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

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16. 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.			
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EXECUTIVE SUMMARY

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.

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. 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. From a patient demand standpoint, telemedicine accessibility became relatively straightforward as regulations became more flexible, allowing individuals to utilize familiar platforms such as FaceTime, Skype, and Zoom (see Shaver, 2022). Additionally, insurance companies began to reimburse for telemedicine services in a manner similar to in-person care, further incentivizing telemedicine utilization (see Cubanski et al., 2023). The high levels of patient satisfaction experienced with telemedicine services also played a significant role in bolstering acceptance and driving patient demand for telehealth (see Orrange et al., 2021). On the providers' supply side, while only 15% of physicians reported offering telemedicine in 2018 and 2019, this number rose to 87% in 2021 (Pylypchuk and Barker, 2021), likely due to necessity, relaxed regulations, and growth of telemedicine platforms and services. However, with the relaxation of lockdown measures and social distancing, telemedicine use appears to have tapered down some, though still definitely much higher compared to pre-COVID levels, indicating that telemedicine has become an integral component of the healthcare landscape (see Anderson et al., 2022, and Oluyede et al., 2022).

The increased adoption of telemedicine in the aftermath of the COVID-19 pandemic has not only transformed healthcare delivery, but also uncovered significant equity and accessibility disparities in health care 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. Notably, by eliminating travel needs for healthcare, the rise of telehealth could influence urban mobility patterns and transportation planning in the long term. This broader perspective is essential for understanding and maximizing the benefits of telemedicine 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 this discussion, our study aims to contribute to earlier investigations of telemedicine adoption in a pandemic-altered world. Using multivariate econometric models, we identify the determinants of telemedicine use shifts in the After-COVID period relative to Before- and During-COVID periods (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). Our study focuses on investigating the individual-level factors that affect telemedicine adoption in the After-COVID period. But 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 continued to be in-person during COVID). Furthermore, our methodology extends beyond analyzing telemedicine adoption trends by incorporating a multivariate probit model to examine the facilitators/deterrents of telemedicine adoption in the After-COVID period.

LITERATURE REVIEW

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. These thematic areas include (a) analyzing sociodemographic determinants of telemedicine adoption (see, for example, Eberly et al., 2020, Jaffe et al., 2020, Zhang et al., 2021, Drake et al., 2022, Xu et al., 2022, and Chandrasekaran, 2023), (b) exploring service-related variables and reasons for telemedicine adoption from the patients' perspective (see, for example, Adams et al., 2021, Fischer et al., 2022, Holtz et al., 2022, and Chandrasekaran, 2023), (c) assessing healthcare professionals' experiences and adaptation to telemedicine (see, for example, Kissi et al., 2020, and Lampickienė and Davoody, 2022), (d) comparing telemedicine adoption by channels (video vs audio) (see, for example, Soliman, 2020, and Molfenter et al., 2021), (e) evaluating the rapid advancements in telemedicine technologies and the necessary technological infrastructure (see, for example, de Oliveira Andrade et al., 2022, Jonasdottir et al., 2022, and Alenoghena et al., 2023), (f) investigating the quality of care provided through telemedicine, including its efficacy, and impact on clinical outcomes (see, for example, Willis et al., 2021, and Demaerschalk et al., 2022), (g) examining the impact on regulations and healthcare policies (see, for example, Shachar et al., 2020, de Oliveira Andrade et al., 2022, and Pandya et al., 2022), and (h) exploring best practices to address concerns around data security (see, for example, Romanovs et al., 2021, and Houser et al., 2023). In this literature overview, we focus on thematic areas (a) and (b) as they are highly relevant for understanding the implications of telemedicine on transportation systems, specifically on the frequency and patterns of travel for healthcare services. Analyzing sociodemographic and built environment factors (research area (a)) enables the identification of patient groups that are more likely to use telemedicine and thus reduce their medical-related travel. Similarly, understanding telemedicine use facilitators/deterrents (research area (b)) can help shape land-use patterns and the design of health delivery mechanisms for promoting the uptake of telemedicine, further impacting travel demand. This dual focus provides valuable insights into how shifts in healthcare delivery can influence transportation planning and infrastructure needs.

In the rest of this section, we first examine the sociodemographic and built-environment factors that influence telemedicine adoption, followed by the literature on the reasons why individuals use or do not use telemedicine. Finally, we outline the contributions of this research within the framework of the existing literature.

Sociodemographic and Residential Location Correlates of Telemedicine Adoption

The emphasis of our study is on studying individual-level decision-making in telemedicine adoption, utilizing datasets with detailed demographic and socioeconomic information. Consequently, in this section, we focus specifically on studies that investigate, at an individual level, either the actual usage of telemedicine or the expressed willingness to adopt telemedicine.[1] We further confine attention to studies that examine a wide patient base receiving a range of services, as they provide a more generalizable understanding of telemedicine usage and accessibility, as opposed to studies that focus on telemedicine adoption in specific medical specialties such as mental health, dermatology, or oncology (see Dhaduk et al., 2021, Jewett et al.,

[1] 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).

