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Breaking Barriers: Improving Patient Adherence to Appointments and Provider Productivity Through Telehealth

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Abstract

Telehealth services became popular due to the COVID-19 pandemic, yet their operational impacts on healthcare organizations are not well-understood. Patient behaviors can vary significantly between telehealth and in-person appointments, introducing new challenges and opportunities for healthcare delivery. We examine two key behaviors contributing to nonadherence to medical appointments: No-shows and unpunctuality. Analyzing 412,415 telehealth and in-person appointments across a major US medical system from 2020 to 2022, we find that telehealth appointments reduce no-shows by 3.0 percentage points (23.1%) and late-arrivals by 11.4 percentage points (35.6%), indicating significant improvements in appointment adherence. We also find that telehealth is particularly effective in improving adherence to follow-up appointments but may be less suitable for initial consultations with new patients. In addition, telehealth improves adherence most among demographic groups with historically lower in-person attendance—women, racial minorities, Medicaid patients, and younger adults—underscoring its potential to reduce disparities in access. Our analysis suggests that while telehealth may increase patient revisit rates and create extra work for providers, the gains from reduced no-shows, particularly for follow-ups, lead to a net boost in provider productivity. Finally, we explore the best strategies to integrate telehealth into a provider's daily scheduling template, showing that scheduling telehealth appointments before in-person visits enhances operational efficiency compared to the opposite sequence. Policymakers should recognize telehealth's capacity to improve appointment adherence, reduce disparities, and enhance productivity, and support its adoption through appropriate regulations. Healthcare organizations should strategically deploy telehealth to address the root causes of patient nonadherence. By offering telehealth appointments to patients facing barriers to in-person care, they can simultaneously optimize both access and productivity.

Keywords

Healthcare Operations, Telehealth, Telemedicine, Appointment Adherence, Provider Productivity

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1 Introduction

Telehealth, or telemedicine, refers to the remote exchange of medical services via telecommunication and electronic technologies (Tuckson et al., 2017). It includes synchronous exchanges, such as video/audio calls between patients and providers, and asynchronous communications through emails and text messages. We focus on the synchronous form of telehealth visits in the ambulatory setting, which has diagnostic and therapeutic functions and can serve as a substitute for conventional in-person visits. Telehealth visits were not widespread before the COVID-19 pandemic, as the Centers for Medicare & Medicaid Services (CMS) only reimbursed such services in rural areas and specific medical facilities (Tuckson et al., 2017). However, the COVID-19 pandemic significantly increased the prevalence and recognition of telehealth visits and their benefits.

The first case of COVID-19 in the United States was reported in January 2020 (CDC, 2020). Shortly thereafter, cases were detected in all 50 states, prompting the need for

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significant measures to contain the virus. On January 31, the federal government declared COVID-19 a public health emergency (Azar, 2020). In response, federal and local governments implemented lockdowns and stay-at-home orders, suspending all nonessential in-person economic and social activities. To ensure continuity of care, the federal government temporarily relaxed restrictive telehealth reimbursement policies. It began reimbursing video telehealth visits for all Medicare beneficiaries at the same rate as office visits, allowed out-of-state physicians to provide telehealth services, and approved the use of applications such as Skype, FaceTime, and Zoom for medical appointments (CMS, 2020). Private payers adopted similar policies.

These changes led to a significant increase in telehealth visits early in the pandemic. According to CMS, virtual ambulatory visits jumped from 13,000 per week before the pandemic to nearly 1.7 million per week in April 2020, with over 9 million beneficiaries using telehealth through June 2020 (Verma, 2020). However, as COVID-19 cases declined, states reopened their economies and healthcare providers resumed in-person visits. Consequently, telehealth visits decreased but stayed higher than prepandemic levels, raising questions about the future of telehealth postpandemic. Surveys indicate that patients are satisfied with telehealth visits and many are willing to continue virtual appointments (Accenture, 2020). However, healthcare providers may reduce telehealth services if prepandemic restrictions are reinstated. Policymakers are currently debating telehealth provisions (Schatz et al., 2023).

Overall, the evidence suggests that telehealth is here to stay and that virtual visits will continue to play a significant role in ambulatory care. However, fundamental questions remain regarding the best ways to use this relatively new mode of care delivery. There is still limited knowledge about the impact of telehealth on patient and provider outcomes and clinic operations.

In this study, we address this gap by exploring the impact of telehealth on an important operational outcome: Patient adherence to medical appointments. We focus on two behaviors that result in nonadherence: (a) No-shows (not showing up without notice) and (b) unpunctuality (showing up late). Both behaviors contribute significantly to inefficiency in the healthcare industry, negatively affecting patient outcomes, provider productivity, and clinic operations (Gupta and Denton, 2008). Gier (2017) estimates that patient no-shows alone cost the US healthcare system \$150 billion annually. Some medical providers perceive unpunctuality even more disruptive than no-shows (Martin et al., 2005).

Does telehealth reduce patient no-shows and improve punctuality, thereby improving adherence to medical appointments? Research has identified transportation issues, competing priorities, inconvenience, and health and safety concerns as primary drivers of patient no-shows and unpunctuality in in-person appointments. Telehealth mitigates these concerns by allowing patients to visit their providers remotely. Therefore, we hypothesize that telehealth decreases patient no-shows and unpunctuality.

To test our hypotheses, we partnered with a major university-affiliated medical system operating dozens of outpatient facilities in Florida. In 2020, the medical system substantially increased its telehealth capabilities due to the COVID-19 pandemic. We analyze a large dataset including 412,415 in-person and telehealth appointments from 129,256 patients across multiple specialties between 2020 and 2022. We use an instrumental variable (IV) approach to estimate the impact of telehealth on patient no-shows and punctuality, while controlling for a wide range of patient and appointment characteristics and environmental factors.

The key findings and conclusions from our empirical analyses are summarized below:

(a) **Main Effects:** We find that, on average, no-show probability decreases by 3.0 percentage points or 23.1%, and late-arrival probability decreases by 11.4 percentage points or 35.6%, when appointments are conducted via telehealth. This suggests that telehealth enhances access to care by not only providing an alternative delivery channel but also improving patient adherence to medical appointments.

(b) **Effects by Appointment Type:** We distinguish between new patient consultations and follow-up appointments. New patients visit the provider for the first time with new conditions that may need timely consultations (Osadchiy and Kc, 2017), while follow-up patients return for ongoing treatment and often prioritize convenience (Liu et al., 2019). We find that telehealth significantly reduces no-show rates for follow-up patients by 3.7 percentage points compared to 0.9 percentage points for new patients. Additionally, telehealth improves punctuality for both groups: Late-arrivals decrease by 13.7 percentage points for new patients and 10.6 percentage points for follow-up patients. These results suggest that telehealth is particularly effective for follow-up appointments and also has broad potential to streamline clinic operations across various appointment types.

(c) **Effects by Patient Group:** We examine the impact of telehealth across various socio-demographic groups. We find that patient groups with historically higher rates of no-shows and late-arrivals in in-person appointments—women, racial minorities, Medicaid patients, and younger adults—show the greatest improvements in these outcomes with telehealth. These results underscore the potential of telehealth to reduce healthcare disparities and enhance access for underserved populations.

(d) **Effects on Provider Productivity:** The above findings suggest that telehealth can enhance provider productivity, assuming it delivers care quality comparable to in-person visits. To explore this, we examine the impact of telehealth on the 30-day revisit probability, a common proxy for care quality (Kajaria-Montag et al., 2024). We find that telehealth is associated with a 1.3 percentage point increase in the 30-day revisit probability, suggesting potential quality degradation. However, this increase is smaller than the reduction in no-shows, indicating a net gain in provider productivity. Importantly, for follow-up visits, telehealth leads to only a 0.8 percentage point increase in revisit rates, whereas for new patient consultations, the increase is larger at 3.6 percentage point. These results suggest that, from a productivity perspective, telehealth may be less effective for new patient consultations.

Our empirical analyses highlight the benefits of telehealth in improving patient adherence to scheduled appointments and enhancing provider productivity. To translate these insights into actionable strategies for clinics, we investigate how telehealth can be integrated into optimized scheduling practices. Specifically, we use discrete stochastic optimization methods to explore the optimal sequencing of telehealth and in-person appointments within a clinical workday. We extend the scheduling model developed by Zacharias and Yunes (2020) to accommodate heterogeneous appointment types—telehealth versus in-person, and new patient versus follow-up visits—while accounting for no-shows, unpunctuality, and general stochastic consultation times. Our computational analysis reveals that heterogeneity in patient no-shows and punctuality across appointment types significantly impacts operational performance. Notably, scheduling telehealth appointments before in-person visits leads to greater clinic efficiency compared to the reverse sequence.

Our findings carry important policy and managerial implications. While telehealth's potential to improve access is often highlighted in the context of rural patients who lack in-person care options, our results show that it also improves access by increasing appointment adherence, even in large metropolitan areas. These gains are especially pronounced among groups with historically lower adherence rates. Policymakers should account for these benefits when shaping telehealth regulations and reimbursement models. For healthcare organizations, telehealth provides a practical and effective tool to reduce appointment nonadherence by lowering logistical and structural barriers to attendance, while also enhancing provider productivity, particularly for follow-up care. We elaborate on the implications of our findings in Section 8.

2 Literature Review and Hypothesis Development

2.1 Literature Review

Our study bridges two bodies of literature: (1) Research on telehealth and its effects on operational performance, and (2) studies on patient nonadherence to medical appointments. First, we review existing research in each area. Next, we explore where these fields intersect, identify gaps, and describe our contributions.

Telehealth and Operational Performance. Several studies have explored how various types of telehealth services impact the demand for online and offline care. Among them, Bavafa et al. (2018), Fan et al. (2023), and Lekwijit et al. (2023) report an increase in in-person visits following the introduction of online patient-provider messaging, online consultations, and video visits, respectively. In contrast, Huang et al. (2021) find that integrating online and offline services in a Chinese healthcare system reduced the demand for in-person visits while increasing overall demand. Similarly, Delana et al. (2023) discover that establishing a telemedicine center in India expanded access, increased overall demand, but reduced hospital visits. Lastly, Ayabakan et al. (2024) find that telehealth services in Maryland hospitals reduced future outpatient visits, especially for conditions with high virtualization potential.

Another stream of this literature explores the impacts of telehealth services on provider and patient outcomes. Bavafa and Terwiesch (2019) find that the introduction of online messaging in an American healthcare system increased physicians' working hours. Sun et al. (2020) find that the availability of telemedicine in New York State hospitals reduced average patient length of stay without compromising care or cost. Li et al. (2021) find that the introduction of telehealth services prompted mental health providers to schedule follow-up visits more closely initially, leading to increased patient throughput but later resulting in heavier workloads and longer visit intervals.

