SHO In-person Not-Timely N (%)	Post-SHO TMH Timely N (%)	Post-SHO TMH Not-Timely N (%)
Inpatient/Jail Discharge		1573 (81.33%)	361 (18.67%)	11 (28.95%)	27 (71.05%)	76 (71.03%)	31 (28.97%)	238 (67.04%)	117 (32.96%)
Routine		22809 (61.51%)	14273 (38.49%)	84 (22.83%)	284 (77.17%)	819 (74.86%)	275 (25.14%)	3103 (58.78%)	2176 (41.22%)
Urgent		85 (63.91%)	48 (36.09%)	2 (28.57%)	5 (71.43%)	14 (93.33%)	1 (6.67%)	29 (56.86%)	22 (43.14%)
Gender									
Inpatient/Jail Discharge	*Female*	651 (33.54%)	1290 (66.46%)	23 (19.49%)	95 (80.51%)	44 (27.16%)	118. (72.84%)	165 (24.19%)	517 (75.81%)
	Male	1359 (46.37%)	1572 (53.63%)	61 (34.86%)	114 (65.14%)	65 (33.16%)	131 (66.84%)	194 (23.75%)	623 (76.25%_
	Trans	4 (44.44%)	5 (55.56%)		2 (100%)			1	1 (100%)
	Unknown	2 (66.67%)	1 (33.33%)						
Routine	*Female*	16541 (34.24%)	31761 (65.76%)	375 (22.75%)	1273 (77.25%)	554 (32.51%)	1150 (67.49%)	2555 (22.03%)	9043 (77.97%)
	Male	14837 (35.62%)	26820 (64.38%)	242 (19.9%)	974 (80.1%)	488 (34.78%)	915. (65.22%)	1973 (22.21%)	6911 (77.79%)
	Trans	99 (39.6%)	(151) 60.4%	1 (11.11%)	8 (88.89%)		7 (100%)	10 (16.13%)	52 (83.87%)
	Unknown	8 (19.05%)	(34) 80.95%		2 (100%)			1 (20%)	4 (80%)
Urgent	*Female*	44 (33.33%)	88 (66.67%)	4 (23.53%)	13 (76.47%)	7 (46.67%)	8 (53.33%)	20 (17.09%)	97 (82.91%)
	Male	58 (39.73%)	(88) 60.27%	2 (33.33%)	4 (66.67%)	8 (44.44%)	10 (55.56%)	24 (27.27%)	64 (72.73%)
	Trans		1 (100%)						
Language									
Inpatient/Jail Discharge	*English*	1887 (42.41%)	2562 (57.59%)	80 (28.88%)	197 (71.12%)	98 (31.21%)	216 (68.79%)	330 (24.61%)	1011 (75.39%)
	Non-English	129 (29.66%)	306 (70.34%)	4 (22.22%)	14 (77.78%)	11 (25%)	33 (75%)	29 (18.24%)	130 (81.76%)
Routine	*English*	27739 (35.76%)	49824 (64.24%)	529 (21.06%)	1983 (78.94%)	927 (33.82%)	1814 (66.18%)	3902 (22.37%)	13542 (77.63%)
	Non-English	3746 (29.52%)	8942 (70.48%)	89 (24.52%)	274 (75.48%)	115 (30.83%)	258 (69.17%)	637 (20.52%)	2468 (79.48%)
Urgent	*English*	87 (34.8%)	163 (65.2%)	5 (26.32%)	14 (73.68%)	15 (46.88%)	17 (53.12%)	40 (22.35%)	139 (77.65%)
	Non-English	15 (51.72%)	14 (48.28%)	1 (25%)	3 (75%)		1 (100%)	4 (15.38%)	22 (84.62%)
Ethnicity									
Inpatient/Jail Discharge	*Hispanic or Latino*	713 (38.52%)	1138 (61.48%)	20 (19.61%)	82 (80.39%)	42 (27.63%)	110 (72.37%)	113 (19.28%)	473 (80.72%)