2022, Qian et al., 2022, and Tisdale et al., 2022). 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. Research indicates a gendered pattern in telemedicine use, with women generally being more likely to utilize virtual care compared to men. This pattern is documented in studies by Eberly et al. (2020), Jaffe et al. (2020), Zhang et al. (2021), Drake et al. (2022), Xu et al. (2022), and Chandrasekaran (2023), and Chen et al. (2023), which collectively suggest that women may have a greater propensity to engage with telemedicine. Conversely, certain studies, such as those by Schifeling et al. (2020), and Sharma et al. (2024), report an insignificant association between gender and telemedicine usage, indicating that the relationship may not be universally applicable across all populations and settings. Similar to gender, age is a significant determinant of telemedicine usage, with distinct preferences observed across age groups. Studies consistently show that younger adults, typically under 45 years old (see Jaffe et al., 2020, Drake et al., 2022, Fischer et al., 2022, and Xu et al., 2022), are the most frequent users of telehealth services. This age group's comfort with technology and flexible healthcare needs likely contribute to their higher rates of telemedicine adoption. Yet, a small subset of research (see Eberly et al., 2020, and Weber et al., 2020) suggests a broader age range of telemedicine users, up to 65 years old. Overall, though, older adults are often reported to be less engaged with telemedicine, particularly video-based services, suggesting age-related barriers to telehealth use. This observation is further supported by research examining telemedicine use by modality, which frequently indicates that older adults prefer engaging with telemedicine through telephone services over video (see Schifeling et al., 2020, and Drake et al., 2022). An exception in the relationship between age and telemedicine adoption is reported by Pierce and Stevermer (2023), who found a higher likelihood of telemedicine usage among older adults in the initial 30 days of the pandemic.

Racial/Ethnic Disparities

The literature extensively documents racial and ethnic disparities in telemedicine utilization, revealing that minority groups often engage with telemedicine services at lower rates than their white counterparts. For instance, Adepoju et al. (2022) utilized data from Texas a few months into the pandemic and found that racial minorities were less likely to have a telemedicine visit. This finding also aligns with the observations by Eberly et al. (2020), using data from a similar time period in Philadelphia, where Black race and Latinx ethnicity were associated with a lower likelihood of using telemedicine services. Similarly, Luo et al. (2021) and Drake et al. (2022) found that Black and Latinx patients were less likely to use telemedicine in Southeast Wisconsin and North Carolina. Additionally, studies utilizing more recent nationally representative data from 2022, such as that by Chandrasekaran (2023), observed that white and Hispanic individuals had higher odds of utilizing telemedicine compared to non-Hispanic African Americans. But, despite a general trend toward lower telemedicine utilization among minority groups, the findings from earlier studies are not uniform. For instance, research by Jaffe et al. (2020), Zhang et al. (2021), and Sharma et al. (2024) did not identify a significant link between race or ethnicity and telemedicine usage. Conversely, other studies by Campos-Castillo and Anthony (2021), Chumbler et al. (2023), and White-Williams et al. (2023) found that non-Hispanic Black and Hispanic patients were more likely to use telemedicine during the pandemic. The intersection of race and telemedicine modality (telephone versus video) further complicates the utilization landscape

among racial and ethnic groups. Luo et al. (2021) and Der-Martirosian et al. (2022) highlighted a clear preference for telephone visits over video among certain minority groups, likely due to barriers such as limited access to technology and internet connectivity issues that hinder the use of video services. Similarly, Rodriguez et al. (2021), and Drake et al. (2022) observed that Black and Hispanic patients were less likely to use video telemedicine within the Mass General Brigham health system in Boston, Massachusetts. In contrast, Fischer et al. (2022) reported a significant willingness among Black adults to use video telemedicine, based on a nationally representative dataset.

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. Studies such as those conducted by Zhang et al. (2021), Choi et al. (2022), and Chandrasekaran (2023) found that married individuals or those cohabitating with a partner are more likely to utilize telemedicine. However, similar to the relationship between telemedicine adoption and other demographic variables, the literature on the relationship between marital status and telemedicine usage is also inconsistent. For instance, Jaffe et al. (2020) presented an opposing view, indicating that married individuals might be less inclined to use telemedicine services.