There are also studies that investigate the design and impacts of telehealth services using analytical modeling. They address topics such as the impact of e-visits on patient health and physician capacity and compensation (Bavafa et al., 2021; Zhong et al., 2018), the effects of telemedicine on patient utility, provider productivity, and social welfare in chronic care (Rajan et al., 2019), the design of on-demand telemedicine platforms integrating general and specialty care (Savin et al., 2021), the impact of telemedicine on health disparities among socioeconomic groups (Sunar and Staats, 2022), and telehealth pay parity and patient access in acute care (Çakıcı and Mills, 2025).

Patient Nonadherence to Medical Appointments. Several studies have examined factors influencing patient appointment nonadherence through patient interviews and statistical analyses (Alibeiki et al., 2022; Campbell et al., 2000; Dantas et al., 2018; Martin et al., 2005; Osadchiy and Kc, 2017; Samuels et al., 2015). They have identified various determinants, including demographic factors (e.g., age, gender, race), appointment characteristics (e.g., time of day), environmental factors (e.g., weather, traffic), and clinical factors (e.g., severity of condition). For example, limited access to resources such as transportation, childcare, and paid-time-off is a significant contributor to appointment nonadherence (Samuels et al., 2015).

Another stream of research focuses on strategies to improve patient appointment adherence, including overbooking, rescheduling, reminders, and financial penalties (Selim et al., 2023). Liu et al. (2019) find accommodating rescheduling requests from patients reduces no-shows, particularly among follow-up appointments. Li et al. (2019) develop a Bayesian nested logit model that considers patients' responses to appointment reminders and other variables to predict no-shows. Liu and Kc (2023) find that including wait time information in appointment reminder texts significantly reduces no-show rates. Williams et al. (2014) find that that withholding care for unpunctual patients effectively improves their punctuality.

There is also extensive literature on optimizing patient flow management, focusing on addressing variability in patient arrivals (such as no-shows and unpunctuality) in scheduling practices (see Cayirli and Veral, 2003 and Ahmadi-Javid et al., 2017 for surveys of such models). They address topics such as determining patient base size, daily capacity levels, and appointment window choices (Green and Savin, 2008; Liu, 2016; Zacharias and Armony, 2017), optimizing intraday scheduling templates (Wang et al., 2020; Zacharias and Yunes, 2020), and managing dynamic appointment scheduling systems under uncertainty (Feldman et al., 2014; Zacharias et al., 2024).

Telehealth and Nonadherence to Medical Appointments. Bridging the above two streams, several medical studies have investigated the impact of telehealth on patient no-shows by comparing the raw rate of missed appointment between telehealth and in-person visits. They find lower rate of missed appointments for telehealth across various patient groups such as orthopedic trauma, spine, and rheumatology patients (e.g., Alkilany et al., 2022; Sumarsono et al., 2023; Ye et al., 2024). However, these studies do not account for confounding factors that could influence these differences.

Adepoju et al. (2022) conduct one of the few studies that control for observable patient characteristics, including demographics and medical history. They find that telehealth is associated with reduced odds of missed appointments, particularly among patients with frequent prior visits and those seeking mental health services. Additionally, Qin et al. (2024) explore how socio-demographic factors impact no-show rates in in-person and telehealth appointments differently. They report that Medicaid status, Black ethnicity, and younger age are stronger predictors of no-shows for in-person appointments compared to telehealth, suggesting that telehealth may mitigate access disparities. Finally, Qin et al. (2025) examine how physician availability affects service completion rates for in-person versus telehealth appointments. They find that delayed care initiation leads to higher rates of service incompletion for telehealth appointments, primarily due to patients leaving before being seen, whereas in-person appointments are unaffected by such delays.

Contributions. Our study advances existing research in several key aspects.

- We extend the scope of previous studies by utilizing data from 27 facilities and multiple medical specialties between 2020 and 2022. This extended timeline captures both the pandemic's initial disruptions and the postpandemic context. Throughout this period, telehealth evolved from a temporary substitute for in-person care to a potentially permanent mode of healthcare delivery (Mikie, 2021).
- Our extensive dataset enables us to control for a wide range of observable patient and appointment characteristics. Leveraging our granular data, we propose an identification strategy to mitigate potential unobservable confounding factors, thereby strengthening evidence for a *causal* relationship between telehealth and appointment adherence.
- We explore how the impacts of telehealth on appointment adherence vary across different appointment types and patient demographics to identify scenarios where telehealth is most effective. Our findings indicate that telehealth significantly enhances adherence for follow-up appointments compared to initial visits. Additionally, patients with historically lower rate of adherence to in-person appointments—women, racial minorities, Medicaid patients, and younger adults—demonstrate the greatest improvement in adherence through telehealth, underscoring telehealth's potential to mitigate access disparities.
- Our study offers one of the first empirical analyses of telehealth's impact on patient punctuality. This often-overlooked outcome in the operations literature has significant implications for clinic efficiency as demonstrated in Section 7. We also explore how telehealth affects patient revisit rates to provide a comprehensive view of its impact on provider productivity. Our findings suggest that while telehealth appointments may prompt earlier patient revisits and additional workload, the reduction in no-shows, especially for follow-up visits, offsets these factors, indicating improved provider productivity through telehealth.
- We draw on recent advances in stochastic intraday scheduling to examine how telehealth capacity can be effectively integrated into optimized scheduling. Specifically, we extend the scheduling model proposed by Zacharias and Yunes (2020) to account for heterogeneity by appointment modality and types to identify the optimal sequence of these appointment types to enhance clinic efficiency.

2.2 Hypotheses Development

Studies have identified five main reasons for patients' appointments nonadherence: (1) Forgetfulness, (2) transportation challenges, (3) schedule conflicts, (4) inconvenience, and (5) safety and stigma concerns.

First, patients may miss their appointments or arrive late simply because they forget the appointment time (Campbell et al., 2000). Second, patients may face transportation problems (Samuels et al., 2015). For example, according to the American Public Transportation Association, 45% of Americans have no access to public transportation (APTA, 2019). The lack of transportation options creates significant barriers for people who require regular medical care but cannot find practical ways to get to their appointments. Third, competing commitments and obligations often clash with scheduled appointments (Martin et al., 2005). For example, parents may struggle to find alternative childcare, and employees may not be able to obtain time off work (Campbell et al., 2000; Samuels et al., 2015). Fourth, to complete an in-person appointment, patients must navigate various stages, from traveling to and from the clinic to completing paperwork and waiting in the clinic. The actual time spent with the healthcare provider is often disproportionately short compared to the overall time spent in the process. This can discourage some individuals from adhering to their appointments (Anderson et al., 2007), especially healthier patients with less urgent needs (Chu et al., 2019). Lastly, concerns about health risks and societal judgments contribute to appointment nonadherence. Factors such as bad weather conditions, heavy traffic, the potential for contracting contagious illnesses like COVID-19, or fears of being stigmatized for seeking specific types of care can deter patients from fully adhering to their appointments (Henderson et al., 2013).

The two most common tactics used by clinics to address patient appointment nonadherence are overbooking and appointment reminders (Selim et al., 2023). Overbooking tackles the problem at the clinic level but does not address the underlying issues mentioned earlier. In contrast, appointment reminders are effective in mitigating patient forgetfulness (Liu and Kc, 2023). However, these reminders do not address challenges related to transportation, scheduling conflicts, inconvenience, and safety or stigma. Selim et al. (2023) underscore the need to explore digital solutions that address these barriers. One such solution is conducting appointments through telehealth.

Telehealth reshapes patient-doctor interactions by facilitating remote consultations from the comfort of one's home or workplace, effectively mitigating the underlying factors contributing to appointment nonadherence. First, for telehealth appointments, patients only need an electronic device, cellular or internet connectivity, and a secure setting. Surveys by Pew Research Center indicate that 97% of American adults have phones, 85% own smartphones, 77% have computers, 93% can access the internet, and 77% enjoy high-speed broadband at home (Pew Research Center, 2021a, 2021b). By reducing travel burdens, telehealth allows patients with transportation problems to better adhere to their appointments. Second, patients with competing commitments—such as parents caring for children or employees unable to secure time off—can engage in telehealth appointments without leaving their caregiving duties or workplace behind. Third, telehealth appointments are much more convenient than in-person appointments. Patients can check in online, complete assessment forms through their electronic devices, wait within their personal spaces, and directly consult with their providers. This increased convenience may improve appointment adherence, particularly among healthier patients who might view in-person appointments as less worthwhile. In addition, this increased convenience enhances the ability of patients with disabilities or physical restrictions to attend appointments. Lastly, the elimination of the need to travel and interact in public spaces creates a safer environment for patients to access care, thereby addressing safety and stigma concerns.

Overall, telehealth reshapes healthcare delivery, alleviating obstacles linked to travel, conflicting commitments, inconvenience, and safety and stigma. Hence, we hypothesize that it can reduce no-shows and improve patient punctuality, thus improving adherence to medical appointments.

Hypothesis 1: Telehealth appointments reduce no-shows and enhance punctuality, thereby improving patient adherence to medical appointments.

Next, we explore how telehealth affects appointment adherence across various appointment types to identify those that may benefit more from telehealth. Specifically, we compare appointments for new patients with follow-up appointments. New patients typically visit the provider for the first time, often presenting new and pressing conditions that require timely intervention or consultation (Liu et al., 2019). In addition, they may be navigating the system for the first time and are motivated to establish trust with their healthcare provider (Kajaria-Montag et al., 2024). In contrast, patients attending follow-up appointments typically have less urgent needs and are often engaged in ongoing care plans, returning to the provider for monitoring or treatment adjustments (Liu et al., 2019). Moreover, they are familiar with the system and have an established relationship with the provider. Therefore, while new patients prioritize timely access to care and trust-building (Osadchiy and Kc, 2017), those with follow-up appointments often prioritize convenience (Liu et al., 2019). Reflecting this distinction, Liu et al. (2019) find that new patients seek quicker access and shorter wait times, whereas patients with follow-up appointments value more flexibility in scheduling.

Telehealth appointments offer greater convenience than in-person visits, which is especially advantageous for follow-up appointments where patients prioritize ease and efficiency. Conversely, new patients, driven by urgent care needs and the desire to build trust, may attend their appointments regardless of the modality. Therefore, telehealth may more effectively reduce no-shows in follow-up appointments. However, the convenience of attending the appointment from one's personal space should improve punctuality for both patients groups. We formalize these hypotheses below:

Hypothesis 1: Telehealth appointments reduce no-shows more significantly for follow-up appointments than for new patient appointments, while also improving patient punctuality across both appointment types.