	No Entry/Unknown	1098 (42.54%)	1483 (57.46%)	57 (34.97%)	106 (65.03%)	62 (35.63%)	112 (64.37%)	198 (27.05%)	534 (72.95%)
	Not Hispanic or Latino	205 (45.35%)	247 (54.65%)	7 (23.33%)	23 (76.67%)	5 (15.62%)	27 (84.38%)	48 (26.37%)	134 (73.63%)
Routine	*Hispanic or Latino*	11532 (32.93%)	23485 (67.07%)	279 (23.39%)	914 (76.61%)	346 (31.66%)	747 (68.34%)	1931 (22.26%)	6742 (77.74%)
	No Entry/Unknown	17587 (35.91%)	31391 (64.09%)	299 (20.40%)	1167 (79.60%)	620 (34.79%)	1162 (65.21%)	2256 (21.85%)	8070 (78.15%)
	Not Hispanic or Latino	2366 (37.82%)	3890 (62.18%)	40 (18.52%)	176 (81.48%)	76 (31.8%)	163 (68.2%)	352 (22.71%)	1198 (77.29%)
Urgent	*Hispanic or Latino*	42 (32.31%)	88 (67.69%)	3 (27.27%)	8 (72.73%)	4 (30.77%)	9 (69.23%)	14 (15.22%)	78 (84.78%)
	No Entry/Unknown	49 (38.89%)	77 (61.11%)	3 (27.27%)	8 (72.73%)	9 (52.94%)	8 (47.06%)	25 (26.32%)	70 (73.68%)
	Not Hispanic or Latino	11 (47.83%)	12 (52.17%)		1 (100%)	2 (66.67%)	1 (33.33%)	5 (27.78%)	13 (72.22%)
Race									
Inpatient/Jail Discharge	*Asian*	32 (36.36%)	56 (63.64%)	2 (33.33%)	4 (66.67%)	1 (20.00%)	4 (80.00%)	5 (29.41%)	12 (70.59%)
	Black	492 (59.06%)	341 (40.94%)	26 (40.62%)	38 (59.38%)	18 (47.37%)	20 (52.63%)	53 (29.12%)	129 (70.88%)
	Multiracial	211 (43.60%)	273 (56.40%)	11 (32.35%)	23 (67.65%)	8 (28.57%)	20 (71.43%)	26 (23.85%)	83 (76.15%)
	Native	13 (50.00%)	13 (50.00%)				1 (100.00%)	2 (33.33%)	4 (66.67%)
	No Entry	701 (35.86%)	1254 (64.14%)	15 (17.44%)	71 (82.56%)	55 (26.96%)	149 (73.04%)	196 (23.84%)	626 (76.16%)
	Unknown/Other	319 (39.29%)	493 (60.71%)	9 (16.67%)	45 (83.33%)	16 (34.78%)	30 (65.22%)	45 (22.06%)	159 (77.94%)
	White	248 (36.15%)	438 (63.85%)	21 (41.18%)	30 (58.82%)	11 (30.56%)	25 (69.44%)	32 (20.00%)	128 (80.00%)
Routine	*Asian*	569 (38.37%)	914 (61.63%)	8 (25.81%)	23 (74.19%)	9 (25.00%)	27 (75.00%)	26 (15.95%)	137 (84.05%)
	Black	7046 (41.68%)	9859 (58.32%)	100 (19.23%)	420 (80.77%)	230 (37.40%)	385 (62.60%)	615 (24.95%)	1850 (75.05%)
	Multiracial	2975 (33.46%)	5917 (66.54%)	67 (22.11%)	236 (77.89%)	64 (30.48%)	146 (69.52%)	276 (20.74%)	1055 (79.26%)
	Native	191 (32.37%)	399 (67.63%)		9 (100.00%)	3 (30.00%)	7 (70.00%)	9 (16.07%)	47 (83.93%)