Socioeconomic status has been identified as another critical determinant of telemedicine access and usage. Similar to the variables explored above, the results are inconsistent across studies with some reporting that lower-income individuals and households are associated 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 obtaining an opposite (see Patel et al., 2021) or statistically insignificant relationship (see Chandrasekaran, 2023 and Ko et al., 2023). Beyond income, several studies explored the role of educational attainment in accessing telemedicine services, though it is noteworthy that education-related variables have been less frequently examined in this context. Again, there is a divide in the literature regarding the impact of educational attainment on telemedicine, with some studies identifying a positive correlation between higher formal educational levels and increased telemedicine usage (see Eberly et al., 2020, Luo et al., 2021, and Rodriguez et al., 2021), while others have found no significant relationship between formal educational attainment and telemedicine adoption during the COVID-19 pandemic (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 growth in willingness to use telemedicine amid the pandemic, compared to their predispositions before the health crisis. Despite this, the overarching trend suggests that those with higher formal levels of education demonstrate a greater willingness to utilize telemedicine, particularly video-based services.

Residential Location

Residential location has also been reported as a significant determinant of telemedicine adoption. While there was a notable increase in telemedicine usage across rural areas following the onset of the pandemic, as documented by Chu et al. (2021), the increase in urban areas was significantly more pronounced. This trend highlights a persistent and clear divide between urban and rural patients, primarily attributable to access barriers prevalent in rural regions. Studies such as those by Iasiello et al. (2023), Ko et al. (2023), and Sharma et al. (2024) have consistently observed these disparities, pointing to the critical challenges faced by rural populations in accessing

telehealth services. Moreover, regional differences across the U.S. influence telemedicine utilization. These variations are often attributed to diverse 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 rates of telehealth usage compared to their counterparts in the West, Midwest, or Northeast. This geographic variability indicates that a one-size-fits-all approach to telehealth implementation and policy may not be effective.

Overall, the reviewed body of literature on telemedicine adoption clearly indicates the variations in telemedicine adoption based on demographic and residential location characteristics, even if the results are not always consistent. The often contrasting results of the effects of variables 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 used data spanning from March and September of 2020, capturing the early stages of the pandemic characterized by the healthcare system's adjustments to escalating COVID-19 cases and the exploration of telemedicine as an alternative for outpatient visits (see Chunara et al., 2020, Weber et al., 2020, Campos-Castillo and Anthony, 2021, Darrat et al., 2021, Choi et al., 2022, and Molina et al., 2023). Other studies incorporated data from late 2020 when there was increased dependence on telemedicine (see Rodriguez et al., 2021, Zhang et al., 2021, Hatef et al., 2022, Chumbler et al., 2023, and White-Williams et al., 2023). Relatively fewer studies were based on data from early 2021, coinciding with the initiation of vaccination campaigns (see Zachrison et al., 2021, Duan et al., 2022, Fischer et al., 2022, and Xu et al., 2022). Even fewer studies utilized data from after the first quarter of 2021, a time when telemedicine had become an integral part of regular healthcare delivery (see Chandrasekaran, 2023, Park et al., 2023, and Sharma et al., 2024). Only one study that we are aware of examines the telemedicine adoption evolution trend over time at an individual level. This is the study by Chen et al., 2023 based on data from August 1st, 2020 to July 31st, 2021. Chen et al. identified two time periods: (1) a telehealth transition period (August 1, 2020 to February 28, 2021) when telemedicine became prevalent as an option, and (2) a telehealth elective period (March 1, 2021 to July 31, 2021) representing the period when the telehealth option had already existed for six months. 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 effect of demographics on telemedicine adoption across the two periods, with the demographic effects in each period being similar to the findings from the studies already discussed earlier. 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.

Reasons for Using (or Not Using) Telemedicine

In addition to understanding the sociodemographic and built-environment factors affecting telemedicine use, it is equally important to explore the underlying reasons that motivate or dissuade different population segments from utilizing telemedicine services. This information helps address the specific barriers and incentives across diverse populations to enhance telemedicine access and acceptance. Due to the sheer volume of research papers related to telemedicine service satisfaction and motivations and obstacles associated with telemedicine adoption, many systematic reviews have emerged; see, for example, Pogorzelska and Chlabicz (2022), Bajgain et al. (2023), and Rowe

Ferrara and Chapman (2024). Many of these studies 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) (see, for example, Kurniawan et al., 2023, and Yang et al., 2024), to explain factors influencing acceptance and the willingness to adopt telemedicine. As highlighted in these studies, Delone and McLean's theory, which emphasizes system quality, information quality, and service quality leading to user satisfaction and usage intentions, aligns well with the telemedicine context. Similarly, the UTAUT theory suggests that patients' perceptions of telemedicine's effectiveness (performance expectancy), ease of use (effort expectancy), social support for its use (social influence), and the availability of the necessary technical infrastructure (facilitating conditions) significantly determine their adoption decisions.

Based on the theories, many studies have empirically examined the facilitators and barriers to telemedicine adoption (see the studies listed in the recent systematic reviews identified earlier, as well as Fischer et al., 2020, Adams et al., 2021, Holtz et al., 2022, Bajgain et al., 2023, Chandrasekaran, 2023, Moulaei et al., 2023, and Pullyblank et al., 2023). The commonly cited facilitators of telemedicine use from these earlier studies include the perceived safety from COVID-19 exposure, easier access to healthcare services, comfort and convenience, the reduction of travel-related obstacles, time savings, shorter wait times, improved provider communication, and enhanced privacy measures. In contrast, the barriers to telemedicine use 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 studies are based on descriptive statistics collected over all individual responses. Indeed, we are aware of only two studies that attempt to explore the barriers to telemedicine use 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 using 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 using 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 (≥200,000 annual income) groups, respectively. However, the study found no gender-based

differences in the reasons for not utilizing 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).

