

**Telemedicine Adoption Before, During, and After COVID-19: The Role of Socioeconomic  
and Built Environment Variables**

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## **ABSTRACT**

The COVID-19 pandemic has led to a significant shift in healthcare delivery, with telemedicine emerging as an important additional service provision channel. This study introduces a novel methodological framework, combining a multiperiod multivariate binary probit (MBP) system and a cross-sectional MBP system, to investigate telemedicine adoption trends, as well as the facilitators and deterrents of adoption. The analysis utilizes data from a three-wave COVID Future Survey (April 2020-November 2021), supplemented by population density and healthcare-related establishment data. The results reveal a generational digital divide, with older adults exhibiting lower adoption rates due to technological barriers and preferences for traditional healthcare interactions. The study also highlights the role of the presence of children, income, transportation access, employment status, and residential location characteristics in telemedicine adoption. Notably, individuals without vehicle access or living in areas with lower geographic accessibility to healthcare providers are more likely to adopt telemedicine, suggesting its potential to reduce healthcare access disparities. The analysis of telemedicine facilitators and deterrents underscores the importance of accessibility, lifestyle preferences, privacy and security issues, technological confidence, and mobility constraints. The study provides valuable insights into policy implications across the public health, telecommunication, transportation, and urban planning sectors.

**Keywords:** telemedicine, telehealth, COVID-19, travel demand, equity

## 1. INTRODUCTION

Telemedicine is the practice of using information-communication technology (ICT) to receive medical care or advice remotely from clinicians, either in real-time or asynchronously. This approach to healthcare delivery offers several advantages, including improved access to care for patients in remote or underserved areas (Ezeamii et al., 2024), potential cost savings for both patients and healthcare systems (Haleem et al., 2021), and increased convenience through reduced travel and wait times (Vaidya et al., 2024). Additionally, telemedicine can facilitate more frequent check-ins, potentially improving the management of chronic conditions (Ezeamii et al., 2024; Vaidya et al., 2024). However, telemedicine poses several challenges, as identified in a recent systematic review by Ftouni et al. (2022). Barriers include technical aspects such as poor internet connections and limited access to technology, especially for older adults and those in areas with restricted internet access. Additionally, concerns persist regarding privacy, data confidentiality, reimbursement, limitations in conducting comprehensive physical examinations and diagnostic procedures, and deficiencies in training for healthcare providers and patients in effectively utilizing telemedicine.

While various forms of remote healthcare delivery have existed for decades, telemedicine was limited in scope and adoption prior to the COVID-19 pandemic (see, Chu et al., 2021, Nittari et al., 2022, and Shaver, 2022). Specifically, in early 2020, telemedicine visits constituted a mere 1% of the total healthcare visits in the United States (U.S.) (Anderson et al., 2022). The pandemic fast-tracked the adoption of telemedicine as a tool to maintain access to healthcare during lockdowns, with telemedicine visits surging to nearly 50% of all medical visits by April 2020 (Anderson et al., 2022). The rapid increase in telemedicine adoption during the COVID-19 pandemic was driven by both heightened demand from patients and expanded supply from healthcare providers. This increased adoption of telemedicine in the aftermath of the COVID-19 pandemic has, of course, transformed healthcare delivery, but also uncovered significant equity and accessibility disparities in healthcare based on age, race, income, and geographic location (see Nouri et al., 2020, Velasquez and Mehrotra, 2020, and Drake et al., 2022). Thus, from a societal standpoint, if telemedicine is to serve as a key universal healthcare tool, it is important to address these equity/accessibility issues. Additionally, it is imperative to properly quantify telemedicine's broader impacts across various sectors. In particular, similar to the widespread adoption of virtual activities, including online shopping, online meal delivery, and teleworking, the surge in telemedicine calls for an in-depth analysis of its relationship with telecommunication infrastructure, accessibility, transportation systems, and activity-based travel models. Importantly, from a transportation perspective, travel demand stems from the need to participate in activities distributed across space and time. Healthcare-related travel, including visits to medical facilities, has traditionally been a significant component of this derived demand. The rise of telemedicine, by potentially reducing or eliminating the need for physical travel to healthcare providers, represents a shift in this demand pattern. This shift could, in turn, influence urban mobility patterns, transportation planning, and even land use dynamics in the long term. Establishing this multidisciplinary perspective related to the impact of telemedicine on activity-travel patterns is important to maximize its benefits in a post-pandemic world, ensuring it serves as a force for equitable/efficient healthcare delivery and activity accessibility across all societal sectors.

Motivated by the above discussion, our study aims to achieve two primary objectives. The first is to investigate the factors influencing telemedicine adoption shifts in the post-pandemic era; the second is to identify and examine the determinants of telemedicine adoption, as well as to understand what the facilitating and deterrent factors are for telemedicine adoption in the After-

COVID period (we consider the period between March 2020 to mid-to-late 2021 as the “During-COVID” period, as vaccinations started becoming widely available about summer of 2021). In doing so, we use individuals’ stated telemedicine adoption during the Before- and During-COVID periods as a means to control for unobserved individual-level factors that affect telemedicine adoption during the After-COVID period. Doing so lends efficiency in our estimation, as well as allows us to more accurately trace the evolution patterns of telemedicine adoption between the Before-COVID and After-COVID periods, while controlling for unobserved individual-level factors (if such unobserved factors are ignored, they can confound the effects of observed individual factors). In this regard, while the During-COVID adoption tendencies are not really of much interest here (because adoption in this period was significantly impacted by external lockdown regulations), this time point in our analysis still contributes in an important way to controlling for unobserved individual-level heterogeneity (as we will note later, despite the lockdown regulations, in-person medical visits were still possible and, in fact, a majority of medical visits, as reported in our sample, continued to be in-person during COVID).

## **2. RELEVANT BACKGROUND**

The literature on telemedicine adoption after the COVID-19 pandemic has focused on several substantive thematic areas, driven by the rapid shift in healthcare delivery methods during and after the pandemic. In this literature overview, we focus on studies that are the most germane to the current study, which include those that (a) investigate the sociodemographic determinants of telemedicine adoption, and (b) explore the service-related variables and other reasons for telemedicine adoption from the patients’ perspective.

### **2.1. Sociodemographic and Residential Location Correlates of Telemedicine Adoption**

In this section, we focus on studies investigating the actual adoption or the expressed willingness to adopt telemedicine at the individual level.<sup>1</sup> Our overview is structured below based on the specific demographic factors that have been found to influence telemedicine adoption.

#### Age and Gender Effects

Age and gender have been found to significantly impact telemedicine utilization. Multiple studies (see Eberly et al., 2020, Jaffe et al., 2020, Zhang et al., 2021, Drake et al., 2022, Xu et al., 2022, Chandrasekaran, 2023, and Chen et al., 2023)) suggest that women may have a greater propensity to take to telemedicine than men, though some research (see Schifeling et al., 2020, and Sharma et al., 2024) reports no significant gender association, indicating variability across population contexts and geographic settings.

Age also has been identified as a significant determinant of telemedicine adoption. Studies consistently show that younger adults, typically under 45 years old (see Fischer et al., 2022 and Xu et al., 2022), are the most likely adopters of telemedicine services, possibly due to technological comfort and flexible healthcare needs. Yet, a small subset of research (see Eberly et al., 2020, and Weber et al., 2020) suggests a broader age range of telemedicine adopters, up to 65 years old. Overall, though, older adults generally adopt telemedicine to a lesser extent, particularly video-based services, preferring telephone over video consultations (Schifeling et al., 2020 and Drake et

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<sup>1</sup> This is as opposed to studies that examine telemedicine adoption/usage at the level of aggregate groupings of individuals, such as by age, gender, race/ethnicity, income, and the extent of rurality of residence (see, for example, Whaley et al., 2020, Hossain et al., 2022, Xu et al., 2022, and Park et al., 2023).

al., 2022). An exception was reported by Pierce and Stevermer (2023), who found a higher likelihood of telemedicine adoption among older adults in the initial 30 days of the pandemic.

### Racial/Ethnic Disparities

The literature extensively documents racial and ethnic disparities in telemedicine uptake, revealing that minority groups often adopt telemedicine services at lower rates than their white counterparts. In particular, studies from multiple geographic locations have noted lower telemedicine adoption among Black and Latinx patients (see Adepoju et al., 2022, Drake et al., 2022, and Chandrasekaran, 2023). However, some studies did not identify a significant link between race or ethnicity and telemedicine usage (see Jaffe et al., 2020, Zhang et al., 2021, and Sharma et al., 2024), while some others even reported higher usage among non-Hispanic Black and Hispanic patients (see Campos-Castillo and Anthony, 2021, Chumbler et al., 2023, and White-Williams et al., 2023).

The intersection of race and telemedicine modality (telephone versus video) further complicates the adoption landscape among racial and ethnic groups. Studies by Rodriguez et al. (2021), Der-Martirosian et al. (2022), and Drake et al. (2022) highlighted a preference for telephone visits over video among certain minority groups, likely due to technology access barriers. Conversely, Fischer et al. (2022) reported a significant willingness among Black adults to adopt video telemedicine.

### Other Demographic Variables

Other demographic variables that have been explored, perhaps to a lesser degree than age, gender, and race/ethnicity, are related to household composition, particularly focusing on marital status. Most studies (see Zhang et al., 2021, Choi et al., 2022, and Chandrasekaran, 2023) have found that married individuals or those cohabitating with a partner are more likely to take to telemedicine, while a few studies have suggested the opposite (Jaffe et al., 2020).

Socioeconomic status also significantly influences telemedicine adoption, though findings are again not consistent. Several studies have associated lower income with reduced telemedicine adoption (see Eberly et al., 2020, Luo et al., 2021, Choi et al., 2022, Drake et al., 2022, Fischer et al., 2022, and Osobase, 2023), while others have noted the opposite (see Patel et al., 2021) or statistically insignificant relationships (see Chandrasekaran, 2023, and Ko et al., 2023). Similarly, some studies have identified a positive correlation between higher formal educational levels and increased likelihood of telemedicine adoption (see Eberly et al., 2020, Luo et al., 2021, and Rodriguez et al., 2021), while others have found no significant relationship (see Chandrasekaran, 2023, Chumbler et al., 2023, and Sharma et al., 2024). Interestingly, Fischer et al. (2022) observed that individuals with lower formal educational levels exhibited the most significant increase in the willingness to adopt telemedicine during the pandemic, relative to their predispositions before the health crisis.

### Residential Location

Residential location has also been reported as a significant determinant of telemedicine adoption. While Chu et al. (2021) reported a notable increase in telemedicine use across rural areas following the onset of the pandemic, the telemedicine use increase in urban areas was significantly more pronounced. This trend highlights a persistent urban-rural divide, primarily attributable to access barriers in rural regions, as observed by Iasiello et al. (2023), Ko et al. (2023), and Sharma et al. (2024). Moreover, regional differences across the U.S. also influence telemedicine adoption,

reflecting variations in healthcare infrastructure, policy environments, and specific population health needs. For instance, Jaffe et al. (2020) found that individuals residing in the Southern states exhibited lower telemedicine adoption rates than their counterparts in the West, Midwest, or Northeast.

Overall, the reviewed body of literature on telemedicine adoption reveals variations in telemedicine adoption based on demographic and residential location characteristics, even if the results are not always consistent. These inconsistencies may be attributed to differences in specific telemedicine modalities studied, the time period during which data were collected, the geographic location of the study, and the particular medical institutions from which data were sourced. For instance, on the temporal dimension, most studies have used data spanning from March and September of 2020, capturing the early stages of the pandemic, while some others employed data collected in later periods of 2020 or early 2021. Only a few studies utilized data from after the first quarter of 2021, when telemedicine had become an integral part of regular healthcare delivery (see Chandrasekaran, 2023, Park et al., 2023, and Sharma et al., 2024). Further, to our knowledge, only one study by Chen et al. (2023) examined the evolution of telemedicine adoption trends over time at an individual level, using data from August 2020 to July 2021. Chen et al. identified two time periods: a telehealth transition period and a telehealth elective period. They examined telemedicine visits during each of these periods, as extracted from New York City's urban public healthcare administrative system, as a function of demographics. In doing so, they controlled for random effects associated with clinicians/facilities using a hierarchical logistic regression. Their results indicated minimal changes in the effects of demographics on telemedicine adoption across the two periods. It is important to note that their study was fundamentally a cross-sectional trend analysis based on different sets of individuals across the two time periods, which confounds the effects of unobserved individual factors affecting telemedicine adoption with the effects of observed individual factors.

## **2.2. Reasons for Adopting (or Not Adopting) Telemedicine**

Many systematic reviews have emerged regarding telemedicine service satisfaction, and the motivations and deterrents associated with telemedicine adoption; see, for example, Pogorzelska and Chlabicz (2022), Bajgain et al. (2023), and Rowe Ferrara and Chapman (2024). These studies generally invoke technology acceptance theories, such as the Delone and McLean's theory of technology use, and the Unified Theory of Adoption and Use of Technology (UTAUT) to explain factors influencing acceptance and the willingness to adopt telemedicine. The commonly cited facilitators of telemedicine adoption, as per these earlier studies, include the perceived safety from COVID-19 exposure, easier access to healthcare services, comfort and convenience, the reduction of travel-related challenges, time savings, shorter wait times, improved provider communication, and enhanced privacy measures. In contrast, the deterrents to telemedicine adoption often include concerns about service quality due to the absence of physical examinations, technical difficulties, challenges in communication, especially with describing symptoms, and difficulty in establishing a rapport between doctor and patient. However, while providing useful information, almost all of these earlier studies are based on descriptive statistics collected over all individual responses. Indeed, we are aware of only two studies; one by Adam et al., 2021 and another by Fisher et al., 2020, that attempt to explore the deterrents to telemedicine adoption by sociodemographic groupings. These two studies are discussed below.

Adams et al. (2021) used a convenience survey sample, collected immediately after the official declaration of COVID-19 as a pandemic in the U.S. (specifically, in March–April 2020),

to identify the reasons for non-adoption by telemedicine non-users. Their study, based on Pearson correlation explorations of non-adoption reasons with a single demographic variable at a time, found that older non-adopters were more likely to select “not being technologically savvy,” “do not have the technology needed,” “worried about confidentiality of private information,” and “worried about the continuity of care” (i.e., concern about not seeing the same provider every time). The study found no statistically significant correlations between insurance status, gender, and race and the reasons for not adopting telemedicine. Surprisingly, the findings regarding income and educational attainment revealed that individuals with higher income and educational attainment expressed concerns about internet quality, challenges of virtual communication, and the availability of required technology. Of course, the apparent use of linearity-based (suitable only for continuous variables) Pearson correlation factors in the study for detecting correlations between categorical variables suggests a need for caution when interpreting the results. In another study undertaken before the pandemic between February and April of 2019, Fischer et al. (2020) also explored the relationship between reasons for not adopting telemedicine and individual sociodemographic characteristics. They found that older individuals (aged >65 years) were more likely than their younger peers to indicate that their physician does not offer telemedicine visits. Additionally, older adults, those identifying as Black, and individuals with lower incomes (<20,000 annual income) were significantly more likely to report technological savviness as a barrier to using telemedicine compared to those in the 21-40 age group, non-Black, and high income ( $\geq 200,000$  annual income) groups, respectively. However, the study found no gender-based differences in the reasons for not adopting telemedicine. As in the study by Adams et al., these relationships were also based on univariate descriptive statistics (that is, the effect of each demographic variable on the reasons for telemedicine non-adoption is examined independently without, at the same time, controlling for other variables).

### **2.3. The Current Study in Context**

In this study, we introduce a new methodological and empirical framework to investigate telemedicine adoption trends in the Before-, During-, and After-COVID periods. The framework also explores the factors driving adoption and non-adoption decisions. Our approach contributes to advancing the existing body of knowledge in five distinct ways.

First, we use a comprehensive multivariate analysis to identify determinant factors from amongst sociodemographic, employment, personality, and built-environment (BE) variables (the BE variables represent in-person accessibility to medical facilities and residential neighborhood characteristics). The use of such a wide range of exogenous variables (see the left side of Figure 1, and the solid-line arrows from the block labeled “Exogenous Variables” to the “Telemedicine Adoption” and “Adoption/Non-adoption Reasons” blocks), all at once, allows for a deeper and more accurate understanding of the effect of each exogenous factor after controlling for other exogenous factors (relative to earlier telemedicine studies that are based on simple bivariate correlations of exogenous variables one at a time with telemedicine adoption). In addition, our analysis is based on a survey that includes a wave corresponding to late 2021 (during a time when the peak of the COVID pandemic was well behind us).