Lastly, we investigate how telehealth affects appointment adherence across various demographic groups to determine patient types that benefit the most from remote consultations. Research has found that women, racial minorities, Medicaid patients, and younger adults tend to have lower odds of appointment adherence than others (Campbell et al., 2000; Dantas et al., 2018; Qin et al., 2024; Samuels et al., 2015).

We observe similar patterns in our data. Across the in-person appointments, the no-show and late-arrival rates are:

- 1.4 and 2.8 percentage points (pps) higher among women than men,
- 5.3 and 4.5 pps higher among racial minorities than Whites,
- 12.5 and 1.5 pps higher among Medicaid patients than those with other insurances, and
- 6.3 and 11.4 higher among patients under 50 years old than older ones.

The literature provides several explanations for these disparities: (1) Women are more likely than men to face competing priorities with respect to childcare and household duties (Campbell et al., 2000); (2) racial minority and Medicaid patients tend to have a lower socioeconomic status and more limited access to resources such as transportation or paid time off (Lowes, 2005); and (3) younger adults are generally healthier and face fewer health repercussions if they miss their appointments (Dantas et al., 2018). Since telehealth mitigates issues related to competing priorities, transportation, and the inconvenience of attending appointments, we hypothesize that it has a stronger effect on the no-show and punctuality outcomes of these underserved groups, thereby reducing disparities in accessing care.

Hypothesis 3: Telehealth is more effective in reducing no-shows and improving punctuality among demographic groups with historically lower adherence to in-person appointments—women, racial minorities, Medicaid patients, and younger adults—thereby reducing disparities in access to care.

3 Data and Variable Definitions

3.1 Data Description

To test our hypotheses, we partner with a large university-affiliated medical system with more than 1,200 physicians and scientists providing care across dozens of outpatient sites and several hospitals in the state of Florida. The medical system significantly expanded its telehealth capacity in 2020 in response to the COVID-19 pandemic. We access 974,269 appointment-level records across 27 outpatient facilities. This includes all appointments for adult patients in three departments, General Medicine, Neurology, and Dermatology, from January 2019 through December 2022. All appointments were scheduled in advance (no walk-in appointments). Each record includes some information about the patient (gender, race, age, and insurance type), the appointment (status, type, modality, scheduled length and time, location), the medical provider who saw the patient, and several timestamps including the patient's check-in time.

We selected general medicine, neurology, and dermatology after consulting our healthcare partner, who believes these specialties are well-suited for telehealth. General medicine covers primary care, neurology deals with nervous system disorders, and dermatology addresses skin disorders. Recent technological advances have enabled remote diagnosis and treatment for many conditions in these fields. The differences in these specialties further allow us to study the effect of telehealth across various patient types and service capacities. In Appendix EC.1.1, we explore the heterogeneous effects of telehealth across these specialties.

3.2 Data Selection

We conduct the following data selection process. First, our partner medical system began to offer telehealth appointments in 2020. Thus, we only focus on the appointments that took place in the year 2020, 2021, and 2022. We use the 2019 data to create a proxy variable for the patients' condition based on the volume of their past visits. Second, the status of each appointment is labeled as "completed" (57%), "no-show" (8%), or "canceled" (35%). We focus only on completed and no-show appointments and exclude canceled appointments for several reasons. First, in this health system, patients receive appointment reminders 7, 3, and 1 day before the appointment (if they have not responded to previous reminders). According to health system practitioners, cancelations are less of a concern than no-shows because patients often cancel in advance electronically, allowing the system to update and enabling schedulers to fill vacated slots with patients on the waiting list. Second, including cancelations would introduce a separate behavioral dimension, conflating appointment adherence with proactive rescheduling decisions. Cancelations may also be influenced by external factors, such as provider availability, rather than a patient's intent to attend their appointment. Finally, our data does not capture the reasons for cancelations or whether these appointments were rescheduled. Given these considerations, excluding cancelations is a standard approach in studies of appointment adherence (e.g., Liu et al. (2019)). Second, the type of each appointment is labeled as "new patient" (23.0%), "follow-up" (66.7%), "procedure" (10.1%), "study" (0.1%), or "others" (0.1%). There are no telehealth records for the last three types of appointments, which require a physical examination or a procedure that can only be carried out in-person. As such, we only include appointments with new patient and follow-up types. Finally, to remove the effect of outliers, we only include appointments for providers that had at least one in-person and one telehealth appointment between 2020 through 2022 (96.2%). Our final sample includes 412,415 appointments involving 129,256 patients and 176 medical providers.

3.3 Variable Definition and Summary Statistics

Dependent Variables. Our first dependent variable is $NoShow_i$, which captures the status of appointment i. We set $NoShow_i = 1$ if the status is "no-show," and $NoShow_i = 0$ if the status is "completed." Our second dependent variable is $Late_i$, which captures the patient's punctuality, or lack thereof, in appointment i. We set $Late_i = 1$ if the patient checked in after the appointment's scheduled time, and $Late_i = 0$ otherwise. In Appendix EC.1.2, we consider alternative thresholds and a continuous measure for patient punctuality.

Independent Variable. Our independent variable of interest is $Telehealth_i$, which captures the modality of appointment i. We set $Telehealth_i = 1$ if the modality was telehealth, and $Telehealth_i = 0$ if the modality was in-person. In our data, 35.9% of the appointments are telehealth.

Control Variables. We control for several factors that can influence patients' outcomes. First, patients' socio-demographic information is a major predictor of their access to resources as well as appointment adherence outcomes (Li et al., 2019). We include categorical variables for gender, race, and insurance status ($Gender_i$, $Race_i$, and $Insurance_i$) and a continuous variable for patients' age (Age_i).

Second, we control for the type of appointment ($ApptType_i$), distinguishing between new patient (0) and follow-up appointments (1), as well as the scheduled length of the appointment ($AppSchLength_i$), as longer slots are allocated for patients needing extended consultations. In addition, we also control for the proportion of follow-up appointments scheduled by the provider of the focal appointment on that day, denoted as $FollowUpRatio_i$. This would account for appointment-type patterns that may correlate with appointment modalities and patient adherence outcomes.

Third, since our data collection partially overlap with the COVID-19 pandemic, we control for several pandemic-related variables to mitigate its effects on patient outcomes. Specifically, we control for the per-capita number of reported COVID-19 cases, deaths, and hospital admissions in the county during the week of appointment i, denoted as $COVIDCases_i$, $COVIDDeaths_i$, and $COVIDAdms_i$, respectively. We obtained these data from the CDC's website (https://data.cdc.gov/). In addition, we include a number of fixed effects for different phases of COVID-19 pandemic in the state of Florida based on the stay-at-home orders and subsequent reopening. We let $COVIDPhases_i$ represent different pandemic phases: The period before a state of emergency was declared on March 9, 2020; the period after the state of emergency but before a statewide stay-at-home order was issued on April 1, 2020; the period after the stay-at-home order but before the start of the final reopening phase on September 25, 2020; and the period after the final reopening phase. See Appendix EC.1.3 for the detailed timeline of pandemic policies in Florida. To enhance the generalizability of our findings to the postpandemic context, we repeat our main analyses for periods when the COVID-19 pandemic was less severe in Appendix EC.1.3.

We also control for provider heterogeneity by creating a dummy variable ($Provider_i$) for each provider in appointment i. These dummies capture the impact of providers' unobservable, time-invariant characteristics (e.g., specialty, skills, interest in technology) on patient outcomes. We also include dummy variables for the time of day ($Hour_i$), day of the week ($WeekDay_i$), month ($Month_i$), and year ($Year_i$) to address time-specific heterogeneity in appointment modalities and patient outcomes and time trends, and incorporate facility fixed effects ($Facility_i$) to account for unobservable, time-invariant differences across facilities (e.g., demographics in different neighborhoods).

Besides these factors, patients' health conditions can also influence both appointment choice and adherence outcomes. Since we lack direct measures of health status, we construct several proxies to approximate their care intensity. First, following Adepoju et al. (2022), we use the number of visits in the past 12 months ($PastVisits_i$): A higher number may reflect ongoing or chronic conditions, while fewer visits suggest better overall health.[1] Second, we include the number of medication orders and refills in the month prior to the appointment ($Orders_i$ and $Refills_i$), which serve as proxies for treatment intensity. Third, we consider the number of online messages and phone calls exchanged with providers in the same period ($Messages_i$ and $Telephones_i$), which may signal the urgency or complexity of the patient's condition. These communications, whether initiated by the patient or provider, reflect engagement with care. Finally, we control for prior telehealth use ($UsedTelehealth_i$), a binary indicator equal to 1 if the patient had previously used telehealth within the system, serving as a proxy for telehealth familiarity. Note that, around 39% of patients had only one visit between 2020 and 2022, meaning these variables default to 0 for them. This may not accurately capture their treatment intensity or telehealth familiarity. To ensure that our findings are robust to this issue, we present the main estimation results both without and with these controls. In both cases, the results remain qualitatively consistent. In addition, in Appendix EC.1.4, we re-estimate our main models for patients with at least 3 annual visits, for whom, these variables may better capture their care plans.

Summary Statistics. We present the definition and summary statistics of the variables overall and across in-person and telehealth appointments in Appendix EC.2. In the raw data, telehealth appointments have a 4.0 percentage points lower no-show rate and a 12.7 percentage points lower late-arrival rate.[2]

4 Model and Identification Strategy

An ideal experiment to test our hypotheses would involve randomly assigning patients to telehealth and in-person appointments and comparing their outcomes. However, this is not practical due to ethical and operational issues. Instead, we use observational data. We begin by developing an econometric model to analyze the impacts of telehealth on patient outcomes and then discuss potential econometric challenges and our identification strategy.

4.1 Econometric Model

Our dependent variables are $NoShow_i$ and $Late_i$, which are both binary. We propose the following probit model:

$$y_i = \mathbb{1}\{\beta_0 + \beta_1 Telehealth_i + \beta_2 \boldsymbol{X_i} + \varepsilon_i \geq 0\}, \qquad (1)$$

where $y_i \in \{NoShow_i, Late_i\}$. $\mathbb{1}\{.\}$ is the indicator function that is equal to 1 if the condition in $\{.\}$ is met, and 0 otherwise. $Telehealth_i$ is our main independent variable of interest. $\boldsymbol{X_i}$ is a vector of control variables and includes all the other variables discussed in Section 3.3. ε_i is the idiosyncratic shock that follows a standard normal distribution. It captures the effect of unobservable variables on the patients' no-show and punctuality outcomes. We use robust standard errors that are clustered by the patient in each appointment (Wooldridge, 2010). This allows the error terms to be correlated among multiple appointments by a single patient. We also tried clustering at higher levels (e.g., provider-level) and found similar results.