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 use and non-use decisions. Our approach contributes to advancing the existing body of knowledge in five distinct ways.

First, as shown in Figure 1, we consider multiple sociodemographic, employment, personality, and built-environment (BE) variables (characterizing in-person accessibility to medical facilities and residential neighborhood characteristics), all at once in a multivariate setting rather than using simple bivariate correlations of determinant factors with telemedicine adoption and with adoption/non-adoption reasons. 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 "Telework Adoption" and "Adoption/Non-adoption Reasons" blocks) allows for a deeper and more accurate understanding of the effect of each exogenous factor after controlling for other exogenous factors. Second, the framework is structured to discern the shifts in the effects of telemedicine adoption factors between the Before- and After-COVID periods. This helps gain a deeper understanding of how socioeconomic and BE variables influenced telemedicine adoption before the pandemic and how the willingness of different segments of society to engage in telemedicine has shifted as a result of the pandemic (see the "Telemedicine Adoption" Block in the middle of Figure 1). While some existing studies have also addressed shifting preferences over time (such as Xu et al., 2022, Chen et al., 2023, and Park et al., 2023), these studies employ methodologies that analyze different periods independently. 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, reflecting intra-individual correlations among the adoption decisions in the three periods. Not accounting for intra-individual correlation effects will, in general, provide biased estimates of the evolution pattern of telemedicine adoption over time. Third, our study explores the reasons for using or not using telemedicine in the After-COVID period from the patient's viewpoint (right side of Figure 1). While the existing literature has explored telemedicine adoption motivators and deterrents using descriptive statistics, only two studies, to our knowledge investigate variations across population segments, and even then only on the barriers for non-telemedicine adopters. In our study, we examine adoption motivators as reported (only) by telemedicine users and adoption barriers as reported (only) by non-telemedicine users, while also accommodating self-selection effects that may tie adoption decisions with motivators/barriers. For example, a person with intrinsically introverted tendencies or with a generic time-sensitive personality may be more likely to be a telemedicine user and also choose such reasons for using 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 are able to 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 barriers amongst the population at-large (regardless of current telemedicine adoption or not). This can inform healthcare providers, policymakers, and other stakeholders seeking to promote telemedicine adoption After-COVID in the entire population. Fourth, we jointly model the reasons for adoption and non-adoption using a cross-sectional MBP model system, to accommodate for unobserved individual factors that can affect multiple reasons simultaneously. In combination with the model system for adoption across the different periods, the overall model then takes the form of a joint multiperiod MBP system for telemedicine adoption combined with a cross-sectional MBP system for motivator/barrier 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. Fifth, our study is also 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. However, telemedicine adoption can also have transportation ramifications, just as virtual participation in other types of activities can (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.

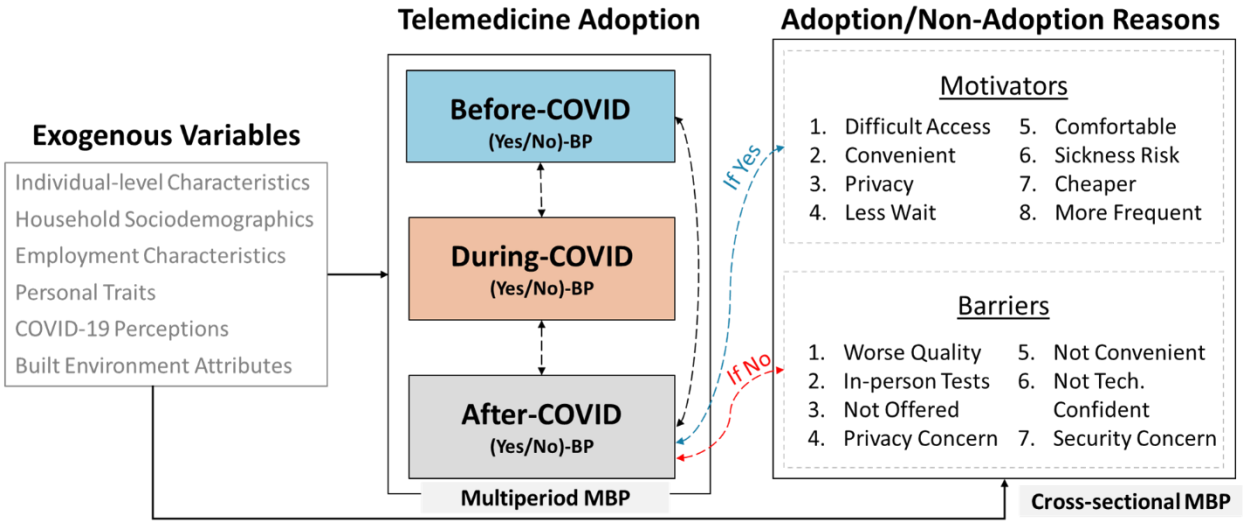

Figure 1 Analysis Framework

DATA

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). 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 either adopting or not adopting telemedicine.