	No Entry	11697 (32.05%)	24804 (67.95%)	270 (22.33%)	939 (77.67%)	543 (33.73%)	1067 (66.27%)	2820 (22.65%)	9628 (77.35%)
	Unknown/Other	5340 (34.96%)	9935 (65.04%)	106 (22.80%)	359 (77.20%)	115 (28.75%)	285 (71.25%)	501 (19.25%)	2101 (80.75%)
	White	3667 (34.58%)	6938 (65.42%)	67 (19.82%)	271 (80.18%)	78 (33.48%)	155 (66.52%)	292 (19.68%)	1192 (80.32%)
Urgent	*Asian*	2 (66.67%)	1 (33.33%)					1 (33.33%)	2 (66.67%)
	Black	16 (42.11%)	22 (57.89%)			4 (66.67%)	2 (33.33%)	5 (22.73%)	17 (77.27%)
	Multiracial	10 (32.26%)	21 (67.74%)		2 (100.00%)	1 (33.33%)	2 (66.67%)	1 (4.55%)	21 (95.45%)
	Native	1 (50.00%)	1 (50.00%)	1 (100.00%)					1 (100.00%)
	No Entry	39 (32.23%)	82 (67.77%)	3 (23.08%)	10 (76.92%)	6 (37.50%)	10 (62.50%)	30 (24.79%)	91 (75.21%)
	Unknown/Other	21 (41.18%)	30 (58.82%)	1 (25.00%)	3 (75.00%)	1 (25.00%)	3 (75.00%)	6 (23.08%)	20 (76.92%)
	White	13 (39.39%)	20 (60.61%)	1 (33.33%)	2 (66.67%)	3 (75.00%)	1 (25.00%)	1 (10.00%)	9 (90.00%)
Age									
Inpatient/Jail Discharge	*Adult*	1301 (45.16%)	1580 (54.84%)	49 (28.49%)	123 (71.51%)	65 (30.95%)	145 (69.05%)	217 (25.44%)	636 (74.56%)
	Elderly	301 (45.26%)	364 (54.74%)	28 (43.08%)	37 (56.92%)	13 (34.21%)	25 (65.79%)	54 (26.87%)	147 (73.13%)
	Y.Adult	282 (33.81%)	552 (66.19%)	7 (15.22%)	39 (84.78%)	18 (26.87%)	49 (73.13%)	58 (19.59%)	238 (80.41%)
	Youth	132 (26.19%)	372 (73.81%)		12 (100.00%)	13 (30.23%)	30 (69.77%)	30 (20.00%)	120 (80.00%)
Routine	*Adult*	18803 (37.06%)	31937 (62.94%)	360 (21.42%)	1321 (78.58%)	614 (34.91%)	1145 (65.09%)	2481 (22.22%)	8684 (77.78%)
	Elderly	6643 (32.95%)	13516 (67.05%)	154 (23.73%)	495 (76.27%)	211 (31.54%)	458 (68.46%)	990 (22.02%)	3506 (77.98%)
	Y.Adult	4124 (37.15%)	6977 (62.85%)	78 (24.22%)	244 (75.78%)	152 (35.02%)	282 (64.98%)	612 (21.85%)	2189 (78.15%)
	Youth	1913 (23.21%)	6330 (76.79%)	26 (11.66%)	197 (88.34%)	65 (25.79%)	187 (74.21%)	455 (21.84%)	1628 (78.16%)
Urgent	*Adult*	45 (30.82%)	101 (69.18%)	5 (33.33%)	10 (66.67%)	7 (46.67%)	8 (53.33%)	30 (25.86%)	86 (74.14%)
	Elderly	26 (48.15%)	28 (51.85%)	1 (16.67%)	5 (83.33%)	4 (80.00%)	1 (20.00%)	3 (8.11%)	34 (91.89%)
	Y.Adult	15 (40.54%)	22 (59.46%)		1 (100.00%)	2 (33.33%)	4 (66.67%)	7 (25.00%)	21 (75.00%)
	Youth	16 (39.02%)	25 (60.98%)		1 (100.00%)	2 (28.57%)	5 (71.43%)	4 (16.67%)	20 (83.33%)