4.2 Econometric Challenges

The synchronous form of telehealth was not used in our partner medical system before the COVID-19 pandemic. The first case of COVID-19 in Florida was reported on March 1, 2020. Florida Governor Ron DeSantis declared a public health emergency on March 9 and issued an executive order limiting all nonessential activities on April 1 (DeSantis, 2020b). At the end of April, the governor instituted a three-phase recovery plan, which was completed on September 25 when he nullified all COVID-19 public health measures (DeSantis, 2020a). In Appendix EC.1.3, we detail the timeline of the pandemic policies in Florida and rerun our main analyses across different time periods.

Figure 1 displays the number of telehealth and in-person appointments during each month of 2020, 2021, and 2022 in our data. Observe how the composition of the appointments changed in response to the pandemic-related policies. Our partner healthcare system introduced telehealth appointments in mid-March 2020. By April and May, the majority of appointments were conducted via telehealth. In subsequent months, telehealth remained an option for all patients. New patients were able to select the modality of their appointments and a range of available dates. A scheduler would then confirm both the date and modality. For follow-up appointments, the provider recommended an approximate time (e.g., 4 weeks) and assessed whether telehealth was a suitable modality, after which the patient communicated the exact time and chosen modality to the scheduler. While our analysis includes a comprehensive set of controls to account for factors influencing patients' decisions, unobservable variables may still affect their choices. Some of these unobserved factors could also be correlated with no-show and punctuality outcomes, potentially introducing bias into our estimations. For example, patients with severe illnesses, such as autoimmune disorders, and those who live far from clinics may prefer telehealth to reduce COVID-19 exposure or travel burden, respectively. Thus, patients' condition severity and distance to clinic may be positively correlated with $Telehealth_i$.

Now, consider the no-show outcome. Patients with more severe illnesses tend to prioritize attending appointments to prevent their condition from worsening. This may lead to a negative correlation between a patient's health condition and $NoShow_i$, introducing negative bias in the estimates of the no-show model. Moreover, patients who live farther from the clinic may face greater logistical challenges than those closer by, resulting in higher rates of missed appointments. As a result, the distance to the clinic may be positively correlated with $NoShow_i$, leading to a positive bias in the no-show model estimates. This implies that a probit regression of (1) may under- or over-estimate the coefficient of $Telehealth_i$.

Next, consider the punctuality outcome. Although a patient's condition may not consistently influence their punctuality, greater distances to the clinic are frequently cited as a significant factor contributing to lateness (Alibeiki et al., 2022). Consequently, distance to the clinic may be positively correlated with both $Telehealth_i$ and $Late_i$, introducing a positive bias in the estimates of the unpunctuality model.

4.3 Identification Strategy

Given that our dependent variables ($NoShow_i$ and $Late_i$) and independent variable of interest ($Telehealth_i$) are all binary, we propose a recursive bivariate probit model (Greene, 2018), which simultaneously estimates (i) an appointment's propensity to be telehealth and (ii) the patient's no-show or punctuality outcomes, while accounting for the potential correlation between the error terms of the two models. The bivariate probit model is commonly used to study the effect of an endogenous binary variable on binary outcomes in the presence of unobservables. For example, Kim et al. (2015) use a bivariate probit model to estimate the effect of ICU admission on patient readmission and mortality, and Liu et al. (2019) use a bivariate probit model to estimate the effect of rescheduling on patient no-shows.

We formulate the patients' choice of modality using a probit model as follows:

$$Telehealth_i = \mathbb{1}\{\gamma_0 + \gamma_1 \boldsymbol{X_i} + \gamma_2 IV_i + \varepsilon_i \geq 0\}, \qquad (2)$$

where $\boldsymbol{X_i}$ is the same vector of controls as in (1), IV_i is an IV, and ε_i is the idiosyncratic shock that captures the effect of unobservable factors on the appointment modality.

While the inclusion of an IV is not required to get consistent estimates, it is recommended that we identify at least one IV that affects the propensity that an appointment is telehealth (relevance criteria) but does not affect the patient's no-show and punctuality outcomes (exclusion criteria) (Wooldridge, 2010). We leverage the medical providers' daily capacities and schedules to construct an IV. First, we calculate the number of appointments scheduled by the provider in appointment i

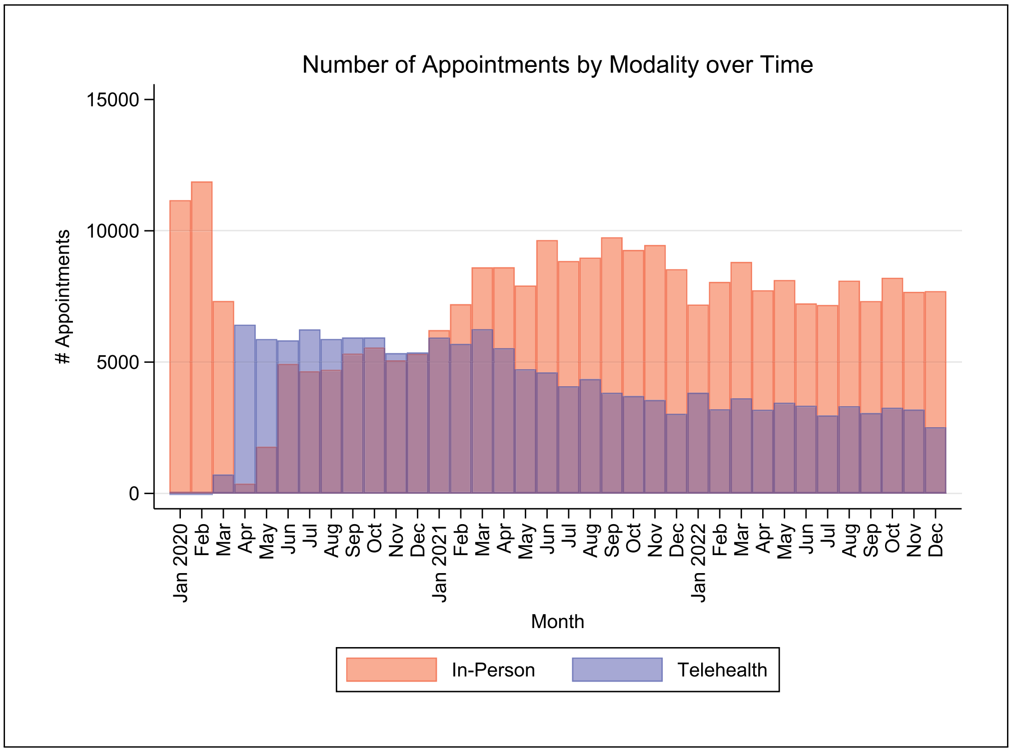

Figure 1. Number of appointments over months (the transparent bars for in-person (red) and telehealth (blue) visits overlap).

during the 7-day period leading up to the focal day. We then use the percentage of these appointments that were telehealth as our instrument, denoted as $Percent7DayTelehealth_i$. The 7-day rolling percentage of telehealth appointments satisfies the relevance condition, as it reflects the provider's propensity to conduct telehealth appointments in the days leading up to the focal day. We report the results of the probit regression of (2) in Appendix EC.3. The $Percent7DayTelehealth_i$ variable has a positive and statistically significant coefficient, suggesting that it is indeed helpful in explaining the variability of $Telehealth_i$. This establishes the relevance criteria.

Although it is not possible to statistically validate the exclusion restriction directly, there are compelling conceptual reasons to believe our instrument satisfies this criterion. The 7-day rolling percentage of telehealth visits reflects provider-level scheduling patterns, which are unlikely to directly affect an individual patient's no-show or punctuality outcomes on the focal day. These outcomes are primarily driven by the patient's own choices and behaviors, which are independent of the broader composition of their provider's appointments. Patients are unlikely to have knowledge of their provider's overall schedule or the modalities of other appointments during the preceding week. That said, there could be indirect links between providers' scheduling practices and patient adherence. For instance, if some providers schedule telehealth visits on specific hours or weekdays associated with higher no-show or punctuality issues, this could introduce a potential relationship. To address such possibilities, we include a robust set of controls that capture key factors related to provider schedules. First, we include physician fixed effects, which account for all time-invariant provider characteristics, such as their scheduling preferences or technological tendencies. Second, we control for hour-of-day and day-of-week fixed effects to account for systematic differences in appointment modalities and patient outcomes across hours and weekdays. Third, we control for the providers' proportion of follow-up appointments on the focal day to control for patterns in appointment types that may be correlated with telehealth usage and patient nonadherence. With these controls, the instrument's effect on appointment adherence should operate solely through its impact on the modality of the focal visit.

To account for the endogeneity of $Telehealth_i$ in (1), we further allow the error terms in (1) and (2) to be correlated and the random vector $(\varepsilon_i, \varepsilon_i)$ to follow a standard bivariate normal distribution with correlation coefficient ρ, which will be estimated along with the other parameters in the model. We conduct the joint estimation of the two models using the full maximum likelihood estimation (Wooldridge, 2010) . We test for the endogeneity of $Telehealth_i$ using a Wald test of the correlation coefficient ρ being nonzero.

In Section 6, we conduct additional analyses to test the robustness of our approach. First, we explore several alternative IVs to demonstrate the robustness of our findings to IV selection. Second, we incorporate patient fixed effects to control for unobservable, time-invariant patient characteristics. We also use a linear probability model to confirm that

Table 1. Results of the estimation and average marginal effect (AME) of (1) for $y_i = NoShow_i$.

	[1]		[2]		[3]		[4]	
Variables	Estimate	AME	Estimate	AME	Estimate	AME	Estimate	AME
$Telehealth_i$	−0.218*** (0.007)	−0.040*** (0.001)	−0.241*** (0.008)	−0.044*** (0.001)	−0.190*** (0.010)	−0.035*** (0.002)	−0.164*** (0.013)	−0.030*** (0.002)
Demographic Var.	No		Yes		Yes		Yes	
Appt Var.	No		Yes		Yes		Yes	
COVID Var.	No		Yes		Yes		Yes	
Provider, Time, and Facility F.E.	No		Yes		Yes		Yes	
Care Proxy Var.	No		No		No		Yes	
ρ					−0.040*** (0.011)		−0.044*** (0.011)	
Observations	412,415		412,415		407,901		407,901	

Standard errors (in parentheses) are heteroscedasticity robust and clustered by the patients. $^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$.

our results are robust across different model specifications. Third, we use propensity score matching to minimize differences between the patients using telehealth versus in-person appointments. We then run regressions on the matched sample, both with and without patient fixed effects and endogeneity adjustments. Fourth, we conduct placebo tests by randomly assigning modalities to appointments. Lastly, we propose an alternative identification strategy using a difference-in-differences framework, leveraging variations in telehealth adoption rates across physicians. Across all these robustness checks, our findings remain consistent with the main results presented in the following section.