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 the “Methodology” section, the entire structure of the multiperiod MBP and cross-sectional MBP in Figure 1 are undertaken jointly, using an econometric structure that we believe is a first in the literature.

Supplementary data regarding the zip code tabulation area population density were appended to the survey data from the 2021 American Community Survey. 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. The zip code-based population density values ranged from $6.97*10^{-06}$ people/m^2 (or 6.9 people/km^2) to 0.05594 people/m^2 (or 55944.7 people/km^2), with an average of 0.00194 people/m^2 (or 1942.9 people/km^2). Among the healthcare-related establishments, only the number of physicians' offices turned out to be of any significance in our analysis, which is intuitive since these are for non-urgent visits that have the potential to be undertaken virtually. The number of zip code-based physicians' offices varied from a low of 0 to a high of 145, with an average count of 34.

Outcome Variables

Table 1 below provides descriptive statistics related to telemedicine usage among respondents at different stages of the COVID-19 pandemic. 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 use 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 use 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. Specifically, it summarizes the reasons for using telemedicine among 802 individuals planning to continue its use post-COVID, as well as the reasons for not using 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). Conversely, individuals who do not intend to use telemedicine cite reasons 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 the "Reasons for Using (or Not Using) Telemedicine" section, respondents in our sample did not indicate limited healthcare choices, insurance coverage, technical issues, or privacy concerns as major barriers 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.

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

Before-COVID Adoption	**During-COVID Adoption**	**After-COVID Adoption**	
		Yes	**No**
Yes (234; 11.47%)	**Yes** (146; 62.39%)	115 *78.77%*	31 *21.23%*
	No (88; 37.61%)	34 *38.64%*	54 *61.36%*
No (1807; 88.53%)	**Yes** (724; 40.07%)	427 *58.98%*	297 *41.02%*
	No (1083; 59.93%)	154 *14.22%*	929 *85.78%*
Total (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
Reasons for adopting telemedicine (N=802)			
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%
Reasons for not adopting telemedicine (N=1533)			
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%

Exogenous Variables

Table 3 provides a detailed description of the individual and household sociodemographic characteristics of the sample respondents along with corresponding benchmarks for the U.S. adult population from the 2021 American Community Survey 5-year estimates.

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 are also overrepresented. One possible explanation for this 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[2] 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).

Beyond the variables discussed above, other categories of explanatory variables were considered, including employment characteristics (including telework arrangements and commute trip transport mode), personal traits (including perspectives toward online shopping, working from home, driving, and technology use), COVID-19 perspectives (including perceived well-being risks during the pandemic), and residential location attributes (including population density as a proxy for urban and rural areas, and number of physicians' offices in the respondent's zip code).

[2] The four U.S. regions were defined according to the U.S. Census definitions. These regions include the Northeast (Connecticut, Main, 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).

Table 3 Sample Distribution of Exogenous Variables

Variable	% in sample	% in ACS	Variable	% in sample	% in ACS
Individual/Household Sociodemographics			***Education***		
Gender			Less than bachelor's degree	38.7	64.4
Men	36.5	48.9	Bachelor's degree	33.2	21.6
Women	63.5	51.1	Graduate degree	28.1	14.0
Lifecycle variables			***Household Income (gross)***		
Single	21.8	28.1	Less than $25,000	12.2	17.2
Single parent	3.9	8.4	$25,000-$49,999	18.2	19.6
Couple no children	45.5	29.2	$50,000-$99,999	34.1	29.6
Couple with children	17.0	18.3	$100,000-$149,999	20.2	16.3
Related adults	8.1	9.1	$150,000-$199,999	7.5	7.8
Roommates	3.7	6.9	$200,000+	7.8	9.5
Race			***Number of Motorized vehicles***		
Asian	4.4	5.9	0	6.4	8.1
Black	6.2	12.2	1	41.2	32.9
White	84.4	60.9	2	39.4	37.1
Other	5.0	21.0	3+	13.0	21.9
Age			**Employment Status**		
≤ 30 years	7.9	18.0	Not employed	48.7	22.7
31 – 40 years	14.4	18.0	Employed part-time	11.3	17.0
41 – 50 years	13.2	16.7	Employed full-time	40.0	60.3
51 – 60 years	18.7	17.4	**Census Region**		
61 – 70 years	27.5	15.6	Northeast	12.1	17.2
≥ 71 years	18.3	14.3	Midwest	23.1	20.7
			South	25.1	38.4
			West	39.7	23.7

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-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 tied to the multiperiod MBP too 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. To our knowledge, this is the first such formulation and application of a joint multiperiod-cross-sectional MBP system. 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/barriers 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 or no, based on reported adoption), (b) the choice of adoption During-COVID (yes or no, based on reported adoption), (c) the choice of adoption After-COVID (yes, based on stated intention of future telemedicine use), 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 then results effectively in an 11-dimensional MBP system (the non-adoption reasons are not available 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 or no, based on reported adoption), (b) the choice of adoption During-COVID (yes or 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 not available 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, which we discuss below assuming 18 outcome dimensions.