Second, our emphasis on modeling shifts in the effects of telemedicine adoption factors between the Before- and After-COVID periods provides insights on how the uptake of telemedicine among different segments of society has shifted through the pandemic (see the “Telemedicine Adoption” Block in the middle of Figure 1). In doing so, we control for unobserved individual factors (such as technology savviness) that can engender an intrinsic association among

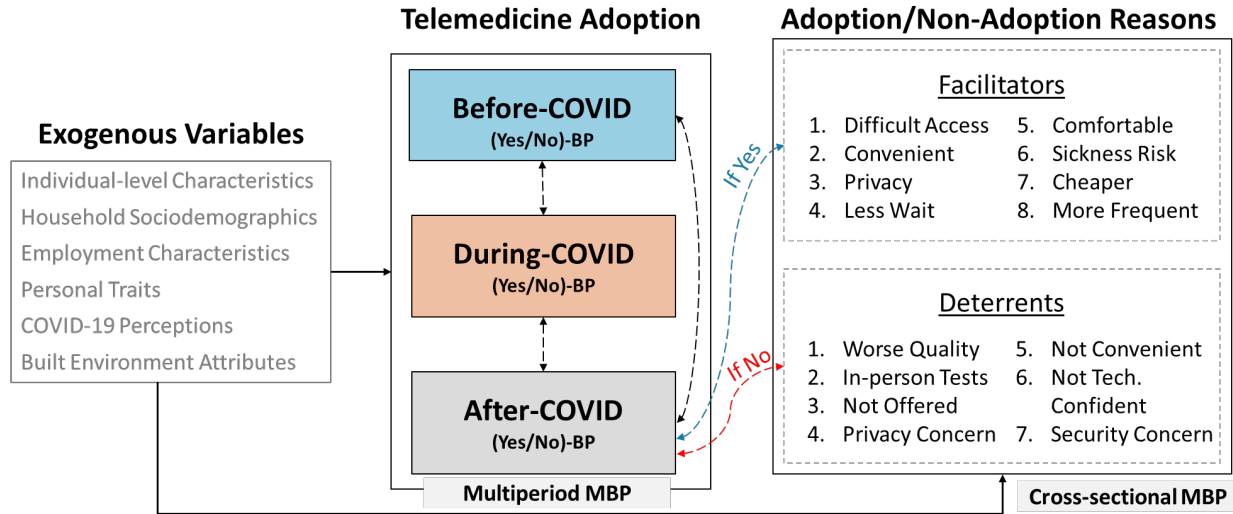
adoption decisions across the Before-COVID, During-COVID, and After-COVID periods (the period-specific adoption choices are modeled using binary probit models, marked by the label “BP” within the middle block of Figure 1; across the three periods, this then results in a multiperiod multivariate binary probit or MBP system for telemedicine adoption). The effects of such unobserved individual factors are represented by doubled-sided dashed-line arrows within the middle block. Not accounting for such unobserved individual factors can get manifested in the form of biased telemedicine adoption shift estimates. We are not aware of any earlier study that accounts for such intra-individual unobserved effects in the context of telemedicine adoption.

Third, while the existing literature has explored telemedicine adoption facilitators and deterrents using descriptive statistics, only two studies, to our knowledge (as discussed in Section 2.2), have investigated variations across population segments, and even then, only on the deterrents for non-telemedicine adopters. Our study goes further by examining adoption facilitators as reported (only) by telemedicine adopters and adoption deterrents as reported (only) by non-telemedicine adopters. This is accomplished through a series of bivariate probit (BP) models (for each reason of adoption or non-adoption), labeled as the cross-sectional MBP model system on the right side of Figure 1, to accommodate unobserved individual factors that can affect multiple reasons simultaneously.

Fourth, our overall model takes the form of a joint multiperiod MBP system for telemedicine adoption combined with the cross-sectional MBP system for facilitator/deterrent reasons specific to the After-COVID period (the facilitator/deterrent reasons were only asked for the After-COVID period). To our knowledge, such a joint model system is a first in the econometric literature. This approach is capable of accommodating self-selection effects that may tie adoption decisions with facilitators/deterrents. For example, a person with intrinsically introverted tendencies or a generic time-sensitive personality may be more likely to be a telemedicine adopter and also choose such reasons for adopting telemedicine as “I like the privacy offered by telemedicine” or “I do not have to wait for long.” And a person who likes in-person interactions or is cybersecurity-concerned may be more likely to not adopt telemedicine and also provide such reasons for non-adoption as “the quality of telemedicine care is worse” or “I am concerned about security with telemedicine.” That is, the adoption decision may be endogenous to the facilitator/deterrent reasons. By jointly modeling adoption in the After-COVID period with the facilitator/deterrent reasons, we can accommodate such self-selection (see the double-sided dashed-line blue and red arrows between the middle and right side blocks of Figure 1, representing correlation effects) and extend the results to obtain insights on the facilitators and deterrents amongst the population at-large (regardless of current telemedicine adoption or not). This comprehensive approach is necessary for informing healthcare providers, policymakers, and other stakeholders seeking to promote telemedicine adoption After-COVID in the entire population.

Finally, our study is the first that we are aware of in the travel behavior literature that focuses on telemedicine adoption. Earlier studies related to virtual participation have investigated tele-adoption in the context of work, shopping, and eating out, but have not considered telemedicine adoption. But, just like these other tele-activities, telemedicine adoption can also have transportation ramifications (including individuals potentially appropriating the freed-up time for pursuing other activities). In this regard, we hope that our study will open up additional research in studying the travel implications of tele-participation in medical-related activities. This should be of particular interest in the context of medical accessibility for the increasingly aging population of many countries, including the U.S.





**Figure 1. Analysis Framework**

### 3. DATA AND VARIABLE DESCRIPTION

#### 3.1. Survey

The primary data used in this study is obtained from the COVID Future Survey (Salon et al., 2022). The survey was undertaken using an online response link, which was disseminated through a combination of a U.S. national purchased list of 450,000 e-mail addresses, another list of 39,000 e-mail addresses from the Phoenix area, social media platform advertising, and invitations to family, friends, and colleagues. The intent of the survey effort was to collect data from the same set of participants over time. The first wave collected data from 8,723 respondents during the early stages of the pandemic from April to October 2020, the second wave collected 2,877 responses from November 2020 to May 2021, and the third wave collected 2,728 responses from October to November 2021, representing the period when the most significant pandemic-related disruptions were receding. The dataset includes sociodemographic information about individuals and their households, details of their travel behaviors, preferences for a variety of mobility and housing options, and responses to the COVID-19 pandemic. Also, the survey elicits information related to telemedicine adoption before, during, and after the pandemic. First, telemedicine adoption before the COVID-19 pandemic (this period is designated as the “Before-COVID” period in the study) was based on individuals’ stated responses of whether they had ever used telemedicine before the onset of the pandemic in March 2020. While the Before-COVID adoption designation is based on recall over a few years in the past, we do not expect major recall bias in the data. This is because the survey question simply required a “yes” or “no” response about telemedicine usage Before-COVID, rather than asking for a detailed recall of frequencies, dates, or other specifics that are more prone to recall problems. Moreover, for most participants, telemedicine adoption pre-pandemic was likely a recent experience (within the last couple of years coinciding with the rise of information and communication technologies), reducing the length of recall required. Telemedicine adoption during the pandemic was obtained based on self-reported adoption during the period from April 2020 to November 2021, and telemedicine adoption in the period after the pandemic (designated as the “After-COVID” period in the study) was based on individuals’ expectations of potential use after a post-COVID new normal is reached (for ease in presentation,

we will refer to this expectation of use as “telemedicine adoption” in the After-COVID period).<sup>2</sup> Utilizing these expected future levels provides a more stable representation of long-term post-pandemic steady-state adoption. Finally, based on the responses to the survey question regarding telemedicine adoption in the After-COVID period, respondents were presented with a series of queries aimed at understanding the underlying reasons behind adoption or non-adoption.

Following data quality assurance procedures, we excluded participants with erroneous or missing data across any of the Before-, During-, and After-COVID periods. A total of 2041 individuals with adoption/non-adoption information across all three periods were retained for the multiperiod MBP analysis of Figure 1. But, for the analysis focusing on the reasons behind adopting or not adopting telemedicine After-COVID, the sample size was slightly larger at 2,335 observations because this analysis solely relied on responses related to post-COVID adoption. This part of the analysis corresponds to the cross-sectional MBP. However, as we discuss in Section 4, the entire structure of the multiperiod MBP and cross-sectional MBP is undertaken jointly.

Supplementary data regarding the zip code tabulation area population density were appended to the survey data from the 2021 American Community Survey (ACS). Additionally, the number of healthcare-related establishments (including outpatient care centers, general medical and surgical hospitals, and offices of physicians) in the zip code, obtained from the U.S. Census Bureau 2021 County Business Patterns (CBP) dataset (U.S. Census Bureau, 2021), was used as a proxy for evaluating individuals’ in-person (physical) accessibility to healthcare.

### 3.2. Outcome Variables

Table 1 below provides descriptive statistics related to telemedicine usage among respondents at different stages of the COVID-19 pandemic. The variables presented in Table 1 correspond to the “Telemedicine Adoption” component of the framework presented in Figure 1. In each cell of the table, we use “Yes” to refer to cases where telemedicine was adopted, and “No” to indicate non-adoption. In parentheses, we present the number of observations and the relative frequency of observations corresponding to each cell.

Before the pandemic (first column in the table), only a small fraction (11.47%) of the sample had prior experience with telemedicine. During the pandemic, the percentage of adoption increased to 42.62%  $[(146+724)*100/2041]$ , with the majority of adopters  $[724*100/(146+724)=83.22\%]$  being first-time users. Not surprisingly, as can be observed from the second column of the table, individuals who had used telemedicine before the pandemic continued to use telemedicine at a higher rate  $[146*100/234 = 62.39\%]$  during the pandemic compared to those who had not used telemedicine before the pandemic (at 40.07%). The entries in the first sub-column of the “After-COVID Adoption” section of Table 1 indicate that 78.77% of respondents who consistently used telemedicine before and during the pandemic (“Yes-Yes” group) plan to maintain this behavior post-pandemic. In contrast, significantly lower intentions to use telemedicine were observed among other groups, notably for the “Yes-No” group (38.64%), the “No-Yes” group (58.98%), and the “No-No” group (14.22%). Interestingly, despite the high adoption rate during the pandemic, the overall anticipation for post-pandemic telemedicine

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<sup>2</sup> If one were to be fastidious, the Before-COVID and During-COVID responses should be labeled as “self-reported recall-based telemedicine adoption”, while the After-COVID response should be labeled as “self-stated anticipated telemedicine adoption”. One can debate whether it is more important to use these more appropriate labels (at the potential expense of wordiness and presentation simplicity), or whether it is more important to focus on presentation simplicity (at the expense of not providing an accurate characterization of how adoption was measured). Here, we opt for the latter, with the hope that, in the rest of this paper, readers will always keep in mind that our common label of telework adoption across periods is relatively “loose” and actually differs across the periods.

adoption slightly decreased to 35.77% (see the last row of the table under the “After-COVID Adoption” column), with a considerable 64.23% indicating no future usage intent. However, the intention to use telemedicine in the future is still significantly higher than the Before-COVID adoption.

Overall, the sample statistics suggest that those who had prior exposure to telemedicine, either Before- or During-COVID, are inclined to continue using it. However, it is worth noting that among those who had utilized telemedicine at least once in their lifetime before or during the pandemic (summing up to  $234+724=958$ ), approximately 39.87%  $[(31+54+297)*100/958]$  are reluctant to embrace telemedicine in the post-pandemic era. These aggregate statistics suggest that telemedicine adoption preferences across time are likely to be a function of not only observed individual elements but also unobserved individual factors, both of whose effects may also vary over the three periods as the environmental circumstances changed. This is the reason that we model the adoption/non-adoption decisions jointly across the three periods, allowing for time-variant effects of exogenous variables as well as time-variant unobserved correlations.

Additionally, Table 2 presents the frequency and percentage of respondents who have selected various reasons for either adopting or not adopting telemedicine. The variables presented in Table 2 correspond to the “Adoption/Non-adoption Reasons” component of the framework presented in Figure 1. Specifically, Table 2 summarizes the reasons for adopting telemedicine among 802 individuals planning to continue its use post-COVID, as well as the reasons for not adopting telemedicine among 1533 respondents who do not intend to use telemedicine in the future. The data highlights that the majority of telemedicine adopters value its convenience, time-savings, comfort-of-home, and lower (disease) contagion risk (consistent with earlier studies, as discussed in Section 2.2). Conversely, non-adopters cite deterrents such as the need for in-person medical testing and procedures, the perception that a traditional healthcare provider's office provides more privacy, and the convenience of in-person medical visits. Interestingly, unlike previous findings summarized in Section 2.2, respondents in our sample did not indicate limited healthcare choices, insurance coverage, technical issues, or privacy concerns as major deterrents to using telemedicine. In fact, due to the substantially low number of individuals selecting “I have a wider choice of healthcare providers,” “I have a wider choice of in-person healthcare providers,” and “My insurance does not cover telemedicine,” these reasons were excluded from the analysis (especially so because the number in Table 2 for each reason category gets further disaggregated when considering specific population segments as defined by the exogenous variables in the analysis). Note that the second column in Table 2, entitled “short labels,” refers to compact characterizations of the original statements without repeating the entire statements verbatim. These short labels (and sometimes just even their acronyms) will be used in the presentation of results later.

### 3.3. Exogenous Variables

Table 3 provides a detailed overview of the variables used in the study. It includes the relative frequency of each variable in the dataset and, when applicable, compares the figures with the 2021 American Community Survey (ACS) five-year estimates for the U.S. adult population. For some continuous variables, the table shows the mean and standard deviations (std. dv.). Also, a dash (“--”) in the “% in ACS” column indicates that the corresponding variable does not have an equivalent estimate in the ACS for the population. The table encompasses several categories of data, including individual/household sociodemographics, employment characteristics, personal

traits and COVID-19 perspectives, and residential location attributes.<sup>3</sup> For time-invariant exogenous variables (such as race), and for exogenous variables that change uniformly over time (such as age), we used the variable values corresponding to the After-COVID period. For exogenous variables that can potentially change significantly over time (such as number of motorized vehicles and employment status), we employed the variable values corresponding to the specific period under consideration.

Overall, as can be observed from Table 3, the sample deviates from the national census distribution in several ways. In terms of individual and household sociodemographics, the sample overrepresents women, couples without children, white individuals, older age groups, individuals who hold high formal degrees, middle-income households, and single-vehicle owners. The overrepresentation of women and white individuals has also been observed in other online surveys (see Smith, 2008, Jang and Vorderstrasse, 2019, and Wu et al., 2022). The underrepresentation of younger adults is surprising, given that the survey was administered online and promoted via social media. A plausible explanation is that older individuals are typically more tuned in to health-related matters, such as pandemic effects. The high proportion of respondents with undergraduate and graduate degrees might be attributed to the survey's digital format. Unemployed individuals and students are also overrepresented. One possible explanation is that they may have more flexible schedules, making them more available to complete surveys. Lastly, the oversampling of the western U.S. Census region<sup>4</sup> directly results from targeted recruitment strategies in those regions (Chauhan et al., 2021).

Despite deviations from census distributions on certain variables, the sample remains suitable for estimating individual-level relationships between exogenous variables and the outcomes of interest that may be generalized to the broader U.S. population. This is because of having a reasonable number of sample observations within each exogenous variable-outcome combination to tease out relationships. Furthermore, because the sample is not based on endogenous sampling (i.e., our sampling of respondents was based on a convenience sample, not one targeted toward individuals with specific telemedicine adoption outcomes or reasons for adoption/non-adoption), employing an unweighted analytical approach is more efficient from an inference standpoint, as observed by Wooldridge (1995) and Solon et al. (2015).

#### 4. METHODOLOGY

This study employs a joint model that simultaneously estimates a multiperiod multivariate binary probit (MBP) system for telemedicine adoption (across the three periods; that is, across the Before-

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<sup>3</sup> “Enjoy working more from home due to COVID” or “Enjoy driving less due to COVID” referred to questions related to the experiences of individuals during the pandemic that they would like to continue into the future. These were collected on a binary scale of “enjoy” or “do not enjoy”. For the perspective that “People’s well-being is/was at risk during the pandemic”, responses of “somewhat agree” or “highly agree” (on the statement “I am concerned that if I, or my friends or family members, catch the coronavirus, we may have a severe reaction”) were categorized as “at risk”, while responses of “neutral,” “somewhat disagree,” or “strongly disagree” were categorized as “Not at risk”. Finally, a similar binary categorization was adopted for “Not technologically savvy” (from a five-point ordinal scale based on the response to the statement “Learning how to use new technologies is often frustrating”).