5 Estimation Results

In Section 5.1, we present the main results on the effect of telehealth on patient no-show and punctuality outcomes. In Section 5.2, we study how these effects vary between new patients and follow-up appointments. In Section 5.3, we explore how patient socio-demographic factors moderate the effects of telehealth on appointment adherence. In Section 5.4, we examine the impact of telehealth on patients' revisit rate, to explore the productivity implications of telehealth for medical providers.

5.1 Main Results

Table 1 reports the estimation results of model (1) for $y_i = NoShow_i$, along with the average marginal effect (AME) of $Telehealth_i$ on the patient no-show probability. The AME is defined as the average expected absolute change in the no-show probability when the appointment is telehealth instead of in-person. We only present the coefficient of $Telehealth_i$. See Appendix EC.4 for the full results.

Column [1] reports the results of the probit regression of (1) in the absence of control variables and endogeneity adjustment. The $Telehealth_i$ variable has a negative and statistically significant coefficient. The AME is −0.040, suggesting a 4.0 percentage points (pps) smaller no-show probability for telehealth appointments, reflecting the gap in the raw data. Column [2] reports the estimation results after controlling for all control variables excluding the proxies for the patients' care plan, suggesting a 4.4 pps smaller no-show probability for telehealth appointments. In column [3], we estimate the bivariate probit regression of (1), which adjusts for the potential endogeneity issue. The AME is reduced to −0.035. The coefficient of ρ is significant and negative, suggesting a negative correlation between unobservable factors influencing patients' selection of telehealth modality and their no-show outcome. Finally, in columns [4], we add the control proxies for the patients' care plan. The AME is −0.030, suggesting a 3.0 pps gap in the no-show probability between the telehealth and in-person appointments (10.0% versus 13.0%, a 23.1% reduction). These results support Hypothesis 1, suggesting that the no-show probability decreases in telehealth appointments.

Table 2 reports the estimation results of model (1) for $y_i = Late_i$, along with the AME of $Telehealth_i$ on the patient late-arrival probability. See Appendix EC.4 for the full results. Column [1] reports the probit estimation results in the absence of control variables and endogeneity adjustment, suggesting a 12.6 pps lower late-arrival probability for the telehealth appointments in the raw data. Columns [2] suggests that the gap is reduced to 10.5 pps after adding all the control variables except the proxies for the patients' care plan. Column [3] reports the bivariate probit estimation results. The coefficient of ρ is significant and positive, which is consistent with our prediction in Section 4.2. The results in the last column, where we also include the care proxy variables, suggest an 11.4 pps gap in the late-arrival probability between telehealth and in-person appointments (20.6% versus 32.0%, a 35.6% reduction). These results support Hypothesis 1, suggesting that the late-arrival probability decreases in telehealth appointments.

Overall, our analyses suggest that telehealth appointments reduce the no-show and late-arrival rates, thereby improving patient adherence to medical appointments.

Table 2. Results of the estimation and average marginal effect (AME) of (1) for $y_i = Late_i$.

	[1]		[2]		[3]		[4]	
Variables	Estimate	AME	Estimate	AME	Estimate	AME	Estimate	AME
$Telehealth_i$	-0.398^{***}	-0.126^{***}	-0.336^{***}	-0.105^{***}	-0.377^{***}	-0.119^{***}	-0.361^{***}	-0.114^{***}
	(0.006)	(0.002)	(0.007)	(0.002)	(0.009)	(0.003)	(0.020)	(0.006)
Demographic Var.	No		Yes		Yes		Yes	
Appt Var.	No		Yes		Yes		Yes	
COVID Var.	No		Yes		Yes		Yes	
Provider, Time, and Facility F.E.	No		Yes		Yes		Yes	
Care Proxy Var.	No		No		No		Yes	
ρ					0.046^{***}		0.045^{***}	
					(0.013)		(0.013)	
Observations	345, 385		345, 385		341, 730		341, 730	

Standard errors (in parentheses) are heteroscedasticity robust and clustered by the patients. $^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$.

5.2 Telehealth for New Patients Versus Follow-up Appointments

In this section, we explore how the effects of telehealth on patient no-show and punctuality outcomes vary between appointments for new patients and follow-up appointments. We hypothesized that telehealth is more effective in reducing no-shows for follow-up appointments where patients have stronger preference for convenience, while it enhances punctuality across both appointment types.

To test this hypothesis, we add an interaction term between the $Telehealth_i$ and $ApptType_i$ (0=new patients, 1=follow-up) variables in our main model in (1). Table 3 reports the estimation results for $y_i = NoShow_i$ and $y_i = Late_i$, suggesting that $ApptType_i$ negatively moderates the effect of telehealth on the no-show probability (column [1]), and positively moderates its effect on the late-arrival probability (column [2]). To illustrate the size of these effects, we display the predicted no-show and late-arrival probabilities by appointment modality and type in the left and right panel of Figure 2, respectively. We find that the no-show probability decreases by 0.9 pps (10.8% versus 11.7%, a 7.7% reduction) for new patients and by 3.7 pps (9.8% versus 13.5%, a 27.4% reduction) for follow-up appointments when the appointments are conducted via telehealth. Interestingly, while follow-up appointments have a higher no-show probability than new patient appointments when conducted in-person, they show a lower no-show probability when conducted via telehealth. This is a significant improvement given that follow-up appointments account for 73.7% of the appointments in our dataset. We also find a significant decrease in late-arrival probability across both appointment types: By 13.7 pps (18.8% versus 32.5%, a 42.2% reduction) for new patients and by 10.6 pps (21.2% versus 31.8%, a 33.3% reduction) for follow-up appointments.

Overall, our findings support Hypothesis 2, suggesting that telehealth is particularly effective in improving adherence to follow-up appointments, where patients may have a stronger preference for convenience due to their less acute needs. Additionally, while the reduction in no-shows for new patients is less significant, there is still a sizable improvement in patient punctuality. These findings highlight the telehealth's potential to streamline clinic operations across various appointment types.

Table 3. The moderating effect of $ApptType_i$.

	[1]	[2]
Variables	$y_i = NoShow_i$	$y_i = Late_i$
$Telehealth_i$	-0.052^{***}	-0.442^{***}
	(0.017)	(0.023)
$Telehealth_i \times ApptType_i$	-0.148^{***}	0.109^{***}
	(0.017)	(0.016)
$ApptType_i$	0.089^{***}	-0.023^{**}
	(0.012)	(0.010)
Control variables and fixed effects	Yes	Yes
ρ	-0.043^{***}	0.044^{***}
	(0.011)	(0.013)
Observations	407,901	341,730

Standard errors (in parentheses) are heteroscedasticity robust and clustered by the patients. $^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$.

5.3 Telehealth for Patients From Different Socio-demographic Groups

In this section,<pag/> we explore the effect of telehealth on patient no-show and punctuality outcomes across patients from different socio-demographic groups. We hypothesized that patients with the lowest rates of adherence to in-person appointments—women, racial minorities, Medicaid patients, and younger adults—show the greatest improvements in adherence through telehealth.

To test our hypotheses, we introduce interaction terms between the $Telehealth_i$ and $Gender_i$, $Race_i$, $Insurance_i$, and Age_i in four separate models. The results of the estimations

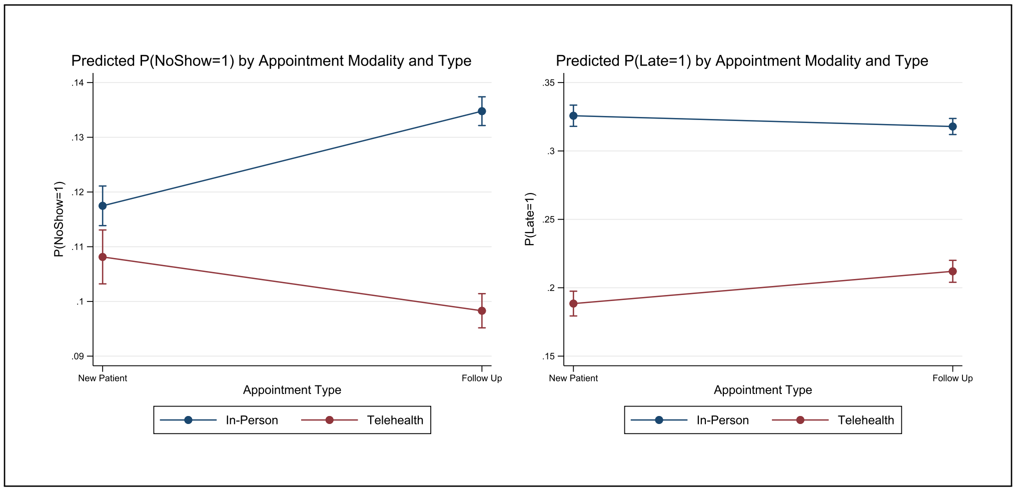

Figure 2. Predicted no-show and late-arrival probabilities with 95% confidence intervals by appointment modality and type.

are reported in Appendix EC.4. Figure 3 displays the AME of the $Telehealth_i$ variable on the no-show (left) and late-arrival (right) probabilities for different values of each variable. Consistent with Hypothesis 3, we find that in telehealth appointments:

- the no-show and late-arrival probabilities decrease more for women (by 3.7 pps and 12.3 pps) than for men (by 1.6 pps and 9.8 pps),
- the no-show probability decreases more for Blacks (by 4.3 pps) and other non-Asian minorities (by 8.2 pps) than for Whites (by 2.6 pps),
- the no-show probability decreases more for Medicaid patients (by 7.2 pps) than for Medicare patients (by 0.5 pps) and those with commercial insurance (by 3.2 pps). The late-arrival probability decreases substantially more for patients with commercial insurance, who are more likely to be employed and experience schedule conflicts when attempting to attend their appointments on time,
- the no-show and late-arrival probabilities decrease significantly more among the younger adults.