Model Structure

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,…, C; C=18 in our case). Define a latent propensity y_c^* underlying the binary variable y_c and consider the following structure:

$$y_c^* = \boldsymbol{\beta}_c^{'}\mathbf{x} + \varepsilon_c,\ y_c = k_c \text{ if } \psi_{c,k_c-1} < y_c^* < \psi_{c,k_c}, \tag{1}$$

where $\mathbf{x}$ is an $(L\times 1)$ vector of exogenous variables (excluding a constant), $\boldsymbol{\beta}_c$ is a corresponding $(L\times 1)$ vector of coefficients to be estimated, and ε_c is a random error term assumed to be standard normally distributed (the scale of ε_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 ε_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 $\tilde{\boldsymbol{\psi}} = (\psi_{1,0}, \psi_{2,0}, ..., \psi_{C,0})'$ 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 $(c = 1, 2, ..., C)$. Accordingly, stack the lower thresholds ψ_{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 ψ_{c,k_c} into another $(C\times 1)$ vector $\boldsymbol{\psi}_{up}$. Also, define $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, ..., \boldsymbol{\beta}_C)'$ [$(C\times L)$ matrix]. Then, in matrix form, the latent propensities underlying the multivariate outcomes may be written as:

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

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

$\boldsymbol{\delta} = \left(\left[\text{Vech}(\boldsymbol{\beta}) \right]', \tilde{\boldsymbol{\psi}}', \left[\text{Vechup}(\boldsymbol{\Xi}) \right]' \right)'$, 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:

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

where the integration domain $D_r = \{\boldsymbol{r} : \boldsymbol{\psi}_{low} < \boldsymbol{r} < \boldsymbol{\psi}_{high}\}$ is simply the multivariate region of the $\mathbf{y}^*$ vector determined by the upper and lower thresholds. $f_C(\boldsymbol{r} \mid \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Xi})$ 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.

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 examined interaction effects across variables, but none were found to be statistically significant.

The final specification is presented in Tables 4 and 5. The parameters in these tables represent the elements of the $\boldsymbol{\beta}$ matrix, which reflects the effect of exogenous variables on the propensity to adopt or not adopt telemedicine or to choose a certain 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.

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 interpretations, 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.

Table 4 Telemedicine Adoption Model Estimation Results

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

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 the next section). 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 use 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 (≤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 over time of non-adoption among older individuals 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 use 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, Figliozzi and Unnikrishnan, 2021, and Kim and Wang, 2021).

Employment Characteristics

Our analysis also explored the relationship between employment status, telework habits, and telemedicine use. 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 use 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 use, 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[3]. 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 use 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 (≤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.

Telemedicine Use Facilitators/Deterrents Model Estimation Results

The second objective of the study was to explore the factors that make telemedicine use more appealing or less appealing. The estimates correspond to the effects on the propensity that each

[3] The responses to the questions regarding experiences that individuals experienced during the pandemic that they enjoyed and would like to continue after COVID-19 is no longer a threat, namely "I enjoyed working from home, at least some of the time" and "I enjoyed driving less," were collected on a binary scale. A response of "Enjoy working more from home due to COVID" or "Enjoy driving less due to COVID" indicated that the individual enjoyed working from home or driving less, while a response of "Do not enjoy" indicated otherwise. For the statements "Learning how to use new technologies is often frustrating" or " I am concerned that if I, or my friends or family members, catch the coronavirus, we may have a severe reaction", responses of "somewhat agree" or "highly agree" were categorized as "Technologically savvy" or "People's well-being is/was at risk during the pandemic" while responses of "neutral," "somewhat disagree," or "disagree" were categorized as "Not technologically savvy" or "Not at risk".

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.

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.[4] 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).

Moving on to the lifecycle variables, telemedicine use 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 use, 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

[4] 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.

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 use. 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 use, 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 use. As we discuss later in the "Magnitude Effects of Variables and Implications", 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 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 use, 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), and (b) perceive telemedicine's inconvenience (IPC) as a barrier 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 motivators and barriers to using 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 also are 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 11th numeric rows and columns of the table), and (d) the correlations among the deterrent reasons (the 12th through 18th 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 barrier 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 use 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, security and privacy of digital telemedicine use are concerns in general, especially among those who feel they are not technologically proficient.