<sup>4</sup> The four U.S. regions were defined according to the U.S. Census definitions. These regions include the Northeast (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania), Midwest (Indiana, Illinois, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota), South (Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas), and West (Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming, Alaska, California, Hawaii, Oregon, and Washington).

COVID, During-COVID, and After-COVID periods) as well an endogenous switching multivariate binary equation system in the form of a cross-sectional MBP system. The “treatment” in the latter cross-sectional component of the joint model system is telemedicine adoption (or not) in the third period, with the outcomes being the multivariate binary list of reasons for adopting (in the positive telemedicine adoption regime) and not adopting (in the negative telemedicine adoption regime). Note that the After-COVID adoption decision is also tied to the multiperiod MBP to accommodate time-varying unobserved individual factors that impact the adoption decisions across all periods. Further, unobserved individual factors that can affect multiple facilitator/deterrent reasons are captured through the correlations in the cross-sectional MBP within each regime. The formulation enables the accurate capture of exogenous variable effects on the adoption decision through the control of unobserved factors, as well as enables the estimation of the factors acting as facilitators and deterrents for adoption in the population at large (regardless of adoption or not determinations, which is where the endogenous switching MBP system comes into play). That is, for any random individual picked from the population, we are able to determine the facilitators/deterrents for telemedicine adoption, thanks to the endogenous switching MBP.

Methodologically speaking, for any given individual, if the individual adopts telemedicine in the After-COVID period, we observe the adoption choices across the three periods and the reasons for adoption (as asked only in the After-COVID period). Thus, the joint probability of interest corresponds to (a) the choice of adoption Before-COVID (yes/no, based on reported adoption), (b) the choice of adoption During-COVID (yes/no, based on reported adoption), (c) the choice of adoption After-COVID (yes, based on stated intention of future telemedicine adoption), and (d) the choice of the reason for adopting telemedicine (yes/no, based on observation on each of the eight adoption reasons (after removing the “I have a wider choice of healthcare providers” reason in Table 2 due to an insufficient number of respondents selecting this reason). This effectively results in an 11-dimensional MBP system (the non-adoption reasons are unavailable for these individuals and do not feature in the estimation). Next, for any individual who does not adopt telemedicine in the After-COVID period, the joint probability of interest corresponds to (a) the choice of adoption Before-COVID (yes/no, based on reported adoption), (b) the choice of adoption During-COVID (yes/no, based on reported adoption), (c) the choice of adoption After-COVID (no, based on stated intentions), and (d) the choice of the reason for non-adoption of telemedicine (yes/no, based on observation on each of the seven non-adoption reasons (after removing the “insurance” and “I have a wider choice of in-person healthcare providers” reasons in Table 2 due to an insufficient number of respondents selecting these reasons). The result is a 10-dimensional MBP system (the adoption reasons are unavailable for these individuals and do not feature in the estimation). For each of the two regimes above (the adoption and non-adoption regimes in the After-COVID period), three dimensions are common (the three adoption/non-adoption decisions in the three periods), which ties the multiperiod and the cross-sectional MBPs. From a presentation ease standpoint, the entire model system can be viewed as an 18-dimensional MBP system, with zero correlations between the Before/During-COVID adoption equations and the reasons for adoption/non-adoption (because the reason questions were asked only for the After-COVID period). Further, because adoption (non-adoption) reasons were sought only from those who adopted (did not adopt) in the After-COVID period, no correlations can be estimated across the two sets of reasons for adoption and non-adoption (but correlations can be estimated within the set of adoption reasons and within the set of non-adoption reasons). However, correlations are estimable between the error term in the adoption/non-adoption choice component for the After-COVID period and the entire set of reasons for adoption and the entire set of non-adoption

(constituting the main switching element of the model). We use such an 18-dimensional MBP set-up to present the model structure (because of presentation ease), though, as indicated earlier, for any individual, during estimation, the dimensionality collapses to either 11 or 10, depending upon adoption or not After-COVID (that is, only the appropriate marginal covariance matrix of 11 or 10 from the original covariance matrix of 18 will feature).

With the above notes, the model structure is essentially that of an MBP system assuming 18 outcome dimensions, as we discuss below.

#### 4.1. Model Structure

The formulation presented in this section is based on the methodological frameworks developed by Bhat (2014) and Bhat (2018). Let  $c$  be the index for telemedicine adoption choices across the three periods, the eight reasons for telemedicine adoption, and the seven reasons associated with non-adoption ( $c = 1, 2, \dots, C$ ;  $C=18$  in our case). Define a latent propensity  $y_c^*$  underlying the binary variable  $y_c$  and consider the following structure:

$$y_c^* = \beta_c' \mathbf{x} + \varepsilon_c, \quad y_c = k_c \text{ if } \psi_{c,k_c-1} < y_c^* < \psi_{c,k_c}, \quad (1)$$

where  $\mathbf{x}$  is an  $(L \times 1)$  vector of exogenous variables (excluding a constant),  $\beta_c$  is a corresponding  $(L \times 1)$  vector of coefficients to be estimated, and  $\varepsilon_c$  is a random error term assumed to be standard normally distributed (the scale of  $\varepsilon_c$  is not identified and so is arbitrarily set to one). Let  $k_c$  represent a specific value of the binary dependent variables, which can be either 0 or 1. Therefore, we can write  $y_c \in \{0,1\}$ . For each outcome, the continuous latent propensity  $y_c^*$  is mapped to the observed outcome variable  $y_c$  through a threshold, denoted by  $\psi_{c,0}$ . This threshold should satisfy the ordering conditions  $(\psi_{c,-1} = -\infty; -\infty < \psi_{c,0} < +\infty, \psi_{c,1} = +\infty)$ . Next, vertically stack the  $C$  latent variables  $y_c^*$  into a  $(C \times 1)$  vector  $\mathbf{y}^*$ , and the  $C$  error terms  $\varepsilon_c$  into another  $(C \times 1)$  vector  $\boldsymbol{\varepsilon}$ . Let  $\boldsymbol{\varepsilon} \sim MVN_C(\mathbf{0}_C, \boldsymbol{\Xi})$ , where  $MVN_C(\mathbf{0}_C, \boldsymbol{\Xi})$  represents the  $C$  dimensional multivariate normal distribution with mean vector  $\mathbf{0}_C$  (a  $(C \times 1)$  vector of zeros) and a correlation matrix of  $\boldsymbol{\Xi}$ . The off-diagonal terms of  $\boldsymbol{\Xi}$  capture the error covariance across the underlying latent continuous propensities of the 18 outcomes. Many of the elements of  $\boldsymbol{\Xi}$  are zero because of the considerations discussed in the previous section.

Also, let  $\tilde{\boldsymbol{\psi}} = (\psi_{1,0}, \psi_{2,0}, \dots, \psi_{C,0})'$  be a  $(C \times 1)$  vector of thresholds across all the 18 model components. Let an individual under consideration be observed to have a value of  $k_c$  ( $c = 1, 2, \dots, C$ ). Accordingly, stack the lower thresholds  $\psi_{c,k_c-1}$  corresponding to the observed values of the individual into a  $(C \times 1)$  vector  $\boldsymbol{\psi}_{low}$ , and the upper thresholds  $\psi_{c,k_c}$  into another  $(C \times 1)$  vector  $\boldsymbol{\psi}_{up}$ . Also, define  $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_C)'$   $[(C \times L)$  matrix]. Then, in matrix form, the latent propensities underlying the multivariate outcomes may be written as:

$$\mathbf{y}^* = \boldsymbol{\beta}' \mathbf{x} + \boldsymbol{\varepsilon}, \quad \boldsymbol{\psi}_{low} < \mathbf{y}^* < \boldsymbol{\psi}_{high}, \quad \text{where } \mathbf{y}^* \sim MVN_C(\boldsymbol{\beta}' \mathbf{x}, \boldsymbol{\Xi}). \quad (2)$$

Lastly, define a vector  $\boldsymbol{\delta}$  that holds the collection of parameters to be estimated:

$\boldsymbol{\delta} = \left( [\text{Vech}(\boldsymbol{\beta})]', \tilde{\boldsymbol{\psi}}', [\text{Vechup}(\boldsymbol{\Xi})]' \right)'$ , where the operator “Vech(.)” row-vectorizes all the non-zero elements of the matrix/vector on which it operates, and the operator Vechup(.) row-vectorizes

the (estimable) upper diagonal elements of a matrix. Then the likelihood function of a single individual may be written as:

$$\begin{aligned} L(\delta) &= \Pr[\boldsymbol{\Psi}_{low} < \mathbf{y}^* < \boldsymbol{\Psi}_{high}], \\ &= \int_{D_r} f_C(\mathbf{r} | \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Xi}) d\mathbf{r}, \end{aligned} \quad (3)$$

where the integration domain  $D_r = \{\mathbf{r} : \boldsymbol{\Psi}_{low} < \mathbf{r} < \boldsymbol{\Psi}_{high}\}$  is simply the multivariate region of the  $\mathbf{y}^*$  vector determined by the upper and lower thresholds.  $f_C(\mathbf{r} | \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Xi})$  is the MVN density function of dimension  $C$  with a mean of  $\boldsymbol{\beta}'\mathbf{x}$  and a correlation matrix  $\boldsymbol{\Xi}$ . In actual estimation, and as discussed in the earlier section, only a subset of dimensions will be relevant in estimation for each individual, with the appropriate marginal correlation matrix extracted from  $\boldsymbol{\Xi}$ . The likelihood function for a sample of  $Q$  decision-makers is obtained as the product of the individual-level likelihood functions defined in Equation (3).

The likelihood function in Equation (3) involves the evaluation of either an 11-dimensional or 10-dimensional orthant probability for each decision-maker. While the symmetry of the multivariate normal distribution collapses the orthant integral to a multivariate normal cumulative distribution (MVNCD) function, evaluating such a high-dimensional MVNCD function can be computationally expensive. However, Bhat's (2018) matrix-based efficient and accurate analytic approximation method for evaluating the multivariate normal cumulative distribution (MVNCD) function was employed to evaluate this integral.'

## 5. EMPIRICAL RESULTS

In developing the final specification, we explored various combinations of variables and functional forms. All variables, except age, number of telework days, population density, and the number of physicians' offices, are in either bracketed categories (such as income) or are naturally discrete. The effects of these bracketed and discrete exogenous variables were tested as dummy variables in the most disaggregate form possible and progressively combined for parsimony based on statistical tests. For the other variables, functional forms, including a linear form, a logarithm form, a piece-wise linear form, and dummy variables for different ranges were tested, but the best representation was in the form of dummy variables except for the effect of the number of physicians' offices that appeared in the raw linear count form for the telemedicine facilitator/deterrent analysis component (the effect of population density was best captured using a simple dummy variable of whether the zip code of the individual's residence was above the average across all zip codes or below, and the effect of the number of physicians' offices in the telemedicine adoption analysis component was in the form of a single dummy variable of greater than 3 offices in the zip code or otherwise). Further, we extensively analyzed potential interaction effects among all major factors, including age, gender, presence of children, income, transportation access, employment status, and residential location characteristics. This analysis involved testing various combinations of these variables to identify any significant interactive effects on telemedicine adoption. However, no statistically significant interaction effects were found, even at the marginal level of a 75% confidence level. Of course, caution needs to be exercised in this regard, because of the relatively small share of telemedicine adopters in the current sample (especially in the pre-COVID sample), as well as small numbers in each category of the reasons for adopting/not adopting telemedicine (which has the effect of further reducing the number of sample points at the intersection of two or more independent variables within each dependent

outcome category). Future research with larger sample sizes should continue to test interactions extensively.

The final specification is presented in Tables 4 and 5. The parameters in these tables represent the elements of the  $\beta$  matrix, which reflects the effect of exogenous variables on the propensity to adopt or not adopt telemedicine or to choose a specific reason. Not all of the included variables are statistically significant at the 95% level. In our specifications, we used a lower 79% confidence level (corresponding to a t-statistic of 1.25) to acknowledge the relatively small sample size of our estimation, which may have contributed to the marginal significance of certain variables (especially with variables corresponding to outcomes with a limited number of observations, such as the reasons for adoption or non-adoption). By being more inclusive in retaining exogenous variables, we hope that our findings will offer valuable insights for future investigations with larger sample sizes. Also, a dash (“--”) next to an exogenous variable in the tables indicates that the corresponding coefficient is not applicable to that specific outcome variable. A blank cell implies that the exogenous variable did not have a statistically significant association with the outcome, even at the 79% confidence level. Finally, in some cases, the same coefficient (and t-statistic) may appear across columns or across rows (or both) because earlier tests of coefficient equality could not be rejected.

### **5.1. Telemedicine Adoption Model Estimation Results**

Table 4 presents the effects of the exogenous variables on telemedicine adoption propensity Before-COVID and After-COVID. While we included telemedicine adoption During-COVID in our model to account for unobserved individual factors across all periods, we present results for the pre-pandemic and post-pandemic periods here. This is because, during the height of the COVID-19 pandemic, limited choices likely drove telemedicine adoption more than individual preferences. Consequently, the effects of exogenous factors on adoption during that period are not especially informative for guiding policy decisions.

The thresholds in the last numeric row do not have any substantive interpretation, but map the latent adoption propensity to the observed binary adoption outcomes in a way that reflects the overall aggregate shares of adoption and non-adoption. The positive and statistically significant thresholds indicate that, after accommodating for observed and unobserved individual factors, there is a remnant generic predisposition in the sample for telemedicine non-adoption (as can also be observed in the aggregate for each of the three periods from Table 1). The results for the exogenous variables are discussed below.

#### Individual/Sociodemographic Effects

The results do not reveal any statistically significant gender differences in telemedicine adoption across all periods, consistent with the findings of Schifeling et al. (2020), and Sharma et al. (2024). In terms of lifecycle and living arrangements, households with children have a generic higher propensity to adopt telemedicine services across both the “Before-COVID” and After-COVID” periods, presumably because of the need for frequent pediatric consultations to monitor symptom progression in children (see Ashman et al., 2023; this explanation is supported by the results related to telemedicine adoption reasons in Section 5.2). The results also indicate a significant increase in the propensity to use telemedicine among individuals living with unrelated adults or roommates after the pandemic. This trend could be linked to the heightened awareness and cautiousness regarding the importance of social bubbles among those sharing living spaces with non-family members, a concern that may have extended beyond when restrictions were lifted (Murphy, 2020).



The age effects in Table 4 indicate that, while those in the middle age group (31 to 50 years) were more likely than their younger and older peers to use telemedicine Before-COVID, the difference in telemedicine adoption between young and middle-aged individuals all but disappeared in the After-COVID period. However, telemedicine adoption substantially reduced in the After-COVID period among older individuals in the age group of 51 years and above relative to their younger peers. The Before-COVID results may be tied to the fact that the youngest group of individuals ( $\leq 30$  years of age) require fewer medical visits given their better health condition (see Ashman et al., 2023), and so did not mind the time investment for their occasional in-person visits. However, the experience During-COVID appears to have created a renewed awareness, even among this youngest age group, of the time-saving benefits of telemedicine even for those occasional medical visits, as supported by the results discussed later on age effects on telemedicine adoption reasons. The general reluctance of older adults to adopt telemedicine Before-COVID may be tied to a relative lack of technological savviness and the need for in-person physical exams and procedures, once again supported by our results on reasons for not adopting telemedicine discussed later. Also, the increasing trend of non-adoption among older individuals over time aligns with findings from some other studies (see, for example, Jaffe et al., 2020, Drake et al., 2022, and Xu et al., 2022).

Individuals from households exceeding \$100,000 in annual income, as well as those who experienced an income increase during the pandemic, are more likely to adopt telemedicine services in the After-COVID period, while individuals in zero-car households have a generic higher intensity for telemedicine adoption through time. The income effect aligns with prior research by Eberly et al. (2020), Luo et al. (2021), Choi et al. (2022), Drake et al. (2022), Fischer et al. (2022), and Osobase, (2023), who ascribed this to the higher value of time among higher-income individuals and the greater access to digital equipment (such as computers and tablets). The vehicle ownership effect is consistent with the notion of limited transportation access to out-of-home activities, and the consequent increase in engagement in virtual activities of all kinds, including telemedicine (see, for example, Dias et al., 2020, Figliozi and Unnikrishnan, 2021, and Kim and Wang, 2021).

### Employment Characteristics

Our analysis also explored the relationship between employment status, telework habits, and telemedicine adoption. While employment status itself did not significantly influence telemedicine adoption, telework arrangements turned out to play a key role. Both before and after the pandemic, individuals who frequently teleworked (multiple times per week or more often) exhibited a greater tendency to utilize telemedicine. This finding may be attributed to two potential reasons. First, frequent teleworkers might already be comfortable using digital platforms, making telemedicine a seamless extension of their work routines. Second, the prevalence of trip chaining during commutes (combining errands with travel) might enhance the convenience of in-person appointments, making non-teleworkers more likely to opt for in-person medical appointments.