These results suggest that telehealth can help reduce disparities in appointment adherence by addressing barriers faced by patients who struggle with in-person visits. However, for these improvements to translate into broader reductions in access disparities, telehealth should be used consistently across different patient groups. The estimation results for the first stage of our bivariate probit model, presented in Appendix EC.3, reveal small differences in telehealth usage by gender, race, and insurance status. Women are 1.5 pps more likely than men to use telehealth, minority patients are 0.3 pps more likely than White patients, and Medicaid patients are 1.0 pps more likely to use telehealth. The most notable difference is by age, with patients under 40 being 3.6 pps more likely to use telehealth compared to older patients. Overall, these findings reinforce the conclusion that telehealth helps reduce access disparities by significantly improving appointment adherence among groups with historically lower adherence rates.

5.4 Telehealth and Revisit Probability

Our analyses show that telehealth significantly improves appointment adherence, which in turn can help healthcare providers boost throughput and productivity. However, these benefits are contingent on telehealth being at least as effective in diagnosis and treatment as in-person visits. The literature is mixed on this point: Some studies suggest telehealth cannot fully replace in-person visits (e.g., Lekwijit et al., 2023), while others indicate it may be comparably effective in specific contexts (Ayabakan et al., 2024).

To draw meaningful conclusions about the benefits of telehealth in improving provider productivity, we examine its effect on patients' revisit intervals with the same provider—a common metric for assessing quality and productivity (Kajaria-Montag et al., 2024). If telehealth appointments are as effective as in-person visits, we would expect no significant difference in revisit intervals. Conversely, a shorter revisit interval may indicate that patents' concerns were not fully addressed during telehealth appointments.

Let $30DayRevisit_i$ equal 1 if a patient schedules another appointment with the same provider within 30 days after a completed appointment, and 0 otherwise. We select a 30-day threshold based on consultations with physicians in our health system, who believe it is short enough to suggest that the revisit may be related to the initial appointment while still allowing sufficient time for the provider to accommodate another visit within their schedule. We also considered 14-day and 60-day thresholds and found consistent results. We construct a binary variable for revisit intervals to assess changes in revisit probability with the 3.0 percentage points (pps) reduction in no-show probability in telehealth appointments. We estimate the effect of telehealth on revisit probability using

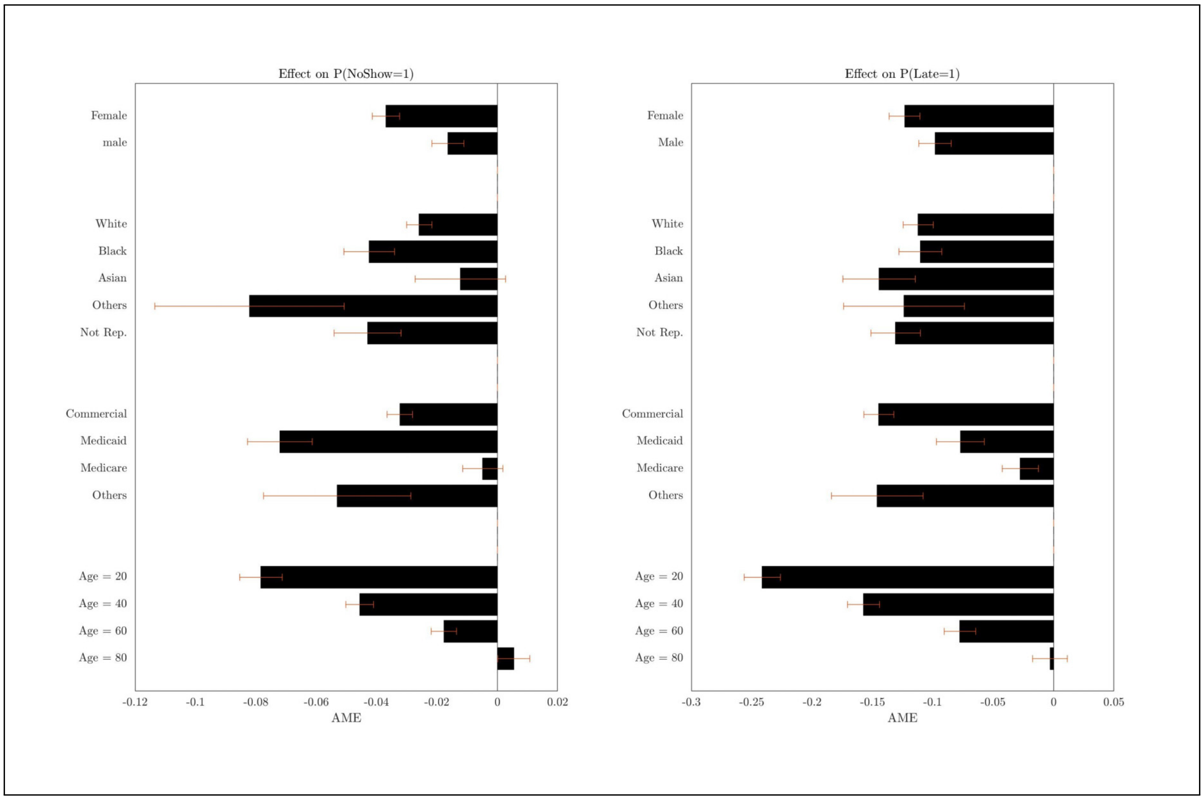

Figure 3. Average marginal effect of telehealth on the no-show and late-arrival probabilities with 95% confidence intervals.

the bivariate probit model with the same specification and instrument as before.

Column [1] in Table 4 presents the estimation results. The AME is 0.013, indicating a 1.3 pps higher 30-day revisit probability for telehealth appointments compared to in-person appointments (19.3% versus 18.0%, a 7.2% increase). These findings suggest that telehealth appointments may not be perfect substitutes for in-person appointments. However, the magnitude of this effect is considerably smaller than the 3.0 pps reduction in the no-show probability, implying a net gain in provider productivity with telehealth.

In column [2], we examine the moderating effect of appointment types. Figure 4 illustrates the predicted 30-day revisit probability by appointment modality and type. We observe a 3.6 pps increase in revisit probability for new patients (22.1% versus 18.5%, a 19.5% increase) and a 0.8 pps increase for follow-up appointments (18.5% versus 17.7%, a 4.5% increase). When comparing these results with our earlier findings—a 0.9 pps reduction in no-shows for new patients and a 3.7 pps reduction for follow-ups—telehealth emerges as an effective substitute only for follow-up appointments. In contrast, conducting initial consultations via telehealth may lead to additional workload for providers.

Table 4. Estimation results for $y_i = 30DayRevisit_i$.

	[1]		[2]
Variables	Estimate	AME	Estimate
$Telehealth_i$	0.057***	0.013***	0.141***
	(0.011)	(0.003)	(0.017)
$Telehealth_i \times ApptType_i$			−0.106***
			(0.016)
$ApptType_i$	−0.067***		−0.038***
	(0.011)		(0.013)
Control variables and fixed effects	Yes		Yes
ρ	−0.038***		−0.040***
	(0.010)		(0.010)
Observations	350,742		350,742

Standard errors (in parentheses) are heteroscedasticity robust and clustered by the patients. ***$p < .01$; **$p < .05$; *$p < .1$. AME = average marginal effect.

6 Robustness Checks

In this section, we discuss several robustness analyses. We present the full results in Appendix EC.5.

Alternative Instrument Variables. We propose several alternative IVs. First, we extend the rolling window from seven days to one month, using the providers' one-month rolling percentages of telehealth appointments as an IV. Second, we

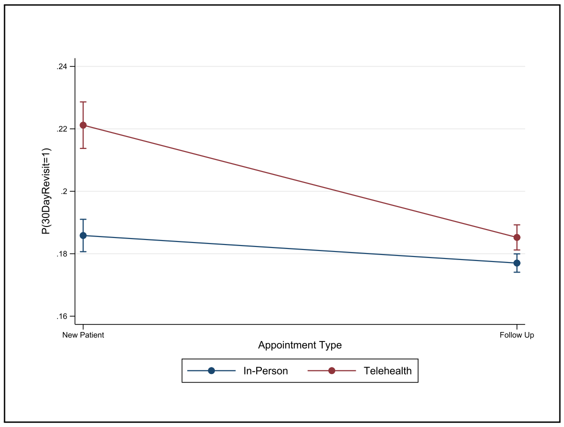

Figure 4. Predicted 30-day revisit probability with 95% confidence intervals by appointment modality and type.

use the past seven-day rolling number of online messages exchanged by the provider with all other patients. Lastly, we combine the past seven-day message counts and telehealth percentage to create a two-IV specification, which allows us to conduct a Sargan test of overidentifying restrictions (Kennedy, 2008). We fail to reject the null hypothesis of no correlation between instruments and the error term. Across all specifications, our findings remain consistent. See Appendix EC.5.1 for details.

Patient Fixed Effects. We incorporate patient fixed effects in our models to account for unobservable, time-invariant patient characteristics (e.g., baseline health, distance to clinic, interest in technology). This allows us to examine the behavior of the same patients between in-person and telehealth appointments. Our findings are consistent with and without patient fixed effects. See Appendix EC.5.2 for details.

Propensity Score Matching. We use propensity score matching to create a control group of patients with in-person appointments that closely matches the treatment group based on observable characteristics, reducing treatment-selection bias. The matching process balances covariates and yields estimates of the telehealth effect on no-show and punctuality consistent with our main results. We then perform regression analyses on the matched sample, with and without patient fixed effects and endogeneity adjustments, and find consistent results across all models. See Appendix EC.5.3 for details.

Placebo Tests. We conduct placebo tests following Staats et al. (2017) and Song et al. (2018) by randomly assigning telehealth treatment and estimating Equation (1) 100 times. This ensures that our telehealth effects are not artifacts of the data structure. The results, presented in Appendix EC.5.4, show that only two placebo models yield statistically significant, but near-zero, AMEs at the 5% level.

Alternative Identification Strategy. We leverage the variation in telehealth adoption rates among different physicians to conduct several difference-in-differences analyses, comparing patient adherence outcomes between physicians with higher and lower telehealth adoption rates. The results, presented in Appendix EC.5.5, align with the findings using our main identification strategy.

7 Implications of Telehealth on Appointment Scheduling Practices

Our empirical analysis suggests that telehealth is particularly effective in improving adherence to follow-up appointments, but may be less suitable for initial consultations with new patients. To translate these findings into actionable insights for clinics, this section explores strategies for integrating telehealth into optimized scheduling practices. Specifically, we examine the optimal sequencing of follow-up telehealth visits and in-person appointments (for both follow-up and new patients) within a day.

Scheduling Model. We consider a single-provider intraday scheduling problem. We extend the scheduling model introduced in Zacharias and Yunes (2020) to account for three heterogeneous appointment types:

- **F**ollow-up, **T**elehealth (abbreviated as type-FT).
- **F**ollow-up, **I**n-person (abbreviated as type-FI).
- **N**ew patient, **I**n-person (abbreviated as type-NI).