Table 5 Telemedicine Use Facilitator/Deterrent Reasons

Explanatory Variables	Telemedicine Use Facilitator/Deterrent Reasons								Telemedicine Use Facilitator/Deterrent Reasons						
(base category)	**DIPA**	**TC**	**TP**	**TS**	**CH**	**LCR**	**LE**	**FCO**	**PTQ**	**NIPT**	**TNA**	**POP**	**IPC**	**NTC**	**TSC**
Individual/Household Sociodemographics															
Gender															
Woman *(base: man)*	0.238	0.164				0.314	-0.298		-0.279						
Lifecycle variables															
Presence of children *(base: no children)*	0.290		0.237					0.278	0.191				0.287		
Race *(base: white)*															
Non-white			0.304		-0.177			0.250					0.283		
Age *(base: 50 years or younger)*															
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	
Formal Education Level *(base: < Bachelor's degree)*															
Bachelor's degree or higher		0.431							0.354				-0.274		
Income *(base: less than $75,000)*															
$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
Income change *(base: no change or increase)*															
Income decreased during COVID	0.304														
Vehicle ownership *(base: ≥1 vehicle)*															
0 vehicles	0.785														
Employment Characteristics															
Employment Status *(base: not employed)*															
Employed full-time or part-time	-0.459		0.503		-0.363					-0.252					
Telework arrangements *(base: no telework or telework less than once a week)*															
Telework daily					0.232	0.214						-0.195	-0.345		
Telework multiple times per week					0.232	0.214						-0.195	-0.345		
Student *(base: not student)*															
Student								0.352							
Commute mode *(base: not car)*															
Car		-0.249													

Explanatory Variables	Telemedicine Use Facilitator/Deterrent Reasons								Telemedicine Use Facilitator/Deterrent Reasons						
(base category)	**DIPA**	**TC**	**TP**	**TS**	**CH**	**LCR**	**LE**	**FCO**	**PTQ**	**NIPT**	**TNA**	**POP**	**IPC**	**NTC**	**TSC**
Personal Traits															
Enjoy working from home *(base: do not enjoy)*	0.235											-0.203			-0.222
Residential Attributes															
Access to healthcare services															
# of physicians' offices in zip code *(count variable)*	-0.005		-0.004										0.002		
Region *(base: Northeast)*															
Midwest		0.216	-0.303								-0.247				
South			-0.303						-0.269						
West			-0.484								-0.243				
Threshold 0|1	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 Use Facilitator Reasons								Telemedicine Use 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	-0.13 (-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 Use 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	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 Use 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

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 $\left[=-L(\hat{\boldsymbol{\delta}})+0.5\times\left(\#\text{ of model parameter}\right)\times\log\left(\text{sample size}\right)\right]$ to compare model performance, where $L(\hat{\boldsymbol{\delta}})$ 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:

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

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.

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 Use 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 Use 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

Magnitude Effects of Variables and Implications

The estimation results in the previous section 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 use 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.

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 encountered 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 use, 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, the higher telemedicine adoption rates in areas where access to in-person medical services is limited (see the ATE of 15.1% corresponding to "# of physicians' offices in zip code") and in low population density areas (ATE of 11.3% corresponding to "Population density") also highlight its potential to bridge healthcare accessibility gaps, especially given that individuals in such "medical service deserts" (MSDs) also value telemedicine privacy (TP) and do not consider in-person convenience (IPC) as being much of a deterrent for telemedicine use. In fact, given an individual's place of residence serves as a critical social determinant of health, significantly influencing the frequency and quality of timely, regular, and preventive medical care (see Estrada et al., 2022), telemedicine can serve as a vital lifeline for patients in such MSDs in rural and underserved areas. Policymakers must prioritize investments in expanding reliable high-speed internet connectivity in such MSDs.

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 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 for working 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.

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 research 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.

Table 9 ATE Results

Variable	Base Level	Treatment Level	% Change in Adopt-ion	% Change in Telemedicine Use Facilitator Reasons								% Change in Telemedicine Use 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
Vehicle ownership	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/m^2)	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

CONCLUSIONS AND POLICY IMPLICATIONS

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.

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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APPENDIX A

In this appendix, we present the results of the effects on the propensity that each reason acts as a telemedicine facilitator or deterrent for a randomly selected individual from the population. Tables 1A and 2A below display these effects along with their corresponding t-statistics, which were excluded from the main manuscript for conciseness.