Prior to the COVID-19 pandemic, students exhibited a higher propensity for telemedicine adoption compared to the general population, perhaps because of the broader access provided by university health services, which were early adopters of remote healthcare offerings (see Gallagher Student Health and Special Risk, 2019, and Hollowell et al., 2022). However, as telemedicine became more mainstream post-pandemic, the general population appears to have begun to adopt telemedicine at rates comparable to those of students, closing the initial usage gap.

### Other Factors

Consistent with the actual telework frequency effect, there is a positive influence of the preference for remote work (in the After-COVID period) on telemedicine adoption, signaling a broader trend toward digital integration in life activities. Not surprisingly, those who report that they enjoyed the lower need to drive during the peak of COVID and those who indicate that individuals' overall well-being was at risk during the pandemic are also more likely to embrace telemedicine adoption. This finding is consistent with the observations made by de Palma et al. (2022) and Haddad et al. (2023), who noted a similar trend in the acceptance of remote services and activities among these individuals. The above three exogenous variables were not obtained for the Before-COVID period, so they do not appear in the Before-COVID column of Table 4. As expected, individuals who self-characterize themselves as not being technologically savvy have a lower telemedicine adoption in both the Before-COVID and After-COVID periods.

Residential location attributes have direct effects on telemedicine preferences. Before the pandemic, when telemedicine was considered a niche service, the influence of geographic accessibility to healthcare providers on telemedicine adoption was insignificant. However, in the post-pandemic period, individuals with higher in-person access to physicians ( $>3$  physician offices in the individual's residence zip code) and those in higher (than average) population density areas are significantly less likely to utilize telemedicine than their counterparts in locations with lower in-person physician access ( $\leq 3$  physician offices in the individual's residence zip code) and lower (than average) population density. The results do not reveal a statistically significant influence of regional factors on telemedicine adoption.

### **5.2. Telemedicine Adoption Facilitators/Deterrents Model Estimation Results**

The second objective of the study was to explore the factors that make telemedicine adoption more appealing or less appealing. The estimates correspond to the effects on the propensity that each reason acts as a telemedicine facilitator/deterrent for a random individual drawn from the population at large. Table 5 presents the results. For ease in presentation and results discussion, we do not provide the t-statistics for the parameters in Table 5, but these are available in an online supplement at <https://www.cae.utexas.edu/prof/bhat/ABSTRACTS/Telemedicine/OnlineSupp.pdf>.

#### Individual/Sociodemographic Effects

The results reveal that, for women, the main reasons for the appeal of telemedicine correspond to the lower contagion risk (LCR), the difficulty in in-person accessibility (DIPA), and telemedicine convenience (TC), in that order.<sup>5</sup> Women also appear less sensitive to any lower cost (LE) benefits of telemedicine compared to men, and are less likely than men to perceive poor telemedicine quality (PTQ). The gender-based result regarding lowering contagion risk (LCR) may be attributed to women having generally more health-related angst (and, therefore, being more contagion risk aware; see, for example, MacSwain et al., 2009 and Alsharawy et al., 2021), while the DIPA and TC results may be tied to the time-poor nature of women given they typically juggle multiple responsibilities of work, household duties, and caregiving for children/older family members (see Bernardo et al., 2015 and Festini et al., 2019). The latter results may also be associated with the lower access of women to household vehicles (see Scheiner and Holz-Rau, 2012, and Infutor, 2021).

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<sup>5</sup> Note that the coefficients of any exogenous variable can be directly compared across reasons because the scales of all the reasons are set uniformly to one for identification without any loss of generality.

Moving on to the lifecycle variables, telemedicine appears to appeal to families with children because of (a) DIPA, (b) the need for more frequent consultation (FCO), and (c) the privacy offered by telemedicine (TP) (in that order), while perceived in-person convenience (IPC) (that is, perceived telemedicine inconvenience relative to IPC) and poor telemedicine quality (PTQ) appear to be deterrents for such families. The telemedicine appeal for families with children again is perhaps indicative of accessibility challenges and time poverty faced by parents (see Bernardo et al., 2015), especially because of the frequent illness bouts of children (see Ashman et al., 2023). On the other hand, the greater concerns about telemedicine inconvenience and quality may reflect the complex healthcare needs of children who require attention to non-verbal cues and physical examinations (see, for example, Freed, 2021, and Tully et al., 2021, and Burns et al., 2024).

The race-related impacts in Table 5 suggest that, for non-white individuals (relative to white individuals), the privacy offered by telemedicine (TP) and the ability for frequent consultation opportunities (FCO) would encourage telemedicine adoption, while the comfort of home (CH) of telemedicine appeals particularly to white individuals. The emphasis of non-white individuals on telemedicine privacy and frequent appointments may stem from cultural or historical factors, such as mistrust in the healthcare system or perceived discrimination, which can create barriers to accessing in-person care (see Powell et al., 2019, and Bazargan et al., 2021).

Age is another significant demographic variable influencing telemedicine preferences, with individuals over 50 being drawn to telemedicine because of increased privacy (TP) and the lower contagion risk (LCR). The latter motivation can be attributed to older individuals being more vulnerable to infections than their younger peers. Individuals over 50 years also are more likely than their younger peers to identify not being technologically confident (NTC) as a reason for shying away from telemedicine, which may be tied to the more digitally-savvy nature of the younger generation. In addition, individuals over 60 are less drawn to telemedicine because of (a) time-savings (TS) (perhaps due to their more flexible schedules), (b) the relative convenience of in-person visits (IPC), and (c) perceived limitations in adequately addressing their complex healthcare needs of in-person tests and procedures (NIPT).

Individuals with bachelor's or graduate university degrees are drawn toward telemedicine due to its convenience benefits (TC) (correspondingly, this group places less importance on the perceived in-person convenience (IPC)), but also are deterred due to the perceived inferior quality of telemedicine healthcare (PTQ). This behavior could possibly stem from their greater comfort in using technology, coupled with a tendency to more rigorously scrutinize and question the quality of telemedicine consultations (see Huber and Kuncel, 2016). Similar results are observed for individuals from high income households (relative to those from low income households), with such individuals also placing a premium on the time-saving (TS) benefits of telemedicine, while not being too drawn by such benefits as telemedicine privacy (TP) and the comfort of medical consulting from home (CH). Further, individuals in this high income group typically enjoy a high level of spatial activity accessibility, and so do not face much difficulty in in-person accessibility (DIPA), as also evidenced in the higher emphasis on DIPA as income decreases (see the positive coefficient on the "Income decreased during COVID" variable in the DIPA column). The last three columns of Table 5 for the income variables reveal that individuals from high income households view technological confidence (NTC), security issues (TSC), and in-person convenience (IPC) as less of barriers to telemedicine adoption. Another perspective on these results is that individuals from low income households do perceive more difficulty in in-person access (DIPA) to medical services. They also are less concerned about any potential degradation in telemedicine quality

(PTQ), and are more positive about telemedicine convenience (TC) and privacy (TP), though also concerned about digital security (TSC) and their own technological confidence (NTC).

As with individuals from low income households, those from households without vehicles appear to value the telemedicine modality due to DIPA, reinforcing the potential of telemedicine to address transportation-related disparities in healthcare access.

### Employment Characteristics

Employed individuals, relative to those not employed, place less emphasis on DIPA as a driver for telemedicine adoption, while appreciating the privacy offered by telemedicine (TP) and being more open to telemedicine from places other than the home (lower CH). In addition, employed individuals attribute less emphasis to the need for in-person tests (NIPT) as a deterrent for telemedicine adoption. As we discuss later in Section 6, these results suggest opportunities to integrate telemedicine within and around workplaces.

Individuals who telework frequently from home (either daily or multiple days per week from home), not surprisingly, identify comfort from home (CH) and the lower COVID risk (LCR) as appealing aspects of telemedicine. They also tend to exhibit diminished concerns regarding convenience (IPC), and privacy (POP) when it comes to telemedicine. Their work-from-home arrangements enhance familiarity with virtual services and offer privacy within the home environment. Related to actual teleworking, but more of a personal trait that we discuss here (though it is positioned under “personal traits and COVID-19 perspectives” in Table 5) is the effect of “enjoy working from home.” Among those who enjoy teleworking (regardless of actual teleworking frequency), DIPA is an incentive for telemedicine adoption, while in-person provider’s office privacy (POP) and telemedicine data security (TSC) concerns are less of a telemedicine deterrent. Teleworkers often receive digital and cybersecurity training through their employment, potentially increasing their comfort with the data security practices of virtual platforms.

Beyond the workplace, students have a favorable perspective regarding telemedicine because of the opportunity to schedule appointments more frequently (FCO), and individuals who commute using a personal vehicle place less of a premium on telemedicine convenience (perhaps an indication of the influence of commute-related trip-chaining in positively shaping the perceived convenience of in-person visits).

### Other Factors

Expectedly, the results related to access to in-person health care services in Table 5 indicate that individuals residing in areas with a higher concentration of physicians within their zip code identify (a) difficulty in in-person accessibility DIPA and the privacy offered by telemedicine as less of reasons for considering telemedicine (reinforcing the lower propensity for telemedicine adoption in such locales, as discussed in Section 5.1), and (b) perceive telemedicine’s inconvenience (IPC) as a deterrent to adoption. Interestingly, while the population density of an individual’s zip code of residence featured in the telemedicine adoption decision, it did not play a significant role in the facilitator/deterrent reasons. Finally, in Table 5, regional factors influence the facilitators and deterrents to adopt telemedicine, though they are introduced primarily as a control for estimating the other individual-level effects more accurately. In general, the results reveal that those living in the Northeast view privacy (TP) as a key appeal of telemedicine services, while those residing in the Midwest view convenience (TC) as the key driver. Those in the Midwest and West are also less likely to believe that telemedicine will not be offered by health

care providers (TNA), while individuals living in southern states demonstrate relatively higher confidence in telemedicine quality (PTQ).

### Unobserved Correlations

Table 6 presents the correlation effects in unobserved factors among (a) the adoption choices across the Before-, During-, and After-COVID periods (the top left 3×3 numeric submatrix), (b) the correlations in the unobserved factors between the adoption choice in the After-COVID period and each of the reasons that constitute facilitators and deterrents of telemedicine adoption (the third numeric row of the table), (c) the correlations among the facilitator reasons (the fourth through 11<sup>th</sup> numeric rows and columns of the table), and (d) the correlations among the deterrent reasons (the 12<sup>th</sup> through 18<sup>th</sup> numeric rows and columns of the table). As discussed earlier, the facilitator/deterrent reasons were sought only for the After-COVID period, and so the columns corresponding to the first two numeric rows (of Before- and During-COVID periods) and the facilitator/deterrent reasons have zeros as entries. Similarly, the facilitator reasons are only obtained from those who actually adopted telemedicine, and the deterrent reasons are obtained only from those who did not adopt telemedicine (in the After-COVID period) and so the entire sub-matrix containing the correlations between the facilitator and deterrent reasons have to be set to zero. In the table, we only provide the t-statistics for correlations that are statistically significant at least at the 76% confidence level.

The top left 3×3 matrix indicates the correlations among the three propensities for telemedicine adoption in the three different periods. While these correlations correspond to common unobserved factors and can take any sign, the positive correlations are rather intuitive. Unobserved individual factors that increase the propensity for telemedicine adoption in any period also tend to increase the propensity of telemedicine adoption at other periods. Controlling for such common (but time-varying) unobserved factors across the periods allows for the consistent estimation of the effects of observed exogenous variables. Of particular importance from a self-selection perspective are the correlations corresponding to the “After-COVID” row and the many telemedicine facilitator/deterrent reasons columns (third numeric rows in Table 6). Self-selection occurs when individuals choose to adopt/not adopt telemedicine based on their unobserved characteristics, such as preferences, attitudes, or constraints, which may also influence their likelihood of citing specific facilitators/deterrents for adoption. As an illustration, the -0.36 correlation between DIPA and telemedicine adoption suggests that unobserved factors that increase the likelihood of citing DIPA as a reason for telemedicine adoption also decrease the likelihood of actually adopting telemedicine. Thus, for example, an individual who has a strong trust in in-person visits (an unobserved factor) and a strong desire to see their doctor face-to-face may perceive a higher level of difficulty in accessing in-person medical services (DIPA). This is because their strong preference for in-person visits may make them feel that they do not have as much accessibility as they would like, creating a sense of difficulty. However, this same individual, due to their strong trust in in-person visits, may be less likely to adopt telemedicine. As a result, in the sub-population of individuals who adopt telemedicine, there is likely to be a weaker positive relationship between DIPA and telemedicine adoption than in the general population. That is, if we ignore the negative correlation between DIPA and telemedicine adoption due to unobserved factors (such as intrinsic trust in in-person visits), we would underestimate the importance of DIPA as a motivator for telemedicine adoption in the general population. Such inaccurate results can lead to misinformed policy implications regarding how to increase telemedicine use (if that were the goal).

The correlations among the facilitator reasons are all positive. Again, while these correlations can be of any sign, the positive correlations are rather intuitive, suggesting that individuals who intrinsically value one aspect of telemedicine also value other aspects in a similar positive manner. Among the many correlations, comfort emerges as a central element having the strongest correlations with other motivating factors. Similarly, several deterrent reasons appear to be intertwined. The strongest correlation (0.55) exists between “not technologically confident” (NTC) and “telemedicine security concern” (TSC) (see the last column and penultimate row of Table 6), suggesting a link between low technical confidence and heightened security worries. Similarly, a strong correlation (0.32) exists between provider’s office privacy (POP) and TSC, suggesting that people who are concerned about digital privacy are also more likely to value digital data security. Clearly, the security and privacy of digital telemedicine use are concerns in general, especially among those who feel they are not technologically proficient.

### 5.3. Goodness-of-Fit Measures

#### Likelihood-Based Data Fit Measures

We compare the data fit provided by our proposed joint model (i.e., the multiperiod-cross-sectional MBP model) relative to a naïve independent model that completely ignores jointness (i.e., the correlations) among the many dimensions, as well as a thresholds-only model. Several metrics can be used for this comparison, as presented in Table 7. First, we use the Bayesian Information Criterion (BIC) statistic  $\left[ = -L(\hat{\delta}) + 0.5 \times (\# \text{ of model parameter}) \times \log(\text{sample size}) \right]$  to compare model performance, where  $L(\hat{\delta})$  is the log-likelihood value at convergence. Table 7 shows that the joint model exhibits a lower BIC statistic compared to the independent model, indicating superior model performance. Moreover, the difference in the average probability of correct prediction and the adjusted likelihood ratio index  $\bar{\rho}^2$  is also substantial, indicating the better fit of the joint model relative to the independent and thresholds-only model. The  $\bar{\rho}^2$  index is calculated as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\delta}) - M}{L(c)} \quad (4)$$

In the above equation,  $L(c)$  represents the thresholds-only log-likelihood function at convergence, and  $M$  is the number of parameters estimated in the model (excluding the thresholds). Lastly, since the joint and independent models are nested (the independent model is a special case of the joint model with additional constraints), we can perform a nested likelihood ratio test. The results of this computation show that the likelihood ratio is much greater than the critical chi-square value corresponding to 67 degrees of freedom at the 0.001 significance level, supporting the superiority of the joint model. In fact, the better data fit of the proposed model is literally definitive relative to the competition, given the large chi-squared test values.

#### Aggregate Data Fit Measures

We also evaluate the data fit of the joint and the independent models at the aggregate level. Technically speaking, we can compare the predicted share of individuals who would choose to adopt telemedicine along with the entire multivariate combination of the facilitator reasons for adoption, and compare this multivariate prediction with the observed multivariate combination. However, this would lead to  $2^8=256$  combinations. Similarly, we can compare the predicted share of individuals who would not choose telemedicine along with the entire multivariate combination

of the deterrent reasons, but this would again lead to  $2^7=128$  combinations. So, we compute the predicted shares of individuals who would adopt telemedicine and identify each facilitator reason individually. For instance, we compute the predicted share of individuals who indicate that they would adopt telemedicine and identify DIPA as a facilitator reason, as well as the predicted share of individuals who indicate they would adopt telemedicine and do not identify DIPA as a facilitator reason. Similarly, we compare the predicted and observed shares for non-adoption and each individual deterrent reason. The results are presented in Table 8. The first broad column in Table 8 shows the observed counts and corresponding shares of individuals who would adopt (or not adopt) telemedicine and identify each facilitator (or deterrent) reason. The second broad column includes the predicted counts and shares from the joint model system, along with the average absolute percentage error (APE) depicting the average absolute difference between observed and predicted values. The third broad column presents the same information as the second, but for the independent model instead of the joint model. Across most rows, the joint model exhibits a lower APE value compared to the independent model. A similar conclusion is obtained when comparing the observed and model-predicted shares using a weighted absolute percentage error (WAPE) value (the weighting here is based on the actual observed share of individuals falling in each row combination of Table 8). The joint model has a WAPE of 23.0%, which is significantly lower than the independent model's WAPE of 54.0%, demonstrating the joint model's superior fit and predictive accuracy.