The goal is to determine the optimal timing and sequence of appointments to balance two competing objectives: Efficient use of provider time and shorter patient wait times. These goals often conflict due to variability in arrivals and consultation durations (Zacharias and Yunes, 2020). We address this trade-off using a *weighted penalty function* that captures the relative importance of different scheduling outcomes. Below, we provide a summary of the model, which accounts for stochastic factors such as no-shows, unpunctuality, and general stochastic consultation times. See Appendix EC.6 for the detailed model.

The regular length of a workday is T minutes (or $T/60$ hours), partitioned into n discrete time slots. The provider may operate overtime as well, beyond T, until all patients are served. Patients' scheduled arrival times are integer multiples of $k = T/n$ and subject to optimization. Assuming that the first slot starts at time zero, then time slot t occupies the time interval $[(t-1)k, tk)$, $t = 1, 2, \ldots, n$. Type-i patients show up for their appointment with probability p_i, and they arrive on time with probability q_i, $i \in \{\mathtt{FT}, \mathtt{FI}, \mathtt{NI}\}$. For unpunctual arrivals, we assume that patients check in one slot late. Consultation times are independent random variables and follow a common distribution R. The schedule for type-i appointments is denoted by a vector $\mathbf{x}_i \in \mathbb{Z}_+^n$, with x_i^t being the number of type-i patients assigned to slot t, $t = 1, 2, \ldots, n$ and $i \in \{\mathtt{FT}, \mathtt{FI}, \mathtt{NI}\}$. An optimal appointment schedule is a triplet $(\bar{\mathbf{x}}_{\mathtt{FT}}, \bar{\mathbf{x}}_{\mathtt{FI}}, \bar{\mathbf{x}}_{\mathtt{NI}}) \in \mathbb{Z}_+^{3n}$ that minimizes a penalty function $f(\mathbf{x}_{\mathtt{FT}}, \mathbf{x}_{\mathtt{FI}}, \mathbf{x}_{\mathtt{NI}})$. The function f is the outcome of stochastic analysis in transient state and measures the weighted sum of expected idle time, overtime, and wait time. Respectively, let

c_i, c_o, and c_w be the per minute penalty for each minute of idle time, overtime, and wait time.

Solution Methodology. Zacharias and Yunes (2020) prove that the objective function is *multimodular* when all patients have a homogeneous show-up probability (i.e., $p_{\mathtt{FT}} = p_{\mathtt{FI}} = p_{\mathtt{NI}}$) and they check in on time (i.e., $q_{\mathtt{FT}} = q_{\mathtt{FI}} = q_{\mathtt{NI}} = 1$). They exploit the multimodularity property to develop a methodology for identifying an optimal schedule effectively and efficiently. Moreover, they prove that the multimodularity property collapses when patients are stochastically unpunctual. For such cases, they propose heuristic solutions that leverage the directional convexity of the problem.

We extend the methodology proposed in Zacharias and Yunes (2020) to approximate heuristically the problem with heterogeneous patients, and we assess the performance of different sequencing rules. In particular, we perform a two-step approach. In the first step, we assume that all three appointment types share a homogeneous no-show probability, and that they check in on time when they show up. Under these assumptions, Algorithm 2 in Zacharias and Yunes (2020) terminates in polynomial time with an optimal aggregate schedule. In the second step, we account for heterogeneous show-up and on-time probabilities, and we assess the performance of different sequencing rules applied on the scheduling template from the first step.

Computational Experiments. In our computational study, we focus on the impact of patient adherence to scheduled appointments under the different modalities. Accordingly, we conduct sensitivity analysis with respect to the six parameters p_i and q_i, $i \in \{\mathtt{FT}, \mathtt{FI}, \mathtt{NI}\}$, while maintaining a fixed input for the remaining model attributes. In particular, we consider a 9-hour workday ($T = 540$ minutes) partitioned into eighteen 30-minute time slots ($k = 30$). Consultation times follow a Beta-Binomial distribution with average 30 minutes, coefficient of variation 0.3, and support on $\{0, 1, \dots, 45\}$. We normalize the per minute cost of idle-time and overtime to 1 ($c_i = c_o = 1$) and we set the wait cost coefficient to 0.05 ($c_w = 0.05$). We refer to Zacharias and Yunes (2020) for justifications about the qualities and appropriateness of these assumptions. Based on our empirical findings, we allow the six parameters p_i and q_i, $i \in \{\mathtt{FT}, \mathtt{FI}, \mathtt{NI}\}$, to take 375 different configurations so that:

- 25% of the total appointments are for type-NI patients (see Appendix EC.2).
- A fraction $\mathtt{a}$ of the total appointments are for type-FT patients.
- A fraction $1 - 0.25 - \mathtt{a}$ of the total appointments are for type-FI patients.
- $\mathtt{a} \in \{0.25, 0.50\}$.
- $\mathtt{a}p_{\mathtt{FT}} + (1 - 0.25 - \mathtt{a})p_{\mathtt{FI}} + 0.25p_{\mathtt{NI}} = 0.85$, i.e., the average no-show probability is 0.15.
- $\mathtt{a}q_{\mathtt{FT}} + (1 - 0.25 - \mathtt{a})q_{\mathtt{FI}} + 0.25q_{\mathtt{NI}} = 0.75$, i.e., the average late-arrival probability is 0.25.
- $1 \geq p_{\mathtt{FT}} \geq p_{\mathtt{NI}} = 1.0208p_{\mathtt{FI}}$ (see Figure 2).
- $1 \geq q_{\mathtt{FT}} \geq q_{\mathtt{NI}} = 1.0104q_{\mathtt{FI}}$ (see Figure 2).
- By solving 8 Linear Programs (4 for each $\mathtt{a}$) with the constraints above we conclude that
  1. $0.854 \leq p_{\mathtt{FT}} \leq 1.00$ and
  2. $0.752 \leq q_{\mathtt{FT}} \leq 1.00$.

The aggregate schedule that heuristically solves the corresponding homogeneous problem with no-show probability 0.15 is:

$$\mathbf{s} = (2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 0) \in \mathbb{Z}_{+}^{18}.$$

Schedule $\mathbf{s}$ is front-loaded and with the last slot empty, hedging against the effects of arrival-process and service-time variability on the dynamically evolving daily workload. Moreover, $\mathbf{s}$ accommodates 20 appointments, instead of 18, in order to prevent idleness due to potential no-shows. The double-booked slots are strategically selected by the optimization algorithm, taking into account the trade-off between containing wait times and overtime workload.

For the second step in our two-step approach, we construct four scheduling templates based on different sequencing rules. We consider sequencing rules such that the provider has to switch delivery method between in-person and telehealth only once during the day, to avoid potential "switching costs." This constraint reflects a realistic operational consideration: Switching between in-person and telehealth modes often involves logistical or cognitive costs, such as relocating to a different setting, changing workflows, or adjusting communication styles. By limiting mode-switching to once per day, we model a more practical and manageable scheduling structure for providers, aligning the analysis more closely with real-world conditions. Accordingly, we consider and contrast the following four sequencing rules:

(1) `FT_FI_NI`: Start with follow-up telehealth visits, then follow-up in-person visits, and end with new patient in-person visits.
(2) `FT_NI_FI`: Start with follow-up telehealth visits, then new patient in-person visits, and end with follow-up in-person visits.
(3) `FI_NI_FT`: Start with follow-up in-person visits, then new patient in-person visits, and end with follow-up telehealth visits.
(4) `NI_FI_FT`: Start with new patient in-person visits, then follow-up in-person visits, and end with follow-up telehealth visits.

We denote the cost of a sequencing rule with

$$F_{\mathtt{a}}(\mathtt{rule}) = f(\mathbf{x}_{\mathtt{FT\_a}}^{\mathtt{rule}}, \mathbf{x}_{\mathtt{FI\_a}}^{\mathtt{rule}}, \mathbf{x}_{\mathtt{NI\_a}}^{\mathtt{rule}}),$$

where $\mathtt{rule} \in \{\mathtt{FT\_FI\_NI}, \mathtt{FT\_NI\_FI}, \mathtt{FI\_NI\_FT}, \mathtt{NI\_FI\_FT}\}$ and $\mathtt{a} \in \{0.25, 0.50\}$.

Figures 5 and 6 show pairwise performance comparisons between the four sequencing rules, based on % performance

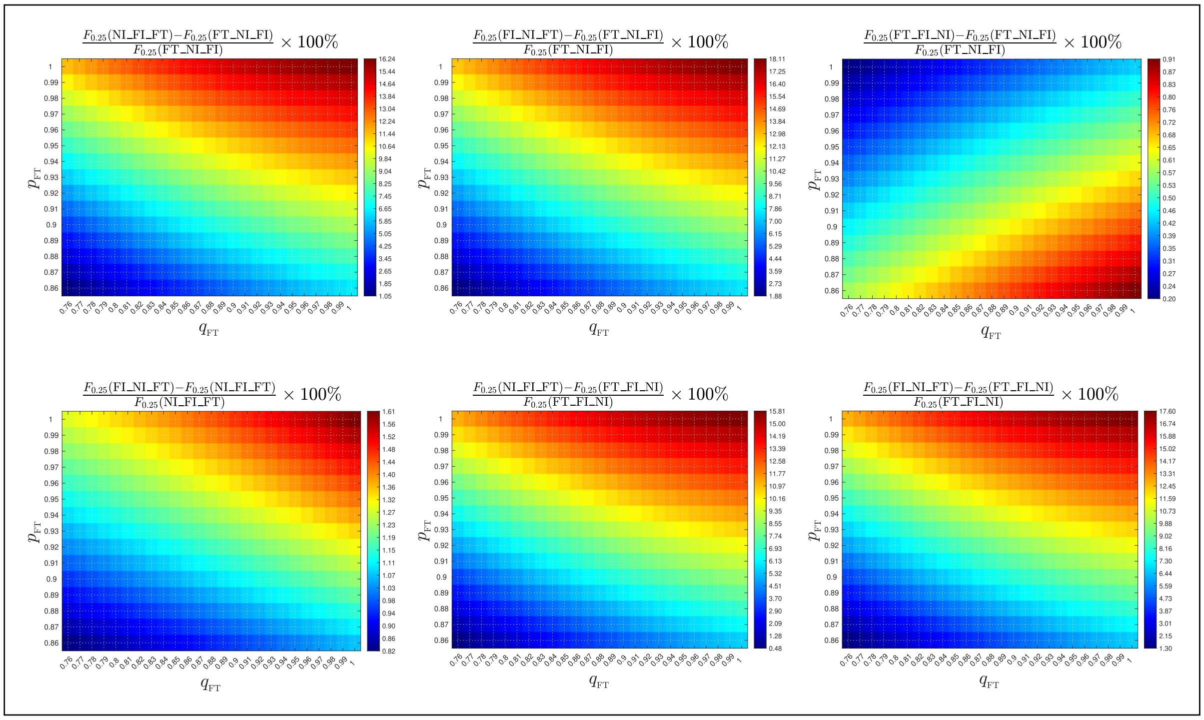

Figure 5. Pairwise comparisons of the four sequencing rules with 25% telehealth appointments.