Mean Adherence Percent

		Pre-SHO		Post-SHO	
		In-Person	*TMH*	*In-Person*	*TMH*
Request Type		Mean Adherence (%)		Mean Adherence (%)	
Inpatient/Jail Discharge		79.51	66.16	80.14	82.61
Routine		77.43	73.05	84.15	84.79
Urgent		74.85	84.80	83.83	81.49
Gender					
Inpatient/Jail Discharge	*Female*	77.35	67.08	80.82	82.11
	Male	80.88	65.46	79.56	83.01
	Trans	85.75	76.80		93.10
	Unknown	80.25			
Routine	*Female*	76.98	73.46	84.14	84.99
	Male	77.94	72.39	84.17	84.56
	Trans	78.71	83.30	82.69	79.91
	Unknown	70.93	87.20		68.21
Urgent	*Female*	76.87	83.55	81.71	79.28
	Male	72.93	88.58	85.55	84.61
	Trans	94.90			
Language					
Inpatient/Jail Discharge	*English*	79.58	65.31	79.43	82.46
	Non-English	78.79	78.94	85.21	83.84
Routine	*English*	76.76	72.85	83.82	84.51
	Non-English	81.55	74.42	86.65	86.35
Urgent	*English*	73.71	86.03	86.76	80.58
	Non-English	84.79	79.89	1.72	87.90
Ethnicity					
Inpatient/Jail Discharge	*Hispanic or Latino*	79.36	69.83	80.71	82.21
	No Entry/Unknown	79.89	65.59	79.06	82.99
	Not Hispanic or Latino	77.84	56.55	83.50	82.34
Routine	*Hispanic or Latino*	78.16	74.10	84.24	84.60
	No Entry/Unknown	76.78	72.01	84.13	84.75
	Not Hispanic or Latino	78.49	74.30	83.90	86.10
Urgent	*Hispanic or Latino*	76.85	87.67	77.70	82.86
	No Entry/Unknown	70.94	80.37	86.97	81.97
	Not Hispanic or Latino	86.21	96.03	92.37	70.52
Race					
Inpatient/Jail Discharge	*Asian*	82.20	85.07	91.07	92.38
	Black	78.71	63.76	75.02	81.88
	Multiracial	80.76	62.41	84.42	78.35
	Native	77.47		88.24	68.39
	No Entry	79.64	70.27	80.80	83.24
	Unknown/Other	79.50	73.86	82.31	82.15
	White	78.98	54.09	74.04	83.16
Routine	*Asian*	82.76	74.41	88.17	86.38
	Black	73.65	72.39	83.63	82.46
	Multiracial	77.37	71.74	85.39	82.72
	Native	76.81	82.90	85.39	77.72
	No Entry	78.49	73.43	84.39	85.76
	Unknown/Other	77.40	72.99	81.70	84.03
	White	79.22	73.48	86.28	83.88
Urgent	*Asian*	32.83			82.83
	Black	70.31		88.01	80.00
	Multiracial	76.43	79.64	86.20	83.62
	Native	69.41	100.00		100.00
	No Entry	79.29	85.23	92.87	79.38
	Unknown/Other	72.93	95.76	52.68	90.78
	White	70.35	58.13	75.45	81.49
Age					
Inpatient/Jail Discharge	*Adult*	79.84	68.54	79.88	82.81
	Elderly	81.23	63.18	69.76	80.90
	Y.Adult	77.63	59.10	82.47	84.37
	Youth	78.26	75.24	87.41	80.18
Routine	*Adult*	76.16	71.80	83.24	84.51
	Elderly	79.94	73.29	84.82	85.95
	Y.Adult	76.52	75.46	84.05	83.48
	Youth	80.38	78.55	89.26	85.56
Urgent	*Adult*	71.13	89.98	80.22	80.26
	Elderly	77.35	71.50	86.46	87.08
	Y.Adult	79.48	100.00	94.67	81.62
	Youth	81.37	87.32	80.11	78.87

Appendix B: Effect Sizes

Effect Size for ANOVA (Type I) - [App. A]

Parameter	Eta2 - Pre	95% CI
Request Type	0.00	[0.00, 1.00]
Modality	0.00	[0.00, 1.00]
Requests per Provider	0.00	[0.00, 1.00]
Age	0.01	[0.03, 1.00]
Race	0.01	[0.02, 1.00]
Employment	0.01	[0.02, 1.00]
Gender	0.00	[0.00, 1.00]
Language	0.00	[0.01, 1.00]

Effect Size for ANOVA (Type I) - Offset Model [App. B]

Parameter	Eta2	95% CI
Request Type	0.00	[0.00, 1.00]
Modality	0.00	[0.00, 1.00]
Age	0.01	[0.01, 1.00]
Race	0.01	[0.01, 1.00]
Employment	0.01	[0.01, 1.00]
Gender	0.00	[0.00, 1.00]
Language	0.00	[0.00, 1.00]