## 6. MAGNITUDE EFFECTS OF VARIABLES AND IMPLICATIONS

### 6.1. ATE Analysis Preparation

The estimation results in Section 5 provide the effects of variables on telemedicine adoption propensity and the propensity of each facilitator/deterrent reason, but do not immediately provide the magnitude of impacts. For example, a positive coefficient for the higher household income brackets (relative to the lower income brackets) indicates a higher likelihood of telemedicine adoption among individuals from higher income households relative to lower income households, but does not quantify the extent of change in the probability of telemedicine adoption between individuals of the different income groups. Such shift estimates may be computed using average treatment effects (ATEs), which can be computed for a change from any specific “Base Level” category (e.g., high income) to a “Treatment Level” category (e.g., low income). For presentation convenience, in this section, we only report the ATEs for a change between a specific pair of states for categorical variables (such as household income) that can take more than two states. For the count variable effect related to the number of physicians’ offices in the zip code (for the facilitator reasons analysis) and the continuous variable of population density (that affects the telemedicine adoption choice), we changed the variable from below average to above average in the ATE analysis.

Table 9 summarizes the computed ATEs for selected exogenous variables. While the ATEs corresponding to telemedicine adoption during the Before-COVID and During-COVID periods were also calculated, they are not included in this analysis as they offer limited value for understanding the current landscape of telemedicine adoption and informing necessary interventions. To illustrate the interpretations of the ATE entries in Table 9, consider the third numeric row corresponding to the age variable. The entry of “-29.7%” in the “telemedicine adoption” column indicates that a random individual in the population who is older than 50 years would be about 30% less likely to take to telemedicine relative to a random individual in the population 50 years or younger (equivalently, the younger individual would be about 1.43

(=100/70) times more likely to be adopting telemedicine relative to the older individual). Similarly, the entry of “23.0%” for the age variable corresponding to the LCR column in Table 9 indicates that a random individual in the population who is older than 50 years would be about 23% more likely (or about 1.23 times more likely) to identify lower contagion risk (LCR) as a motivating factor to adopt telemedicine than a random individual in the population who is 50 years or younger. Other entries may be similarly interpreted. In the rest of this section, we discuss the policy implications of the ATEs from Table 9 in three categories: (1) Equity implications, (2) Telemedicine integration in the workplace, and (3) Transportation and urban planning implications.

## **6.2. Equity Implications**

The ATE results in Table 9 provide important insights regarding how telemedicine may be effectively utilized to elevate the provision of health services in general, and bridge the equity gap across different demographic and place-based groups in particular.

Women and individuals with children in the household view telemedicine as an effective means to circumvent difficulties in accessing in-person medical appointments. For women, perceptions of telemedicine as being convenient and mitigating the risk of contracting illnesses, combined with a belief that telemedicine is not inherently inferior to in-person visits in terms of quality, suggest that there is potential to increase telemedicine use and elevate the general focus on women’s health issues (particularly because telemedicine adoption rates currently are not different by gender). The timing to do so also aligns well with President Biden’s recent “White House Initiative on Women’s Health Research” initiative with a \$12 billion investment in new funding (The White House, 2024). Similarly, families with children value the privacy, as well as the potential for more frequent medical consultations, offered by telemedicine, while adopting telemedicine at a higher rate (18.0%). Approaches that maximize the health benefits for women and caregivers may include online clinics staffed with licensed professionals who specialize in women’s and children’s health issues. These virtual clinics could offer round-the-clock availability and tailored expertise, effectively addressing the unique healthcare needs of women and families, while also satisfying the demand for more frequent appointments, particularly among households with children. However, unlike the case of women, households with children perceive telemedicine as inconvenient (IPC) and of lower quality (PTQ) compared to in-person care, indicating that merely increasing telemedicine provision is not enough to encourage widespread adoption among these households. To address this challenge, healthcare providers should consider implementing hybrid care models that combine telemedicine with essential in-person visits. This may be pursued by leveraging virtual technologies (such as remote patient monitoring and interactive educational tools), combined with strategically scheduled in-person visits, to better understand the non-verbal cues of children for accurate diagnosis and treatment. Healthcare providers can also collaborate with child development experts to enhance the interpretation of non-verbal cues in telemedicine consultations, ultimately improving the quality of care delivered. Such initiatives not only enhance convenience and accessibility, but also empower women and caregivers to proactively manage their health and the well-being of their families.

The negative ATE (-29.7%) for those over 50 indicates a significant gap in telemedicine adoption, stemming, as per Table 9, from in-person convenience (IPC) relative to telemedicine and “not being technologically confident” (NTC). This trend highlights a digital divide that could exclude older adults from the full advantages of telemedicine, even as older individuals appear to distinctly appreciate the privacy (TP) and low contagion risk (LCR) benefits of telemedicine. To



address this gap, efforts are needed to bolster digital literacy among older adults and develop user-friendly telehealth platforms tailored to their specific needs. Collaborative initiatives between healthcare providers and community stakeholders can play a pivotal role. For instance, healthcare providers can partner with senior centers, libraries, and community organizations to offer digital literacy workshops focused on basic computer skills, navigating telemedicine platforms, and online safety. Moreover, equipping such centers with requisite technological infrastructure, including computers, cameras, and designated private spaces (especially since our results indicate that older adults are more likely to benefit from the privacy offered by telemedicine with an ATE of 52.4%), facilitates seamless access to telemedicine consultations in a supportive environment, with trained personnel on hand to offer assistance as needed. Initiatives such as providing loaner devices pre-loaded with telehealth applications can also alleviate barriers associated with equipment constraints. Additionally, healthcare providers can rely on input from focus groups to learn about the main technological impediments encountered by older adults. This user-centered approach can lead to more effective platform designs. Clear and succinct on-screen instructions throughout the appointment process could further streamline the telemedicine experience. Alternatively, pre-telemedicine visit telephone calls with instructions could also increase the likelihood of successful virtual consultations, as indicated by Gusdorf et al. (2023). Lastly, to cater to diverse preferences and comfort levels, healthcare providers should offer alternatives such as telephone-based appointments alongside video conferencing to enhance accessibility and inclusivity. As such, efforts to bridge the digital gap and enhance telemedicine accessibility for seniors not only promote health equity, but also improve quality-of-life considerations over their life span.

Telemedicine also addresses accessibility challenges faced by individuals with low household incomes and less access to motorized vehicles. Similar to the case of women, the combination of individuals' heightened challenges in accessing in-person appointments, and their perception that telemedicine does not diminish privacy and is not necessarily inferior to in-person visits (see Table 9), strongly suggests that targeted strategies toward these demographic groups could increase telemedicine adoption (especially given the current adoption rates are lower for these groups compared to their peer groups). However, merely increasing the availability of telemedicine for these individuals without ensuring they possess the necessary tools for access will not yield effective results. Low-income individuals face significant digital accessibility challenges that hinder their adoption of telemedicine services, which then also appear to get translated into the perceived inconvenience of telemedicine (higher IPC), technological limitations (higher NTC), and security apprehensions (higher TSC). In particular, the lack of reliable internet connectivity, limited access to digital devices, and inadequate digital literacy skills among low-income individuals, as has been established in many earlier studies (see Vogels, 2021, and Connected Nation, 2023), make it difficult for low-income individuals to navigate and effectively use telemedicine platforms. Government healthcare initiatives can bridge this digital divide by subsidizing internet access and devices for low-income households. Collaborative efforts among healthcare providers, technology companies, and non-profit organizations that provide loaner or subsidized smartphones or tablets pre-loaded with user-friendly telemedicine applications may also help. For instance, after the onset of the pandemic, several government programs, such as the Emergency Broadband Benefit (EBB), the federal Lifeline program, the Affordable Connectivity Program (ACP), and school initiatives, have emerged to offer free or heavily subsidized devices, tablets, phones, and data plans to low-income individuals and families (see Get Government Grants and Help, 2024, and Rajan, 2024). Some local housing authorities, nonprofits, and libraries have

also started technology assistance programs distributing free refurbished devices. Additionally, as with older individuals, providing free digital literacy training programs can help impart essential skills to navigate telemedicine platforms, understand privacy and security features, and effectively communicate with healthcare providers virtually.

The implications of the employment-related ATEs in Table 9 are discussed in the next section. In terms of residential location, our findings demonstrate the significant impact of transportation accessibility and infrastructure on the adoption of telemedicine. Previous studies have established that an individual's place of residence plays a crucial role in determining their access to healthcare, affecting the frequency and quality of medical care received (Estrada et al., 2022). Given this context, our findings indicate that telemedicine serves as a critical tool in addressing healthcare accessibility disparities based on location. Prior to the COVID-19 pandemic, when telemedicine was not widely utilized, the attributes of residential locations did not significantly influence telemedicine adoption decisions, as illustrated in Table 4. This may have led to lower overall healthcare utilization in areas with limited access. However, the post-pandemic landscape reveals a different narrative, suggesting a lasting shift in healthcare access patterns. Specifically, following the COVID-19 outbreak, we observe significantly higher telemedicine adoption rates in areas with limited access to in-person medical services, as indicated by a lower number of physicians' offices in the zip code, and in areas with low population density, with adoption rates increasing by 15.1% and 11.3% respectively. These findings highlight the potential of telemedicine in bridging healthcare accessibility gaps, particularly in “medical service deserts” (MSDs), which are typically characterized by limited transportation infrastructure or inadequate public transit options. Our results from the reasons for using telemedicine further support this interpretation, indicating that individuals in areas with limited access are 7.3% more likely to cite using telemedicine to overcome difficulties in in-person accessibility (DIPA). This emphasizes the role of telemedicine in mitigating transportation-related healthcare barriers, especially in rural areas where long travel distances and lack of reliable transportation can significantly impede healthcare access (Douthit et al., 2015). Moreover, our findings suggest that for people in MSDs, telemedicine is not merely a temporary solution but a preferred mode of healthcare delivery. The results indicate that individuals in these areas also show a stronger preference for telemedicine privacy (TP) and have lower concerns about in-person convenience (IPC). These preferences indicate a potential long-term shift in healthcare delivery models, particularly in underserved areas. However, it is important to note that the effectiveness of telemedicine in areas with limited accessibility is dependent on robust digital infrastructure. As telemedicine increasingly serves as a vital lifeline for patients in MSDs, the need for reliable high-speed internet becomes paramount. Additionally, as Chen et al. (2021) emphasized, although telemedicine has made remarkable strides in bridging healthcare accessibility gaps, it cannot meet all healthcare needs. Thus, transportation and healthcare providers must continue exploring strategies to guarantee that lack of transportation does not hinder timely medical care for individuals facing transportation challenges.

### **6.3. Telemedicine Integration in the Workplace**

The ATE analysis highlights the contrasting telemedicine-related behaviors and perceptions between individuals employed in traditional in-person work settings and those engaged in teleworking arrangements. Furthermore, the results differentiate between existing telework arrangements and the personality trait of enjoying working from home. The ATE analysis demonstrates a substantial positive adoption effect (ATE of 18.1%) among frequent teleworkers

(at least multiple times per week) relative to individuals who do not or only occasional telework, implying that those working more in-person are less likely to use telemedicine. The results also reveal that in-person workers tend to cite privacy concerns (POP) and lack of telemedicine convenience relative to in-person convenience (IPC) as being the main telemedicine adoption deterrents. Such concerns are much less of an issue for frequent teleworkers who appear to leverage the comfort of their home environments for virtual healthcare consultations. Additionally, those with a high desire to work from home (regardless of actual teleworking frequency) are less likely to cite the privacy preference for physicians' offices and telemedicine security as deterrents.

Based on these findings, it appears that a lack of privacy at in-person work sites (and perhaps even simply the act of being seen taking some time off for telemedicine visits in the presence of others) are deterrents for in-person workers. It would be beneficial for office environments to provide designated quiet rooms or soundproof booths, ensuring employees have the privacy needed for virtual healthcare consultations. Alternatively, similar to the concept of "third workplaces" (that is, having a remote site that is not home and not the regular workplace), communities can consider setting up sites away from workplaces but close to employment centers for the exclusive purpose of telemedicine use. Also, implementing policies that allow for short breaks or flexible scheduling for telemedicine appointments can empower employees to manage their healthcare needs without disrupting work schedules. Such measures could create a win-win situation, saving time and potential lost productivity for both employers and employees. Furthermore, while the results indicate that teleworking setups facilitate increased telemedicine uptake, neglecting the compounding effect of enjoying working from home could limit the potential reach and impact of virtual healthcare services. To maximize the benefits of telemedicine, in-depth consumer studies need to be undertaken to explore the underlying factors and preferences that lead individuals to enjoy working from home, which can assist in the design of targeted strategies and customized telemedicine provisions to appeal to a broader range of individuals, regardless of their work arrangements. For instance, some individuals may enjoy working from home due to the flexibility it provides, while others may value the reduced commute time or the ability to create a personalized work environment. By catering to these specific preferences and addressing the unique needs of different consumer segments, telemedicine services can become more appealing and accessible to a wider population.

#### **6.4. Transportation and Urban Planning Considerations**

The most direct connection between telemedicine and transportation is the reduced need for physical travel to access medical services, as well as the need for medical professionals to commute to their in-person workplace. Quantifying the potential decrease in vehicular trips is important for informing planning decisions, as even modest reductions can improve traffic conditions, especially in congested urban areas. This is particularly relevant because of the spatial and temporal characteristics of such trips. First, medical appointment trips and commutes by medical professionals concentrate around locations such as hospitals, clinics, and medical centers, which are often located in urban areas or along major transportation corridors and can contribute to localized congestion. Second, medical appointment trips may also be combined with other trip purposes, such as commute trips, as also suggested by the lower telemedicine adoption rates among individuals working in in-person workplaces. This trip-chaining behavior, coupled with commutes by medical professionals themselves, can lead to higher volumes of medical-related trips during the morning and afternoon rush hours, exacerbating peak-period traffic congestion. Moreover, telemedicine can prove particularly advantageous in reducing vehicle miles of travel

for individuals residing in rural or underserved areas, where accessing in-person healthcare may necessitate long-distance trips.

The reduced reliance on vehicle usage for medical trips not only decreases trip-making and vehicle miles of travel, but also presents opportunities to redirect investments from expanding parking facilities and road networks around healthcare centers to other transportation infrastructure improvements (such as investing more in public transit and pedestrian facilities) and initiatives that support the expansion of broadband infrastructure. This shift in investment priorities can contribute to creating more sustainable, accessible, and equitable transportation systems that cater to the changing needs of healthcare access. Additionally, the decreased demand for driving due to increased telemedicine adoption can enhance the effectiveness of innovative transportation solutions, such as on-demand shuttles or ride-sharing programs that connect people to their healthcare providers. As the need for in-person visits diminishes, these alternative transportation modes can serve as efficient and cost-effective options for individuals who still require physical access to healthcare facilities.

An increase in telemedicine use also has significant implications for land use and urban planning. As virtual healthcare services gain traction, the demand for traditional physical healthcare facilities may gradually decline. This presents opportunities for repurposing or redeveloping existing healthcare infrastructure in innovative ways. One such approach involves replacing large, underutilized facilities with a network of mobile clinics strategically located to complement and support telemedicine services. These mobile clinics could provide essential on-site services, such as diagnostic testing, sample collection, or specialized treatments, while leveraging telemedicine for consultations and follow-up care. The strategic redevelopment of healthcare sites, particularly those located in and around employment centers, can have a profound impact on alleviating localized congestion and parking demand. By reducing the need for medical-related travel to these areas, urban planners can create more livable and sustainable communities. However, to fully capitalize on these opportunities, urban planners must proactively monitor telemedicine adoption clusters and identify underutilized facilities. This approach can inform strategic re-zoning and land use policies that align with the evolving healthcare landscape. Moreover, the increased demand for robust telecommunications infrastructure to support telemedicine services prompts the integration of digital connectivity considerations into urban design guidelines and zoning codes.