gap, for fixed $\mathtt{a} \in \{\mathtt{0.25}, \mathtt{0.50}\}$, and different values of p_{FT} and q_{FT}. Figure 7 compares performance across the two values of $\mathtt{a} \in \{\mathtt{0.25}, \mathtt{0.50}\}$. We highlight several key insights from the results:

(i) `FT_NI_FI` dominates the other rules across the whole parameter space.
(ii) `NI_FI_FT` outperforms `FI_NI_FT` by up to 1.6% (0.8%) when $\mathtt{a} = 0.25$ (0.50).
(iii) `FT_NI_FI` outperforms `FT_FI_NI` by up to 0.9% (0.28%) when $\mathtt{a} = 0.25$ (0.50).
(iv) These results suggest that the order of in-person appointments (new vs. follow-up) has little effect on performance, as long as they are grouped together—either before or after telehealth visits.
(v) `FT_NI_FI` outperforms `NI_FI_FT` and `FI_NI_FT` by up to 18% (36%) when $\mathtt{a} = 0.25$ (0.50), with the gap increasing in both $p_{\mathtt{FT}}$ and $q_{\mathtt{FT}}$.
(vi) There is little difference between $\mathtt{a} = 0.25$ and $\mathtt{a} = 0.50$, as long as telehealth appointments are scheduled first.

Based on these insights, we recommend the following scheduling guidelines for clinics:

(i) Heterogeneity in no-show and punctuality rates between telehealth and in-person appointments significantly impacts operational efficiency and should be incorporated into scheduling templates.
(ii) A segregated scheduling template should sequence telehealth appointments before in-person visits. The order of in-person visits—whether follow-ups or new patients—has little effect on performance.

8 Concluding Remarks

We empirically investigate the impact of telehealth appointments on patient adherence to medical appointments and provider productivity. Using a comprehensive dataset of 412,415 appointments from a major American medical system, we analyze how telehealth affects patient no-shows and punctuality. Our findings reveal that telehealth significantly reduces no-shows and improves punctuality, especially for follow-up appointments and patient groups historically less adherent to in-person visits. We also observe that while telehealth appointments may increase revisit rates, the decrease in no-shows results in a net improvement in provider productivity, particularly evident with follow-up appointments. Finally, our study explores optimal scheduling strategies, highlighting that scheduling telehealth appointments before in-person visits throughout the day enhances operational efficiency compared to scheduling in-person visits first. These findings hold substantial implications for policymakers and healthcare organizations.

Policy Implications: Much of the discourse around telehealth's impact on access to care focuses on rural patients who lack alternative means of reaching healthcare providers. Our study highlights another important dimension: Telehealth can enhance access by improving appointment adherence even

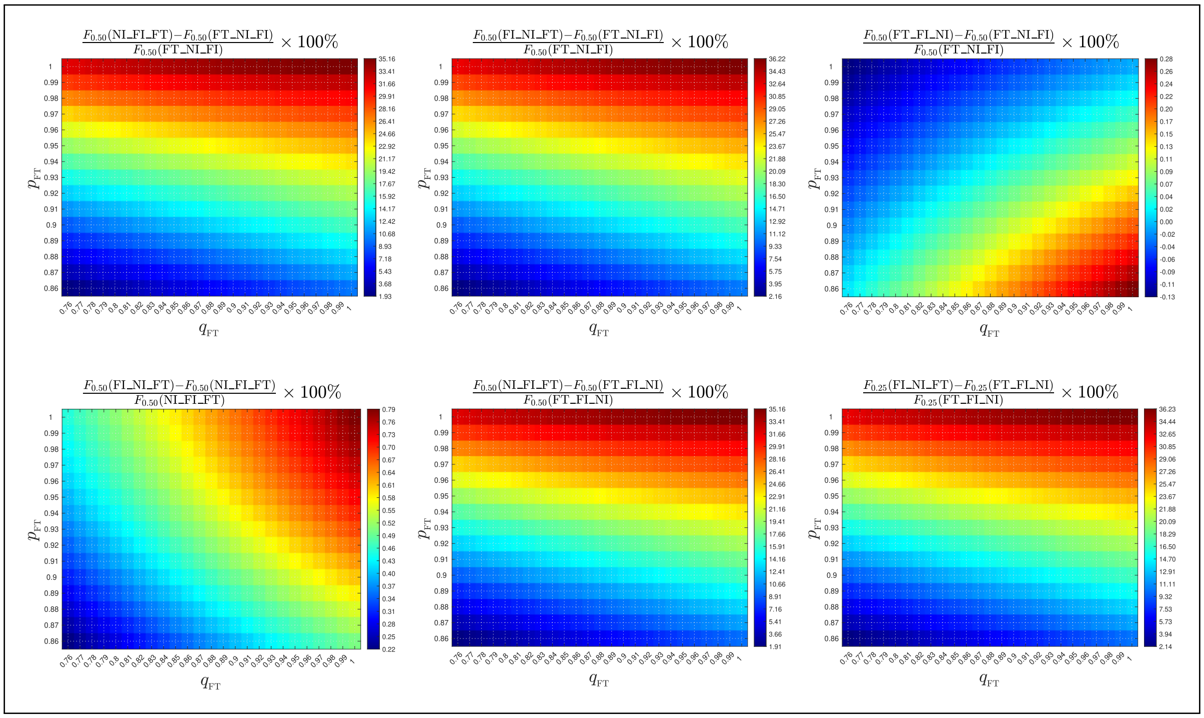

Figure 6. Pairwise comparisons of the four sequencing rules with 50% telehealth appointments.

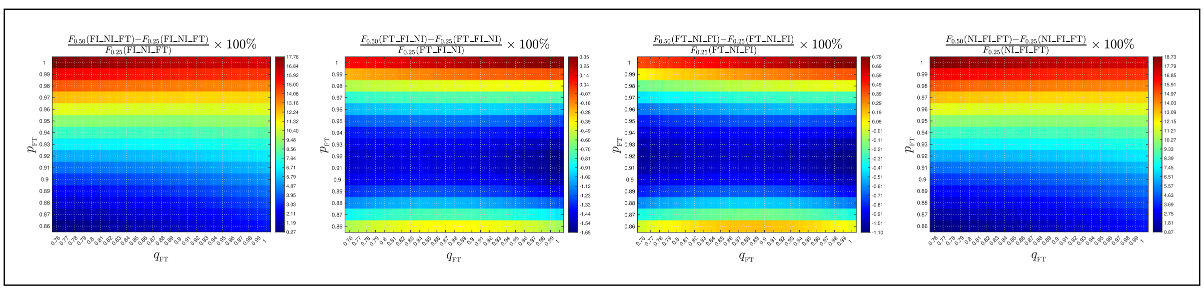

Figure 7. Impact of telehealth capacity on operational performance.

among patients in large metropolitan areas. This reveals an often overlooked benefit of telehealth: Enhancing appointment adherence not only broadens access but also enables providers to serve more patients, helping to alleviate the provider shortages that further limit access. Policymakers should recognize these benefits and continue to support telehealth adoption by aligning regulations and reimbursement models with its usage. Our findings also underscore telehealth's effectiveness in improving adherence among groups with historically lower rate of adherence to in-person appointments including women, racial minorities, Medicaid recipients, and younger adults. These results suggest that telehealth can help address common barriers to care, such as transportation challenges and scheduling conflicts. Policymakers and healthcare leaders should leverage telehealth as a tool to improve both access and equity in healthcare delivery.

Managerial Implications: Our findings have significant implications for healthcare organizations. First, traditional strategies such as overbooking and appointment reminders fail to address the root causes of patient nonadherence, whereas telehealth can effectively mitigate these barriers. Healthcare organizations should view telehealth appointments as a valuable tool to improve patient adherence. Second, despite concerns about pay disparities between telehealth and in-person appointments, our analyses show that telehealth can enhance provider productivity and generate additional revenue by reducing patient no-shows, particularly for follow-up appointments. This productivity gain can help offset any potential revenue shortfalls. Healthcare organizations should continue offering both telehealth and in-person options to optimize revenue potential. Third, telehealth is especially well-suited for follow-up visits, where comprehensive evaluations may not be necessary, but may be less appropriate for initial consultations with new patients. Strategic deployment of telehealth for follow-up visits and to patient groups with historically lower adherence to in-person visits—and reserving in-person appointments for those requiring more thorough assessments—can optimize both access and productivity. Lastly, scheduling telehealth appointments earlier in the day, followed by in-person visits, effectively ensures efficient patient flow and optimal provider utilization.

Limitations and Future Directions: Our study suggests several promising avenues for future research. First, while we focused on appointment adherence, future studies could explore the quality of care delivered via telehealth compared to traditional in-person visits. Identifying the contexts in which telehealth can effectively replace in-person care without compromising quality is essential. Second, our data lack key clinical variables, such as comorbidities and diagnostic orders. To address this limitation, we constructed proxy variables using the volume of patients' visits, orders, refills, messages, and calls. Future studies should examine whether these clinical factors influence the likelihood of choosing telehealth and, in turn, impact adherence outcomes. Third, our data come from a health system in a large U.S. metropolitan area and partially overlap with the COVID-19 pandemic. Future studies should investigate whether our findings hold in different geographic settings and using postpandemic data. Lastly, our findings underscore the need to adapt existing capacity planning models, which were originally designed for traditional in-person clinics, to account for the distinct patient behaviors associated with telehealth. Exploring the optimal balance between in-person and telehealth appointments presents a valuable avenue for future research.

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Notes

1. We construct the number of prior visits as a continuous variable. We also tested categorical indicators for visit frequency and found consistent results.
2. Note that of the 363,631 completed appointments, check-in times are missing for 18,246 cases. According to medical system personnel, these omissions occasionally occur due to human or system errors. To prevent measurement errors, we exclude these appointments from our punctuality analyses. If the missing records are nonrandom, this could introduce selection bias. In Appendix EC.1.2, we demonstrate that accounting for this selection would actually strengthen our results.

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