Appendix C: Alternate for Approach A to compare results by SHO

Approach A: Summary and Results

Model	**Model Fit**	**Modality**	**Request Type**
Y = Timely Appointments (Binary); Logistic Regression			
Pre-SHO	χ^2 (17) = 1973.57, p = 0.00 Pseudo-R^2 (Cragg-Uhler) = 0.07, Pseudo-R^2 (McFadden) = 0.04, AIC = 47369.10, BIC = 47522.88	TMH (AME): -0.42*** TMH (OR): .14***	Urgent or Inpatient/Jail Discharge (AME): .17*** Urgent or Inpatient/Jail Discharge (OR): 2.32***

Post-SHO	χ^2 (17) = 1906.58, p = 0.00, Pseudo-R^2 (Cragg-Uhler) = 0.44, Pseudo-R^2 (McFadden) = 0.30, AIC = 4467.47, BIC = 4584.70	TMH (AME): -0.08*** TMH (OR): .61***	Urgent or Inpatient/Jail Discharge (AME): .17*** Urgent or Inpatient/Jail Discharge (OR): 3.15***
Y = Appointment Adherence (Continuous); OLS Regression			
Pre-SHO	F (17,35500) = 113.25, p = 0.00, R^2 = 0.05, Adj. R^2 = 0.05	TMH: -5.16**	Urgent or Inpatient/Jail Discharge: 1.63**
Post-SHO	F (17,4708) = 40.87, p = 0.00, R^2 = 0.13, Adj. R^2 = 0.13	TMH: 5.99***	Urgent or Inpatient/Jail Discharge: 3.83***

Pre-SHO Timely Appointments

	AME	Odds Ratio	Estimate	Std. Error	z value	p-value
Intercept		2.48	0.91	0.08	10.70	0.00***
Request Type						
Routine						
Urgent; Inpatient/Jail Discharge	0.17	2.32	0.84	0.05	17.31	0.00***
Modality						
In-Person						
TMH	-0.42	0.14	-1.98	0.14	-14.12	0.00***
Requests Per Provider						
Per Request (High Average,0-1)						
Per Request (Low Average, 1-2)	-0.01	0.95	-0.05	0.03	-1.71	0.09
Per Request (High, 3-4)	-0.01	0.95	-0.05	0.03	-1.55	0.12
Per Request (Low, >5)	0.00	0.99	-0.01	0.03	-0.32	0.75
Age Group						
Elderly (>55yrs)						
Adult (26-55yrs)	0.04	1.20	0.18	0.03	6.67	0.00***
Young Adult (19-25yrs)	-0.02	0.93	-0.07	0.04	-1.97	0.05.
Youth (<19yrs)	-0.19	0.44	-0.82	0.06	-14.68	0.00***
Race						
White						
Black	0.00	1.02	0.02	0.03	0.84	0.40
Asian	0.09	1.53	0.42	0.05	7.97	0.00***
Multiracial	-0.06	0.77	-0.27	0.03	-8.50	0.00***
Employment Status						
Full-Time						
Part Time	-0.17	0.46	-0.77	0.09	-8.58	0.00***
Welfare Work	-0.36	0.21	-1.54	0.09	-17.08	0.00***
Not in Labor Force	-0.08	0.68	-0.39	0.08	-5.16	0.00***
Unemployed	0.04	1.20	0.18	0.09	2.14	0.03*
Gender						
Male						
Female	-0.03	0.89	-0.12	0.02	-5.26	0.00***
Language						
English						
Non-English	-0.02	0.93	-0.07	0.05	-1.65	0.10

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Post-SHO Timely Appointments