Finally, widespread telemedicine adoption may lead to shifts in travel behavior patterns that need to be monitored and forecasted over time. From a modeling standpoint, telemedicine adoption has an immediate bearing on activity generation, and the spatial-temporal patterns and scheduling of medical trips. The telemedicine adoption results from the current paper may be embedded within a larger agent-based activity-travel system to examine the impact of changing in-person medical activity participations on overall individual activity-travel patterns (and, thereby, on healthcare-related trip patterns at any geographic scale and by any specific demographic group). Such efforts can be enhanced through targeted surveys of patients and healthcare providers to gather granular information regarding appointment locations, frequency and reasons for telemedicine consultations, travel distances from patients' residences (for non-telemedicine appointments), and the modes of transportation utilized (for non-telemedicine appointments). Such surveys should also encompass a range of factors, including sociodemographic characteristics and employment arrangements, which were identified as significant in our analysis. More generally, future activity-travel surveys need to be more intentional in collecting information on different types of tele-activities and not simply on trip-

making. By proactively integrating tele-activity trends into travel demand models, transportation agencies can future-proof their forecasting capabilities and ensure that infrastructure investments are aligned with an evolving digital landscape.

## 7. CONCLUSIONS AND LIMITATIONS

The pandemic has acted as a catalyst for a significant shift in healthcare delivery methods toward telemedicine. This shift has not only transformed patient-provider interactions, but also brought to the forefront various socioeconomic and built-environmental factors that influence the adoption of telemedicine. In this study, we have introduced a new methodological framework that takes the form of a joint multiperiod and cross-sectional MBP system to investigate telemedicine adoption trends as well as the facilitators and deterrents of telemedicine adoption. The primary data used in this study is obtained from the COVID Future Survey undertaken in the timeframe of April 2020–November 2021, which was supplemented by population density data from the 2021 American Community Survey and the number of healthcare-related establishment data from the U.S. Census Bureau 2021 County Business Patterns (CBP) dataset.

The findings from the telemedicine adoption component of the study underscore the impact of a multitude of demographic and place-based characteristics. The study identifies a generational digital divide, with older adults exhibiting lower telemedicine adoption rates, potentially due to technological barriers and a preference for traditional healthcare interactions. Additionally, the results reveal the role of the presence of children, income, transportation access, employment status, and residential location characteristics. The sustained use of telemedicine by individuals who do not have access to a vehicle or who live in areas with lower geographic accessibility to healthcare providers highlights a promising potential to reduce disparities in healthcare access related to geographical barriers. Also, the shift to teleworking appears to strongly affect telemedicine adoption with frequent teleworkers more likely to embrace telemedicine use.

The results from the telemedicine facilitator/deterrent analysis component of the study delineate the critical role of accessibility, lifestyle preferences, privacy and security issues, technological confidence, and practical constraints in driving telemedicine adoption for addressing access challenges. The ATE analysis in the study provides important insights related to policy implications for multiple sectors, including public health, telecommunication, as well as transportation, and urban planning. Interestingly, the results highlight how telemedicine adoption is intrinsically influenced by transportation systems and urban contexts, while also playing a transformative role by changing the dynamics of urban mobility.

The research in this study may be advanced in many ways. First, our study scope was limited to adoption and did not extend to detailed aspects such as the frequency of telemedicine consultations, the nature of these visits (whether routine check-ups, illness-related, or specialty care), or the specific healthcare needs being met. Future research on these more detailed aspects can lead to a better understanding of the nuanced ways in which telemedicine can serve diverse healthcare requirements. Similarly, from an activity-travel standpoint, additional research is needed to investigate the interactions between in-person visits and telemedicine adoption at the level of each generated medical episode, along with the spatial/temporal/scheduling dimensions of such episodes. This can lead to a fuller picture of the effects on travel patterns. Second, for families with children, the analysis does not differentiate between telemedicine consultations conducted for the respondents themselves and those for their children. This distinction is important for accurately capturing telemedicine adoption rates and understanding its role in family healthcare management as well as family travel patterns. Third, the dataset used in this study limited our analysis to

individual telemedicine adoption behaviors rather than to household behaviors. Consequently, the results do not capture telemedicine-related use interactions among multiple household members, which can offer a more comprehensive view of its impact on household healthcare access and activity-travel decision-making.

In conclusion, telemedicine has substantial potential to transform the health and urban landscapes of our cities and rural areas, and help build resilient, inclusive, and sustainable healthcare and transportation systems. The current research contributes to the field in this direction.

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## REFERENCES

- Adams, R. B., Nelson, V. R., and Holtz, B. E. (2021). Barriers for Telemedicine Use Among Nonusers at the Beginning of the Pandemic. *Telemedicine Reports*, 2(1), 211–216. <https://doi.org/10.1089/tmr.2021.0022>
- Adepoju, O. E., Chae, M., Ojinnaka, C. O., Shetty, S., and Angelocci, T. (2022). Utilization Gaps During the COVID-19 Pandemic: Racial and Ethnic Disparities in Telemedicine Uptake in Federally Qualified Health Center Clinics. *Journal of General Internal Medicine*, 37(5), 1191–1197. <https://doi.org/10.1007/s11606-021-07304-4>
- Alsharawy, A., Spoon, R., Smith, A., and Ball, S. (2021). Gender Differences in Fear and Risk Perception During the COVID-19 Pandemic. *Frontiers in Psychology*, 12. <https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2021.689467>
- Anderson, B., Carr, K., and Donahue, C. (2022). Telehealth Now a Permanent Fixture for U.S. Healthcare Delivery. Chartis. <https://www.chartis.com/insights/telehealth-now-permanent-fixture-us-healthcare-delivery>
- Ashman, J. J., Santo, L., and Okeyode, T. (2023). Characteristics of Office-based Physician Visits by Age, 2019 [National Health Statistics Report]. <https://www.cdc.gov/nchs/data/nhsr/nhsr184.pdf>
- Bajgain, B., Rabi, S., Ahmed, S., Kiryanova, V., Fairie, P., and Santana, M. J. (2023). Patient-reported experiences and outcomes of virtual care during COVID-19: A systematic review. *Journal of Patient-Reported Outcomes*, 7(1), Article 1. <https://doi.org/10.1186/s41687-023-00659-8>
- Bazargan, M., Cobb, S., and Assari, S. (2021). Discrimination and Medical Mistrust in a Racially and Ethnically Diverse Sample of California Adults. *Annals of Family Medicine*, 19(1), 4–15. <https://doi.org/10.1370/afm.2632>
- Bernardo, C., Paleti, R., Hoklas, M., and Bhat, C. (2015). An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A: Policy and Practice*, 76, 71–91.
- Bhat, C. R. (2014). The Composite Marginal Likelihood (CML) Inference Approach with Applications to Discrete and Mixed Dependent Variable Models. *Foundations and Trends® in Econometrics*, 7(1), 1–117. <https://doi.org/10.1561/08000000022>

- Bhat, C. R. (2018). New matrix-based methods for the analytic evaluation of the multivariate cumulative normal distribution function. *Transportation Research Part B: Methodological*, 109, 238–256.
- Burns, S. K., Krishnamurti, T., Doan, T. T., Hanmer, J., Hoberman, A., Kahn, J. M., Schweiberger, K., and Ray, K. N. (2024). Parent Perceptions of Telemedicine for Acute Pediatric Respiratory Tract Infections: Sequential Mixed Methods Study. *JMIR Pediatrics and Parenting*, 7(1), e49170. <https://doi.org/10.2196/49170>
- Campos-Castillo, C., and Anthony, D. (2021). Racial and ethnic differences in self-reported telehealth use during the COVID-19 pandemic: A secondary analysis of a US survey of internet users from late March. *Journal of the American Medical Informatics Association: JAMIA*, 28(1), 119–125. <https://doi.org/10.1093/jamia/ocaa221>
- Chandrasekaran, R. (2023). Telemedicine in the Post-Pandemic Period: Understanding Patterns of Use and the Influence of Socioeconomic Demographics, Health Status, and Social Determinants. *Telemedicine and E-Health*. <https://doi.org/10.1089/tmj.2023.0277>
- Chauhan, R. S., Bhagat-Conway, M. W., Capasso Da Silva, D., Salon, D., Shamshiripour, A., Rahimi, E., Khoeini, S., Mohammadian, A., Derrible, S., and Pendyala, R. (2021). A database of travel-related behaviors and attitudes before, during, and after COVID-19 in the United States. *Scientific Data*, 8(1), Article 1. <https://doi.org/10.1038/s41597-021-01020-8>
- Chen, K. L., Brozen, M., Rollman, J. E., Ward, T., Norris, K. C., Gregory, K. D., and Zimmerman, F. J. (2021). How is the COVID-19 pandemic shaping transportation access to health care? *Transportation Research Interdisciplinary Perspectives*, 10, 100338. <https://doi.org/10.1016/j.trip.2021.100338>
- Chen, K., Zhang, C., Gurley, A., Akkem, S., and Jackson, H. (2023). Patient Characteristics Associated with Telehealth Scheduling and Completion in Primary Care at a Large, Urban Public Healthcare System. *Journal of Urban Health*, 100(3), 468–477. <https://doi.org/10.1007/s11524-023-00744-9>
- Choi, N. G., DiNitto, D. M., Marti, C. N., and Choi, B. Y. (2022). Telehealth Use Among Older Adults During COVID-19: Associations With Sociodemographic and Health Characteristics, Technology Device Ownership, and Technology Learning. *Journal of Applied Gerontology*, 41(3), 600–609. <https://doi.org/10.1177/07334648211047347>
- Chu, C., Cram, P., Pang, A., Stamenova, V., Tadrous, M., and Bhatia, R. S. (2021). Rural Telemedicine Use Before and During the COVID-19 Pandemic: Repeated Cross-sectional Study. *Journal of Medical Internet Research*, 23(4), e26960. <https://doi.org/10.2196/26960>
- Chumbler, N. R., Chen, M., Harrison, A., and Surbhi, S. (2023). Racial and Socioeconomic Characteristics Associated with the use of Telehealth Services Among Adults With Ambulatory Sensitive Conditions. *Health Services Research and Managerial Epidemiology*, 10, 23333928231154334. <https://doi.org/10.1177/23333928231154334>
- Connected Nation. (2023). Mind the Gap: Closing the Digital Divide through affordability, access, and adoption. [connectednation.org/DigitalDivide2023](https://connectednation.org/DigitalDivide2023)
- de Palma, A., Vosough, S., and Liao, F. (2022). An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. *Transportation Research Part A: Policy and Practice*, 159, 372–397. <https://doi.org/10.1016/j.tra.2022.03.024>
- Der-Martirosian, C., Chu, K., Steers, W. N., Wyte-Lake, T., Balut, M. D., Dobalian, A., Heyworth, L., Paige, N. M., and Leung, L. (2022). Examining telehealth use among primary care patients, providers, and clinics during the COVID-19 pandemic. *BMC Primary Care*, 23(1), 155. <https://doi.org/10.1186/s12875-022-01738-3>

- Dias, F. F., Lavieri, P. S., Sharda, S., Khoeini, S., Bhat, C. R., Pendyala, R. M., Pinjari, A. R., Ramadurai, G., and Srinivasan, K. K. (2020). A comparison of online and in-person activity engagement: The case of shopping and eating meals. *Transportation Research Part C: Emerging Technologies*, 114, 643–656.
- Douthit, N., Kiv, S., Dwolatzky, T., and Biswas, S. (2015). Exposing some important barriers to health care access in the rural USA. *Public Health*, 129(6), 611–620. <https://doi.org/10.1016/j.puhe.2015.04.001>
- Drake, C., Lian, T., Cameron, B., Medynskaya, K., Bosworth, H. B., and Shah, K. (2022). Understanding telemedicine’s “new normal”: Variations in telemedicine use by specialty line and patient demographics. *Telemedicine and E-Health*, 28(1), 51–59.
- Eberly, L. A., Kallan, M. J., Julien, H. M., Haynes, N., Khatana, S. A. M., Nathan, A. S., Snider, C., Chokshi, N. P., Eneanya, N. D., Takvorian, S. U., Anastos-Wallen, R., Chaiyachati, K., Ambrose, M., O’Quinn, R., Seigerman, M., Goldberg, L. R., Leri, D., Choi, K., Gitelman, Y., et al. (2020). Patient Characteristics Associated With Telemedicine Access for Primary and Specialty Ambulatory Care During the COVID-19 Pandemic. *JAMA Network Open*, 3(12), e2031640. <https://doi.org/10.1001/jamanetworkopen.2020.31640>
- Estrada, L. V., Levasseur, J. L., Maxim, A., Benavidez, G. A., and Pollack Porter, K. M. (2022). Structural Racism, Place, and COVID-19: A Narrative Review Describing How We Prepare for an Endemic COVID-19 Future. *Health Equity*, 6(1), 356–366. <https://doi.org/10.1089/heq.2021.0190>
- Ezeamii, V. C., Okobi, O. E., Wambai-Sani, H., Perera, G. S., Zaynieva, S., Okonkwo, C. C., Ohaiba, M. M., William-Enemali, P. C., Obodo, O. R., and Obiefuna, N. G. (2024). Revolutionizing Healthcare: How Telemedicine Is Improving Patient Outcomes and Expanding Access to Care. *Cureus*, 16(7), e63881. <https://doi.org/10.7759/cureus.63881>
- Festini, S. B., Hertzog, C., McDonough, I. M., and Park, D. C. (2019). What makes us busy? Predictors of perceived busyness across the adult lifespan. *The Journal of General Psychology*, 146(2), 111–133. <https://doi.org/10.1080/00221309.2018.1540396>
- Figliozi, M., and Unnikrishnan, A. (2021). Exploring the impact of socio-demographic characteristics, health concerns, and product type on home delivery rates and expenditures during a strict COVID-19 lockdown period: A case study from Portland, OR. *Transportation Research Part A: Policy and Practice*, 153, 1–19.
- Fischer, S. H., Predmore, Z., Roth, E., Uscher-Pines, L., Baird, M., and Breslau, J. (2022). Use Of And Willingness To Use Video Telehealth Through The COVID-19 Pandemic. *Health Affairs (Project Hope)*, 41(11), 1645–1651. <https://doi.org/10.1377/hlthaff.2022.00118>
- Fischer, S. H., Ray, K. N., Mehrotra, A., Bloom, E. L., and Uscher-Pines, L. (2020). Prevalence and Characteristics of Telehealth Utilization in the United States. *JAMA Network Open*, 3(10), e2022302. <https://doi.org/10.1001/jamanetworkopen.2020.22302>
- Freed, G. (2021). Virtual Visits for Kids. *Mott Poll Report*, 38(4). <https://mottpoll.org/reports/virtual-visits-kids>
- Ftouni, R., AlJardali, B., Hamdanieh, M., Ftouni, L., and Salem, N. (2022). Challenges of Telemedicine during the COVID-19 pandemic: A systematic review. *BMC Medical Informatics and Decision Making*, 22(1), 207. <https://doi.org/10.1186/s12911-022-01952-0>
- Gallagher Student Health and Special Risk. (2019). Understanding the issue: Telemedicine Access, Utilization Trends and Challenges in Student Health Insurance. <https://www.gallagherstudent.com/news/article/student-health-telemedicine-access>



- Get Government Grants and Help. (2024). Free Government Tablet 2024—Online Application For Low Income. <https://www.linkedin.com/pulse/free-government-tablet-2024-online-application-yvy4c/>
- Gusdorf, R. E., Shah, K. P., Triana, A. J., McCoy, A. B., Pabla, B., Scoville, E., Dalal, R., Beaulieu, D. B., Schwartz, D. A., Horst, S. N., and Griffith, M. L. (2023). A patient education intervention improved rates of successful video visits during rapid implementation of telehealth. *Journal of Telemedicine and Telecare*, 29(8), 607–612. <https://doi.org/10.1177/1357633X211008786>
- Haddad, A. J., Mondal, A., and Bhat, C. R. (2023). Eat-in or eat-out? A joint model to analyze the new landscape of dinner meal preferences. *Transportation Research Part C: Emerging Technologies*, 147, 104016.
- Haleem, A., Javaid, M., Singh, R. P., and Suman, R. (2021). Telemedicine for healthcare: Capabilities, features, barriers, and applications. *Sensors International*, 2, 100117. <https://doi.org/10.1016/j.sintl.2021.100117>
- Hollowell, A., Swartz, J., Myers, E., Erkanli, A., Hu, C., Shin, A., and Bentley-Edwards, K. (2022). Telemedicine Services in Higher Education: A Review of College and University Websites. *Journal of American College Health: J of ACH*, 1–6. <https://doi.org/10.1080/07448481.2022.2047703>
- Hossain, M., Dean, E. B., and Kaliski, D. (2022). Using Administrative Data to Examine Telemedicine Usage Among Medicaid Beneficiaries During the Coronavirus Disease 2019 Pandemic. *Medical Care*, 60(7), 488–495. <https://doi.org/10.1097/MLR.0000000000001723>
- Huber, C. R., and Kuncel, N. R. (2016). Does College Teach Critical Thinking? A Meta-Analysis. *Review of Educational Research*, 86(2), 431–468. <https://doi.org/10.3102/0034654315605917>
- Iasiello, J. A., Rajan, A., Zervos, E., Parikh, A. A., and Snyder, R. A. (2023). Racial Differences in Patient-Reported Access to Telehealth: An Important and Unmeasured Social Determinant of Health | JCO Oncology Practice. *JCO Oncol Pract*, 19(12). <https://doi.org/10.1200/OP.23.00006>
- Infutor. (2021). U.S. car owners as of 2021, by gender [Dataset]. <https://www.statista.com/statistics/1041215/us-car-owners-by-sex/>
- Jaffe, D. H., Lee, L., Huynh, S., and Haskell, T. P. (2020). Health Inequalities in the Use of Telehealth in the United States in the Lens of COVID-19. *Population Health Management*, 23(5), 368–377. <https://doi.org/10.1089/pop.2020.0186>
- Jang, M., and Vorderstrasse, A. (2019). Socioeconomic Status and Racial or Ethnic Differences in Participation: Web-Based Survey. *JMIR Research Protocols*, 8(4), e11865. <https://doi.org/10.2196/11865>
- Kim, W., and Wang, X. C. (2021). To be online or in-store: Analysis of retail, grocery, and food shopping in New York city. *Transportation Research Part C: Emerging Technologies*, 126, 103052.
- Ko, J. S., El-Toukhy, S., Quintero, S. M., Wilkerson, M. J., Nápoles, A. M., Stewart, A. L., and Strassle, P. D. (2023). Disparities in telehealth access, not willingness to use services, likely explain rural telehealth disparities. *The Journal of Rural Health*, 39(3), 617–624. <https://doi.org/10.1111/jrh.12759>
- Luo, J., Tong, L., Crotty, B. H., Somai, M., Taylor, B., Osinski, K., and George, B. (2021). Telemedicine Adoption during the COVID-19 Pandemic: Gaps and Inequalities. *Applied Clinical Informatics*, 12(4), 836–844. <https://doi.org/10.1055/s-0041-1733848>