Table 10A Telemedicine Use Facilitator Reasons Model Estimation Results

Explanatory Variables *(base category)*	Telemedicine Use Facilitator Reasons															
	DIPA		TC		TP		TS		CH		LCR		LE		FCO	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Individual/Household Sociodemographics																
Gender																
Woman *(base: man)*	0.238	1.70	0.164	1.42							0.314	3.10	-0.298	-2.43		
Lifecycle variables																
Presence of children *(base: no children)*	0.290	1.95			0.237	1.62									0.278	1.91
Race *(base: white)*																
Non-white					0.304	2.12			-0.177	-1.51					0.250	1.67
Age *(base: 50 years or younger)*																
51 to 60 years old					0.446	3.22					0.356	3.00				
61 years or older					0.446	3.22	-0.254	-2.15			0.356	3.00				
Formal Education Level *(base: < Bachelor's degree)*																
Bachelor's degree or higher			0.431	2.14												
Income *(base: less than $75,000)*																
$75,000 to $99,999					-0.463	-2.49	0.254	1.78	-0.264	-1.49						
$100,000 to $149,999	-0.267	-1.79			-0.501	-2.98	0.254	1.78	-0.264	-1.49						
$150,000 to $199,999	-0.267	-1.79			-0.420	-2.25	0.254	1.78	-0.264	-1.49						
$200,000 or more	-0.267	-1.79	0.516	2.07	-0.420	-2.25	0.254	1.78	-0.264	-1.49						
Income change *(base: no change or increase)*																
Income decreased during COVID	0.304	1.32														
Vehicle ownership *(base: ≥1 vehicle)*																
0 vehicles	0.785	3.94														
Employment Characteristics																
Employment Status *(base: not employed)*																
Employed full-time or part-time	-0.459	-3.31			0.503	3.21			-0.363	-3.18						

Explanatory Variables *(base category)*	Telemedicine Use Facilitator Reasons															
	DIPA		TC		TP		TS		CH		LCR		LE		FCO	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Telework arrangements *(base: no telework or telework less than once a week)*																
Telework daily									0.232	1.85	0.214	1.82				
Telework multiple times per week									0.232	1.85	0.214	1.82				
Student *(base: not student)*																
Student															0.352	1.90
Commute mode *(base: not car)*																
Car			-0.249	-2.08												
Personal Traits																
Enjoy working from home *(base: do not enjoy)*	0.235	1.78														
Residential Attributes																
Access to healthcare services																
# of physicians' offices in zip code *(count variable)*	-0.005	-1.43			-0.004	-1.54										
Region *(base: Northeast)*																
Midwest			0.216	1.50	-0.303	-1.68										
South					-0.303	-1.68										
West					-0.484	-2.57										
Threshold 0|1	1.024	4.09	-0.606	-2.09	0.323	1.03	-0.060	-0.39	-0.149	-0.65	0.323	1.72	0.705	2.13	1.004	4.60

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 11 Telemedicine Use Deterrent Reasons Model Estimation Results

Explanatory Variables *(base category)*	Telemedicine Use Deterrent Reasons													
	PTQ		NIPT		TNA		POP		IPC		NTC		TSC	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Individual/Household Sociodemographics														
Gender														
Woman *(base: man)*	-0.279	-2.78												
Lifecycle variables														
Presence of children *(base: no children)*	0.191	1.47							0.287	2.40				
Race *(base: white)*														
Non-white									0.283	2.43				
Age *(base: 40 years or younger)*														
41 to 50 years														
51 to 60 years old											0.209	1.26		
61 years or older			0.182	1.38					0.202	2.07	0.209	1.26		
Formal Education Level *(base: < Bachelor's degree)*														
Bachelor's degree or higher	0.354	2.43							-0.274	-2.41				
Income *(base: less than $25,000)*														
$25,000 to $74,999														
$75,000 to $99,999														
$100,000 to $149,999									-0.186	-1.81	-0.271	-1.57	-0.277	-2.03
$150,000 to $199,999	0.201	1.35							-0.186	-1.81	-0.422	-1.64	-0.277	-2.03
$200,000 or more	0.201	1.35			0.323	1.50			-0.186	-1.81	-0.651	-2.13	-0.277	-2.03
Employment Characteristics														
Employment Status *(base: not employed)*														
Employed full-time or part-time			-0.252	-2.62										
Telework arrangements *(base: no telework or telework less than once a week)*														
Telework daily							-0.195	-1.44	-0.345	-2.21				
Telework multiple times per week							-0.195	-1.44	-0.345	-2.21				
Personal Traits														
Enjoy working from home *(base: do not enjoy)*							-0.203	-1.45					-0.222	-1.25

Explanatory Variables *(base category)*	Telemedicine Use Deterrent Reasons													
	PTQ		NIPT		TNA		POP		IPC		NTC		TSC	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Residential Attributes														
Access to healthcare services														
# of physicians' offices in zip code > 3 *(categorical variable)*									0.002	1.61				
Region *(base: Northeast)*														
Midwest					-0.247	-1.63								
South	-0.269	-2.31												
West					-0.243	-1.86								
Threshold 0|1	1.026	3.52	-0.212	-1.62	1.221	5.16	0.346	2.56	-0.164	-0.96	0.839	3.79	0.966	4.37

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