	AME	Odds Ratio	Estimate	Std. Error	z value	p-value
Intercept		1.39E+08	18.75	496.51	0.04	0.97
Request Type						
Routine						
Urgent; Inpatient/Jail Discharge	0.17	3.15	1.15	0.11	10.70	0.00***
Modality						
In-Person						
TMH	-0.08	0.61	-0.49	0.09	-5.70	0.00***
Requests Per Provider						
Per Request (High Average,0-1)						
Per Request (Low Average, 1-2)	0.00	1.02	0.02	0.11	0.19	0.85
Per Request (High, 3-4)	0.01	1.05	0.05	0.08	0.63	0.53
Per Request (Low, >5)	0.01	1.05	0.05	0.12	0.36	0.72
Age Group						
Elderly (>55yrs)						
Adult (26-55yrs)	0.07	1.46	0.38	0.08	4.73	0.00***
Young Adult (19-25yrs)	0.44	6.92E+07	18.05	402.69	0.04	0.96
Youth (<19yrs)	0.44	2.32E+08	19.26	703.31	0.03	0.98
Race						
White						
Black	0.22	3.48	1.25	0.08	15.77	0.00***
Asian	0.45	5.93E+07	17.90	707.43	0.03	0.98
Multiracial	-0.09	0.61	-0.49	0.09	-5.24	0.00
Employment Status						
Full-Time						
Part Time	-0.39	0.00	-19.18	496.51	-0.04	0.97
Welfare Work	-0.97	0.00	-38.77	878.46	-0.04	0.96
Not in Labor Force	-0.32	0.00	-18.78	496.51	-0.04	0.97
Unemployed	-0.73	0.00	-21.11	496.51	-0.04	0.97
Gender						
Male						
Female	0.05	1.34	0.29	0.07	4.04	0.00***
Language						
English						
Non-English	0.37	9.69E+07	18.39	707.43	0.03	0.98

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pre-SHO Appointment Adherence

	Estimate	Std. Error	t value	p-value
Intercept	67.51	1.09	61.72	0.00***
Request Type				
Routine				
Urgent; Inpatient/Jail Discharge	1.63	0.60	2.74	0.01**
Modality				
In-Person				
TMH	-5.16	2.11	-2.45	0.01**
Requests Per Provider				
Per Request (High Average,0-1)				
Per Request (Low Average, 1-2)	0.11	0.37	0.29	0.77
Per Request (High, 3-4)	-0.47	0.40	-1.18	0.24
Per Request (Low, >5)	-0.44	0.39	-1.11	0.27
Age Group				
Elderly (>55yrs)				
Adult (26-55yrs)	-5.43	0.36	-15.11	0.00***
Young Adult (19-25yrs)	-2.25	0.50	-4.51	0.00***
Youth (<19yrs)	-12.93	0.79	-16.45	0.00***
Race				
White				
Black	-3.56	0.35	-10.25	0.00***
Asian	-1.11	0.66	-1.68	0.09
Multiracial	5.48	0.42	13.13	0.00***
Employment Status				
Full-Time				
Part Time	24.23	1.15	20.99	0.00***
Welfare Work	10.46	1.18	8.89	0.00***
Not in Labor Force	16.21	0.98	16.59	0.00***
Unemployed	17.92	1.08	16.65	0.00***
Gender				
Male				
Female	-3.95	0.29	-13.58	0.00***
Language				
English				
Non-English	1.40	0.60	2.34	0.02**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Post-SHO Appointment Adherence

	Estimate	Std. Error	t value	p-value
Intercept	81.14	2.91	27.92	0.00***
Request Type				
Routine				
Urgent; Inpatient/Jail Discharge	3.83	1.20	3.19	0.00***
Modality				
In-Person				
TMH	5.99	1.11	5.40	0.00***
Requests Per Provider				
Per Request (High Average,0-1)				
Per Request (Low Average, 1-2)	-0.39	1.21	-0.32	0.75
Per Request (High, 3-4)	-0.92	0.98	-0.93	0.35
Per Request (Low, >5)	-0.72	1.44	-0.50	0.62
Age Group				
Elderly (>55yrs)				
Adult (26-55yrs)	5.74	1.05	5.44	0.00***
Young Adult (19-25yrs)	-13.05	2.08	-6.29	0.00***
Youth (<19yrs)	-11.99	3.34	-3.59	0.00***
Race				
White				
Black	8.55	1.01	8.46	0.00***
Asian	33.47	3.35	9.99	0.00***
Multiracial	8.78	1.23	7.14	0.00***
Employment Status				
Full-Time				
Part Time	-4.99	3.10	-1.61	0.11
Welfare Work	3.69	3.92	0.94	0.35
Not in Labor Force	-20.22	2.31	-8.74	0.00***
Unemployed	-15.49	2.55	-6.07	0.00***
Gender				
Male				
Female	-4.56	0.87	-5.27	0.00***
Language				
English				
Non-English	24.70	3.32	7.44	0.00***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1