- MacSwain, K. L. H., Sherry, S. B., Stewart, S. H., Watt, M. C., Hadjistavropoulos, H. D., and Graham, A. R. (2009). Gender differences in health anxiety: An investigation of the interpersonal model of health anxiety. *Personality and Individual Differences*, 47(8), 938–943. <https://doi.org/10.1016/j.paid.2009.07.020>
- Murphy, H. (2020, April 17). We All Live in Bubbles Now. How Safe Is Yours? *The New York Times*. <https://www.nytimes.com/2020/04/17/health/cheating-on-an-isolation-bubble-coronavirus.html>
- Nittari, G., Savva, D., Tomassoni, D., Tayebati, S. K., and Amenta, F. (2022). Telemedicine in the COVID-19 Era: A Narrative Review Based on Current Evidence. *International Journal of Environmental Research and Public Health*, 19(9), Article 9. <https://doi.org/10.3390/ijerph19095101>
- Nouri, S., Khoong, E. C., Lyles, C. R., and Karliner, L. (2020). Addressing equity in telemedicine for chronic disease management during the Covid-19 pandemic. *NEJM Catalyst Innovations in Care Delivery*, 1(3).
- Osobase, R. (2023). Evaluating U.S. Household Telemedicine Use in Primary Care Settings [Walden University]. <https://scholarworks.waldenu.edu/cgi/viewcontent.cgi?article=13072andcontext=dissertations>
- Park, J.-H., Lee, M. J., Tsai, M.-H., Shih, H.-J., and Chang, J. (2023). Rural, Regional, Racial Disparities in Telemedicine Use During the COVID-19 Pandemic Among US Adults: 2021 National Health Interview Survey (NHIS). *Patient Preference and Adherence*, 17, 3477–3487. <https://doi.org/10.2147/PPA.S439437>
- Patel, S. Y., Mehrotra, A., Huskamp, H. A., Uscher-Pines, L., Ganguli, I., and Barnett, M. L. (2021). Variation In Telemedicine Use And Outpatient Care During The COVID-19 Pandemic In The United States. *Health Affairs (Project Hope)*, 40(2), 349–358. <https://doi.org/10.1377/hlthaff.2020.01786>
- Pierce, R. P., and Stevermer, J. J. (2023). Disparities in the use of telehealth at the onset of the COVID-19 public health emergency. *Journal of Telemedicine and Telecare*, 29(1), 3–9. <https://doi.org/10.1177/1357633X20963893>
- Pogorzelska, K., and Chlabicz, S. (2022). Patient Satisfaction with Telemedicine during the COVID-19 Pandemic—A Systematic Review. *International Journal of Environmental Research and Public Health*, 19(10), Article 10. <https://doi.org/10.3390/ijerph19106113>
- Powell, W., Richmond, J., Mohottige, D., Yen, I., Joslyn, A., and Corbie-Smith, G. (2019). Medical Mistrust, Racism, and Delays in Preventive Health Screening Among African-American Men. *Behavioral Medicine*, 45(2), 102–117. <https://doi.org/10.1080/08964289.2019.1585327>
- Rajan, X. (2024). Free Tablets From Government: Eligibility, Programs, and Alternatives. <https://www.linkedin.com/pulse/free-tablets-from-government-eligibility-programs-alternatives-x-foomc/>
- Rodriguez, J. A., Betancourt, J. R., Sequist, T. D., and Ganguli, I. (2021). Differences in the use of telephone and video telemedicine visits during the COVID-19 pandemic. *The American Journal of Managed Care*, 27(1), 21–26. <https://doi.org/10.37765/ajmc.2021.88573>
- Rowe Ferrara, M., and Chapman, S. A. (2024). Rural Patients' Experiences with Synchronous Video Telehealth in the United States: A Scoping Review. *Telemedicine Journal and E-Health: The Official Journal of the American Telemedicine Association*. <https://doi.org/10.1089/tmj.2023.0410>

- Salon, D., Bhagat-Conway, M. W., Chauhan, R., Magassy, T., Mirtich, L., Rahimi, E., Costello, A., Derrible, S., Mohammadian, K., and Pendyala, R. (2022). COVID Future Wave 3 Survey Data v1.1.0 (Version V1) [Dataset]. ASU Library Research Data Repository. <https://doi.org/10.48349/ASU/9O5TIA>
- Scheiner, J., and Holz-Rau, C. (2012). Gender structures in car availability in car deficient households. *Research in Transportation Economics*, 34(1), 16–26. <https://doi.org/10.1016/j.retrec.2011.12.006>
- Schifeling, C. H., Shanbhag, P., Johnson, A., Atwater, R. C., Koljack, C., Parnes, B. L., Vejar, M. M., Farro, S. A., Phimphasone-Brady, P., and Lum, H. D. (2020). Disparities in Video and Telephone Visits Among Older Adults During the COVID-19 Pandemic: Cross-Sectional Analysis. *JMIR Aging*, 3(2), e23176. <https://doi.org/10.2196/23176>
- Sharma, P., Kamath, C., Brockman, T. A., Roche, A., Sinicrope, P., Jiang, R., Decker, P. A., Pazdernik, V., and Patten, C. (2024). Demographics and Social Factors Associated With Persistent Nonuse of Video Appointments at a Multisite Health Care Institution: Cross-Sectional Study. *JMIR Formative Research*, 8, e50572. <https://doi.org/10.2196/50572>
- Shaver, J. (2022). The State of Telehealth Before and After the COVID-19 Pandemic. *Primary Care: Clinics in Office Practice*, 49(4), 517–530. <https://doi.org/10.1016/j.pop.2022.04.002>
- Smith, W. G. (2008). Does gender influence online survey participation? A record-linkage analysis of university faculty online survey response behavior. Online Submission.
- Solon, G., Haider, S. J., and Wooldridge, J. M. (2015). What are we weighting for? *Journal of Human Resources*, 50(2), 301–316.
- The White House. (2024). FACT SHEET: President Biden Issues Executive Order and Announces New Actions to Advance Women’s Health Research and Innovation. The White House. <https://www.whitehouse.gov/briefing-room/statements-releases/2024/03/18/fact-sheet-president-biden-issues-executive-order-and-announces-new-actions-to-advance-womens-health-research-and-innovation/>
- Tully, L., Case, L., Arthurs, N., Sorensen, J., Marcin, J. P., and O’Malley, G. (2021). Barriers and Facilitators for Implementing Paediatric Telemedicine: Rapid Review of User Perspectives. *Frontiers in Pediatrics*, 9. <https://www.frontiersin.org/articles/10.3389/fped.2021.630365>
- U.S. Census Bureau. (2021). County Business Patterns [Dataset]. <https://www.census.gov/programs-surveys/cbp.html>
- Vaidya, V., Patil, V., Oswal, J., Narula, A., Khare, Y., Patil, P., Deshpande, R., Lunge, S., Dasgupta, S., Dahiphale, R., Kulkarni, R., Mahajan, A., Chelluri, S., and Teli, A. (2024). Healthcare in the Modern Era: Launching a Telemedicine-Based OPD Consultation in Rural Pune (Process, Results, and Challenges). *Cureus*, 16(5), e60310. <https://doi.org/10.7759/cureus.60310>
- Velasquez, D., and Mehrotra, A. (2020). Ensuring the growth of telehealth during COVID-19 does not exacerbate disparities in care. *Health Affairs Forefront*.
- Vogels, E. (2021). Digital divide persists even as Americans with lower incomes make gains in tech adoption. <https://www.pewresearch.org/short-reads/2021/06/22/digital-divide-persists-even-as-americans-with-lower-incomes-make-gains-in-tech-adoption/>
- Weber, E., Miller, S. J., Astha, V., Janevic, T., and Benn, E. (2020). Characteristics of telehealth users in NYC for COVID-related care during the coronavirus pandemic. *Journal of the American Medical Informatics Association: JAMIA*, 27(12), 1949–1954. <https://doi.org/10.1093/jamia/ocaa216>

- Whaley, C. M., Pera, M. F., Cantor, J., Chang, J., Velasco, J., Hagg, H. K., Sood, N., and Bravata, D. M. (2020). Changes in Health Services Use Among Commercially Insured US Populations During the COVID-19 Pandemic. *JAMA Network Open*, 3(11), e2024984. <https://doi.org/10.1001/jamanetworkopen.2020.24984>
- White-Williams, C., Liu, X., Shang, D., and Santiago, J. (2023). Use of Telehealth Among Racial and Ethnic Minority Groups in the United States Before and During the COVID-19 Pandemic. *Public Health Reports*, 138(1), 149–156. <https://doi.org/10.1177/00333549221123575>
- Wooldridge, J. M. (1995). Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics*, 68(1), 115–132.
- Wu, M.-J., Zhao, K., and Fils-Aime, F. (2022). Response rates of online surveys in published research: A meta-analysis. *Computers in Human Behavior Reports*, 7, 100206. <https://doi.org/10.1016/j.chbr.2022.100206>
- Xu, P., Hudnall, M., Zhao, S., Raja, U., Parton, J., and Lewis, D. (2022). Pandemic-Triggered Adoption of Telehealth in Underserved Communities: Descriptive Study of Pre- and Postshutdown Trends. *Journal of Medical Internet Research*, 24(7), e38602. <https://doi.org/10.2196/38602>
- Zhang, D., Shi, L., Han, X., Li, Y., Jalajel, N. A., Patel, S., Chen, Z., Chen, L., Wen, M., Li, H., Chen, B., Li, J., and Su, D. (2021). Disparities in telehealth utilization during the COVID-19 pandemic: Findings from a nationally representative survey in the United States. *Journal of Telemedicine and Telecare*, 30(1), 90–97. <https://doi.org/10.1177/1357633X211051677>

**Table 1. Descriptive Statistics for Telemedicine Adoption (N=2,041)**

Before-COVID Adoption	During-COVID Adoption	After-COVID Adoption	
		Yes	No
<b>Yes</b> (234; 11.47%)	<b>Yes</b> (146; 62.39%)	115 78.77%	31 21.23%
	<b>No</b> (88; 37.61%)	34 38.64%	54 61.36%
<b>No</b> (1807; 88.53%)	<b>Yes</b> (724; 40.07%)	427 58.98%	297 41.02%
	<b>No</b> (1083; 59.93%)	154 14.22%	929 85.78%
<b>Total</b> (2041; 100%)		730 35.77%	1311 64.23%

**Table 2. Descriptive Statistics for the Reasons Associated with Adopting or Not Adopting Telemedicine (N=2335)**

Reasons	Short Labels	Frequency	Rel. Frequency
<b>Reasons for adopting telemedicine/ Telemedicine adoption facilitators (N=802)</b>			
Getting to medical appointments is difficult for me	Difficulty in-person accessibility (DIPA)	122	15.21%
Telemedicine is more convenient for me	Telemedicine convenience (TC)	591	73.69%
I like the privacy offered by telemedicine	Telemedicine privacy (TP)	138	17.21%
I do not have to wait as long	Time-savings (TS)	375	46.76%
My home is more comfortable than a healthcare provider's office	Comfort of home (CH)	337	42.02%
I do not have to risk getting sick from others in a healthcare provider's office	Lower contagion risk (LCR)	365	45.51%
Telemedicine is cheaper	Less expensive (LE)	122	15.21%
I can go see healthcare providers more often	Frequent consultation opportunities (FCO)	110	13.72%
I have a wider choice of healthcare providers	Wider provider choice (WPO)	60	7.48%
<b>Reasons for not adopting telemedicine/ Telemedicine adoption deterrents (N=1533)</b>			
The quality of care is worse	Poor telemedicine quality (PTQ)	220	14.35%
Most of my medical appointments require in-person tests or procedures	Need in-person tests (NIPT)	552	35.36%
I do not expect my healthcare provider to offer telemedicine	Telemedicine not available (TNA)	105	6.85%
I like the privacy of a healthcare provider's office	Provider's office privacy (POP)	363	23.68%
I have a wider choice of in-person healthcare providers	Wider provider choice (WPO)	58	3.78%
My insurance does not cover telemedicine	Insurance	22	1.44%
In-person appointments are more convenient	In-person convenience (IPC)	403	26.29%
I am not confident using technology to access my appointments	Not. Tech. Confident (NTC)	169	11.02%
I am concerned about security with telemedicine	Telemedicine security concern (TSC)	116	7.57%

**Table 3. Sample Distribution of Exogenous Variables**

Variable	% in sample	% in ACS	Variable	% in sample	% in ACS
<b>Individual/Household Sociodemographics</b>			<b>Employment Characteristics</b>		
<b>Gender</b>			<b>Employment Status</b>		
Men	36.5	48.9	Not employed	48.7	22.7
Women	63.5	51.1	Employed part-time	11.3	17.0
<b>Lifecycle variables</b>			Employed full-time	40.0	60.3
Single	21.8	28.1	<b>Telework arrangements</b>		
Single parent	3.9	8.4	Telework daily	14.9	--
Couple no children	45.5	29.2	Telework multiple times per week	34.7	--
Couple with children	17.0	18.3	No telework or telework less than once a week	50.4	--
Related adults	8.1	9.1	<b>Student</b>		
Roommates	3.7	6.9	Yes	6.1	8.7
<b>Race</b>			No	93.9	91.3
Asian	4.4	5.9	<b>Personal Traits and COVID-19 Perspectives</b>		
Black	6.2	12.2	Enjoy working more from home due to COVID	27.7	--
White	84.4	60.9	Enjoy driving less due to COVID	30.6	--
Other	5.0	21.0	People's well-being is/was at risk during the pandemic	66.5	--
<b>Age</b>			Not technologically savvy	11.6	--
≤ 30 years	7.9	18.0	<b>Residential Location Attributes</b>		
31 – 40 years	14.4	18.0	<b>Access to Healthcare Services</b>		
41 – 50 years	13.2	16.7	# of physicians' offices in zip code (count variable)	(mean) 34	(std. dv.) 21.282
51 – 60 years	18.7	17.4	# of physicians' offices in zip code > 3 (binary)	70.2	--
61 – 70 years	27.5	15.6	<b>Population Density</b>		
≥ 71 years	18.3	14.3	Population density person/m <sup>2</sup> (continuous)	(mean) 0.00194	(std. dv.) 0.00358
<b>Formal Education Level</b>			Population density ≥ 0.00194 person/m <sup>2</sup> [mean] (binary)	73.6	--
Less than bachelor's degree	38.7	64.4	<b>Census Region</b>		
Bachelor's degree	33.2	21.6	Northeast	12.1	17.2
Graduate degree	28.1	14.0	Midwest	23.1	20.7
<b>Household Income (gross)</b>			South	25.1	38.4
Less than \$25,000	12.2	17.2	West	39.7	23.7
\$25,000-\$49,999	18.2	19.6			
\$50,000-\$99,999	34.1	29.6			
\$100,000-\$149,999	20.2	16.3			
\$150,000-\$199,999	7.5	7.8			
\$200,000+	7.8	9.5			
<b>Number of motorized vehicles</b>					
0	6.4	8.1			
1	41.2	32.9			
2	39.4	37.1			
3+	13.0	21.9			

**Table 4. Telemedicine Adoption Model Estimation Results**

Explanatory Variables (base category)	Telemedicine Adoption			
	Before-COVID		After-COVID	
	Coeff.	t-stat	Coeff.	t-stat
<b>Individual/Household Sociodemographics</b>				
<b>Gender</b>				
Woman ( <i>base: man</i> )				
<b>Lifecycle variables</b>				
Presence of children ( <i>base: no children</i> )	0.178	1.78	0.178	1.78
Live with unrelated adults ( <i>base: not live with unrelated adults</i> )			0.381	2.55
<b>Age</b> ( <i>base: 30 years or younger</i> )				
31 to 40 years old	0.221	2.87		
41 to 50 years old	0.221	2.87		
51 to 60 years old			-0.366	-5.14
61 years or older			-0.366	-5.14
<b>Household income</b> ( <i>base: less than \$100,000</i> )				
\$100,000 or more			0.176	2.37
<b>Income change</b> ( <i>base: no change or decrease</i> )				
Income increased during COVID	--	--	0.177	2.49
<b>Number of motorized vehicles</b> ( <i>base: <math>\geq 3</math> vehicles</i> )				
0 vehicles	0.211	2.92	0.211	2.92
1 – 2 vehicles	0.211	2.92		
<b>Employment Characteristics</b>				
<b>Telework arrangements</b> ( <i>base: no telework or telework less than once a week</i> )				
Telework daily	0.185	3.82	0.185	3.82
Telework multiple times per week	0.185	3.82	0.185	3.82
<b>Student</b> ( <i>base: not student</i> )				
Student	0.219	1.52		
<b>Personal Traits and COVID-19 Perspectives</b>				
Enjoy working more from home due to COVID ( <i>base: do not enjoy</i> )	--	--	0.198	2.67
Enjoy driving less due to COVID ( <i>base: do not enjoy</i> )	--	--	0.253	4.08
People's well-being is/was at risk during the pandemic ( <i>base: not at risk</i> )	--	--	0.220	3.50
Not technologically savvy ( <i>base: technologically savvy</i> )	-0.114	-2.18	-0.114	-2.18
<b>Residential Location Attributes</b>				
<b>Access to healthcare services</b> ( <i>base: <math>\# \leq 3</math> offices</i> )				
# of physicians' offices in zip code > 3			-0.167	-2.01
<b>Population density</b> ( <i>base: &lt; average</i> )				
Population density ( $\geq 0.00194$ person/m <sup>2</sup> [average])			-0.129	-2.07
<b>Threshold 0 1</b>	1.734	16.07	0.889	6.51



**Table 5. Telemedicine Adoption Facilitator/Deterrent Reasons**

Explanatory Variables	Telemedicine Adoption Facilitator/Deterrent Reasons								Telemedicine Adoption Facilitator/Deterrent Reasons						
	DIPA	TC	TP	TS	CH	LCR	LE	FCO	PTQ	NIPT	TNA	POP	IPC	NTC	TSC
<b>Individual/Household Sociodemographics</b>															
<b>Gender</b>															
Woman ( <i>base: man</i> )	0.238	0.164				0.314	-0.298		-0.279						
<b>Lifecycle variables</b>															
Presence of children ( <i>base: no children</i> )	0.290		0.237					0.278	0.191				0.287		
<b>Race</b> ( <i>base: white</i> )															
Non-white			0.304		-0.177			0.250					0.283		
<b>Age</b> ( <i>base: 50 years or younger</i> )															
41 to 50 years old															
51 to 60 years old			0.446			0.356								0.209	
61 years or older			0.446	-0.254		0.356				0.182			0.202	0.209	
<b>Formal education level</b> ( <i>base: &lt; Bachelor's degree</i> )															
Bachelor's degree or higher		0.431							0.354				-0.274		
<b>Household income</b> ( <i>base: &lt; \$75,000</i> )															
\$75,000 to \$99,999			-0.463	0.254	-0.264										
\$100,000 to \$149,999	-0.267		-0.501	0.254	-0.264								-0.186	-0.271	-0.277
\$150,000 to \$199,999	-0.267		-0.420	0.254	-0.264				0.201				-0.186	-0.422	-0.277
\$200,000 or more	-0.267	0.516	-0.420	0.254	-0.264				0.201		0.323		-0.186	-0.651	-0.277
<b>Income change</b> ( <i>base: no change or increase</i> )															
Income decreased during COVID	0.304														
<b>Number of motorized vehicles</b> ( <i>base: ≥1 vehicle</i> )															
0 vehicles	0.785														
<b>Employment Characteristics</b>															
<b>Employment status</b> ( <i>base: not employed</i> )															
Employed full-time or part-time	-0.459		0.503		-0.363					-0.252					
<b>Telework arrangements</b> ( <i>base: no telework or telework less than once a week</i> )															
Telework daily					0.232	0.214						-0.195	-0.345		
Telework multiple times per week					0.232	0.214						-0.195	-0.345		
<b>Student</b> ( <i>base: not student</i> )															
Student								0.352							

Explanatory Variables	Telemedicine Adoption Facilitator/Deterrent Reasons								Telemedicine Adoption Facilitator/Deterrent Reasons						
	DIPA	TC	TP	TS	CH	LCR	LE	FCO	PTQ	NIPT	TNA	POP	IPC	NTC	TSC
<b>Commute mode</b> ( <i>base: not car</i> )															
Car		-0.249													
<b>Personal Traits</b>															
Enjoy working from home ( <i>base: do not enjoy</i> )	0.235											-0.203			-0.222
<b>Residential Location Attributes</b>															
<b>Access to healthcare services</b>															
# of physicians' offices in zip code ( <i>count variable</i> )	-0.005		-0.004											0.002	
<b>Census region</b> ( <i>base: Northeast</i> )															
Midwest		0.216	-0.303								-0.247				
South			-0.303						-0.269						
West			-0.484								-0.243				
<b>Threshold 0 1</b>	1.023	-0.606	0.342	-0.060	-0.149	0.323	0.705	1.004	1.026	-0.212	1.221	0.346	-0.164	0.839	0.966

DIPA - Getting to medical appointments is difficult for me; PTQ - The quality of care is worse; TC - Telemedicine is more convenient for me; NIPT - Most of my medical appointments require in-person tests or procedures; TP - I like the privacy offered by telemedicine; TNA - I do not expect my healthcare provider to offer telemedicine; TS - I do not have to wait as long; POP - I like the privacy of a healthcare provider's office; CH - My home is more comfortable than a healthcare provider's office; IPC - In-person appointments are more convenient; LCR - I do not have to risk getting sick from others in a healthcare provider's office; NTC - I am not confident using technology to access my appointments; LE - Telemedicine is cheaper; TSC - I am concerned about security with telemedicine; FCO - I can go see healthcare providers more often

**Table 6. Correlation Matrix**

Outcome Variables		Telemedicine Adoption			Telemedicine Adoption Facilitator Reasons								Telemedicine Adoption Deterrent Reasons						
		Before-COVID	During-COVID	After-COVID	DIPA	TC	TP	TS	CH	LCR	LE	FCO	PTQ	NIPT	TNA	POP	IPC	NTC	TSC
Telemedicine Adoption	Before-COVID	1.00	0.24 (4.85)	0.35 (7.52)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	During-COVID		1.00	0.64 (8.42)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	After-COVID			1.00	-0.36 (-2.79)	-0.33 (-2.53)	-0.28 (-2.08)	-0.04 (-1.13)	-0.07	-0.12	-0.08	-0.27 (-1.91)	0.00	-0.21 (-1.23)	0.13	0.11	0.22 (1.64)	0.20 (1.31)	
Telemedicine Adoption Facilitator Reasons	DIPA				1.00	0.18 (1.61)	0.10	0.15 (1.69)	0.23 (2.66)	0.12 (1.35)	0.24 (2.51)	0.19 (1.80)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	TC					1.00	0.00	0.03 (3.44)	0.27 (3.44)	-0.02	0.10	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	TP						1.00	0.23 (3.03)	0.38 (5.04)	0.34 (4.33)	0.10	0.22 (2.28)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	TS							1.00	0.38 (6.57)	0.27 (4.46)	0.13 (1.59)	0.14 (1.72)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	CH								1.00	0.42 (7.39)	0.23 (2.83)	0.17 (2.10)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LCR									1.00	0.09	0.18 (2.22)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LE										1.00	0.31 (3.56)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	FCO											1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Telemedicine Adoption Deterrent Reasons	PTQ												1.00	-0.23 (-3.72)	-0.18 (-1.86)	-0.01	-0.16 (-2.36)	0.09	0.11 (1.42)
	NIPT													1.00	-0.16 (-2.11)	-0.19 (-3.38)	-0.30 (-5.65)	-0.15 (-2.00)	-0.10 (-1.30)
	TNA														1.00	-0.32 (-4.09)	-0.19 (-2.25)	-0.03	-0.14 (-1.27)
	POP															1.00	0.21 (3.85)	0.18 (2.53)	0.32 (4.73)
	IPC																1.00	0.13 (1.75)	-0.02
	TNC																	1.00	0.55 (8.93)
	TSC																		1.00

DIPA - Getting to medical appointments is difficult for me; PTQ - The quality of care is worse; TC - Telemedicine is more convenient for me; NIPT - Most of my medical appointments require in-person tests or procedures; TP - I like the privacy offered by telemedicine; TNA - I do not expect my healthcare provider to offer telemedicine; TS - I do not have to wait as long; POP - I like the privacy of a healthcare provider's office; CH - My home is more comfortable than a healthcare provider's office; IPC - In-person appointments are more convenient; LCR - I do not have to risk getting sick from others in a healthcare provider's office; NTC - I am not confident using technology to access my appointments; LE - Telemedicine is cheaper; TSC - I am concerned about security with telemedicine; FCO - I can go see healthcare providers more often

**Table 7. Likelihood-Based Data Fit Measures**

Summary Statistics	Joint Model	Independent Model	Thresholds-only Model
Log-likelihood at convergence	-9147.91	-10206.968	-11090.87
Number of parameters	180	113	18
Bayesian Information Criterion (BIC)	9451.02	10397.25	11121.18
Average probability of correct prediction	0.111	0.097	0.087
$\bar{\rho}^2$	0.16	0.07	--
Nested likelihood ratio test: Joint model versus independent/Thresholds-only models	--	LR= 2118.12>>>> $\chi^2_{(67,0.001)} = 108.54$	LR= 3885.92>>>> $\chi^2_{(162,0.001)} = 223.36$

**Table 8. Aggregate Fit Measures**

			Observed		Joint Model Prediction			Independent Model Prediction		
			No. of Individuals	Share (%)	No. of Individuals	Share (%)	APE (%)	No. of Individuals	Share (%)	APE (%)
Telemedicine Adoption Facilitator Reasons	DIPA	Yes	122	5.2%	125	5.4%	2.5%	202	8.7%	65.9%
		No	680	29.1%	677	29.0%	0.4%	600	25.7%	11.8%
	TC	Yes	591	25.3%	608	26.1%	2.9%	672	28.8%	13.7%
		No	211	9.0%	194	8.3%	8.1%	130	5.6%	38.4%
	TP	Yes	138	5.9%	151	6.5%	9.4%	216	9.3%	56.5%
		No	664	28.5%	651	27.9%	2.0%	586	25.1%	11.7%
	TS	Yes	375	16.1%	397	17.0%	5.9%	408	17.5%	8.8%
		No	427	18.3%	405	17.4%	5.2%	394	16.9%	7.7%
	CH	Yes	337	14.4%	361	15.5%	7.1%	400	17.1%	18.7%
		No	465	19.9%	441	18.9%	5.2%	402	17.2%	13.5%
	LCR	Yes	365	15.6%	391	16.8%	7.1%	412	17.7%	12.9%
		No	437	18.7%	411	17.6%	5.9%	390	16.7%	10.8%
	LE	Yes	122	5.2%	127	5.4%	4.1%	151	6.5%	23.8%
		No	680	29.1%	675	28.9%	0.7%	651	27.9%	4.3%
	FCO	Yes	110	4.7%	114	4.9%	3.6%	128	5.5%	16.4%
		No	692	29.7%	688	29.5%	0.6%	674	28.9%	2.6%
Telemedicine Adoption Deterrent Reasons	PTQ	Yes	220	9.4%	216	9.3%	1.8%	180	7.7%	18.2%
		No	1313	56.3%	1317	56.5%	0.3%	1353	58.0%	3.0%
	NIPT	Yes	552	23.7%	486	20.8%	12.0%	488	20.9%	11.6%
		No	981	42.0%	1047	44.9%	6.7%	1045	44.8%	6.5%
	TNA	Yes	105	4.5%	119	5.1%	13.3%	101	4.3%	3.8%
		No	1428	61.2%	1414	60.6%	1.0%	1432	61.4%	0.3%
	POP	Yes	363	15.6%	339	14.5%	6.6%	365	15.6%	0.6%
		No	1170	50.2%	1194	51.2%	2.1%	1168	50.1%	0.2%
	IPC	Yes	403	17.3%	414	17.7%	2.7%	440	18.9%	9.2%
		No	1130	48.4%	1119	48.0%	1.0%	1093	46.8%	3.3%
	NTC	Yes	169	7.2%	149	6.4%	11.8%	182	7.8%	7.7%
		No	1364	58.5%	1384	59.3%	1.5%	1351	57.9%	1.0%
	TSC	Yes	116	5.0%	131	5.6%	12.9%	157	6.7%	35.3%
		No	1417	60.7%	1402	60.1%	1.1%	1376	59.0%	2.9%
WAPE					23.0%			54.0%		

DIPA - Getting to medical appointments is difficult for me; PTQ - The quality of care is worse; TC - Telemedicine is more convenient for me; NIPT - Most of my medical appointments require in-person tests or procedures; TP - I like the privacy offered by telemedicine; TNA - I do not expect my healthcare provider to offer telemedicine; TS - I do not have to wait as long; POP - I like the privacy of a healthcare provider's office; CH - My home is more comfortable than a healthcare provider's office; IPC - In-person appointments are more convenient; LCR - I do not have to risk getting sick from others in a healthcare provider's office; NTC - I am not confident using technology to access my appointments; LE - Telemedicine is cheaper; TSC - I am concerned about security with telemedicine; FCO - I can go see healthcare providers more often

**Table 9. ATE Results**

Variable	Base Level	Treatment Level	% Change in Adoption	% Change in Telemedicine Adoption Facilitator Reasons								% Change in Telemedicine Adoption Deterrent Reasons							
			After-COVID	DIPA	TC	TP	TS	CH	LCR	LE	FCO	PTQ	NIPT	TNA	POP	IPC	NTC	TSC	
Individual/Household Sociodemographics																			
Gender	Man	Woman		15.1	9.0				20.0	-23.4		-17.3							
Presence of children	No	Yes	18.0	16.6		23.1					24.5	13.6				31.1			
Age	50 years or younger	Over 50 years	-29.7			52.4	-19.5		23.0				16.1			23.0	17.6		
Household income	≥\$100,000	<\$50,000	-17.2	16.0	-29.8	39.0	-21.9	19.8				-14.1		-29.0		17.9	35.6	22.6	
Number of motorized Vehicles	Zero vehicles	More than 2 vehicles	-20.1	-28.4															
Employment Characteristics																			
Employment status and telework frequency	Unemployed	Employed working in-person		-23.3		59.5		-28.6					-19.9						
	Employed working in-person	Employed teleworking at least multiple times per week	18.1					25.3	11.9						-14.9	-32.8			
Personal Traits																			
Enjoy working more from home due to COVID	No	Yes	18.9	14.2											-15.5			-18.5	
Residential Location Attributes																			
# of physicians' offices in zip code	> 34 physicians (average value in the dataset)	Zero physicians	15.1	7.3		11.4										-8.4			
Population density	Above Average (0.00194 person/m²)	Below average	11.3																

DIPA - Getting to medical appointments is difficult for me; PTQ - The quality of care is worse; TC - Telemedicine is more convenient for me; NIPT - Most of my medical appointments require in-person tests or procedures; TP - I like the privacy offered by telemedicine; TNA - I do not expect my healthcare provider to offer telemedicine; TS - I do not have to wait as long; POP - I like the privacy of a healthcare provider's office; CH - My home is more comfortable than a healthcare provider's office; IPC - In-person appointments are more convenient; LCR - I do not have to risk getting sick from others in a healthcare provider's office; NTC - I am not confident using technology to access my appointments; LE - Telemedicine is cheaper; TSC - I am concerned about security with telemedicine; FCO - I can go see healthcare providers more often