

Observational study of travel distance between participants in U.S. telemedicine sessions with estimates of emissions savings

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Abstract

Background: Digital health and telemedicine are potentially important strategies to decrease healthcare's environmental impact and contribution to climate change by reducing transportation-related air pollution and greenhouse gas emissions. However, we currently lack robust national estimates of emissions savings attributable to telemedicine.

Objective: This study aimed to (1) determine the travel distance between participants in U.S. telemedicine sessions, and (2) estimate the net reduction in carbon dioxide (CO₂) emissions attributable to telemedicine in the United States, based on national, observational data describing the geographical characteristics of telemedicine session participants.

Methods: We conducted a retrospective observational study of telemedicine sessions in the United States between Jan. 1, 2022 and Feb. 21, 2023. Using Google Distance Matrix, we determined the median travel distance between participating providers and patients for a proportional sample of sessions. Further, based on the best available public data, we estimated the total annual emissions costs and savings attributable to telemedicine in the U.S.

Results: The median round-trip travel distance between patients and providers was 49 miles. The median CO₂ emissions savings per telemedicine session was 19.81 kg CO₂. Accounting for the energy costs of telemedicine and U.S. transportation patterns, among other factors, we estimate that the use of telemedicine in the U.S. during the years 2021- 2022 resulted in approximate annual CO₂ emissions savings of 1,443,800 metric tons.

Conclusions: These estimates of travel distance and telemedicine-associated CO₂ emissions costs and savings, based upon national data, indicate that telemedicine may be an important strategy in reducing the healthcare sector's carbon footprint. Clinical Trial: N/A

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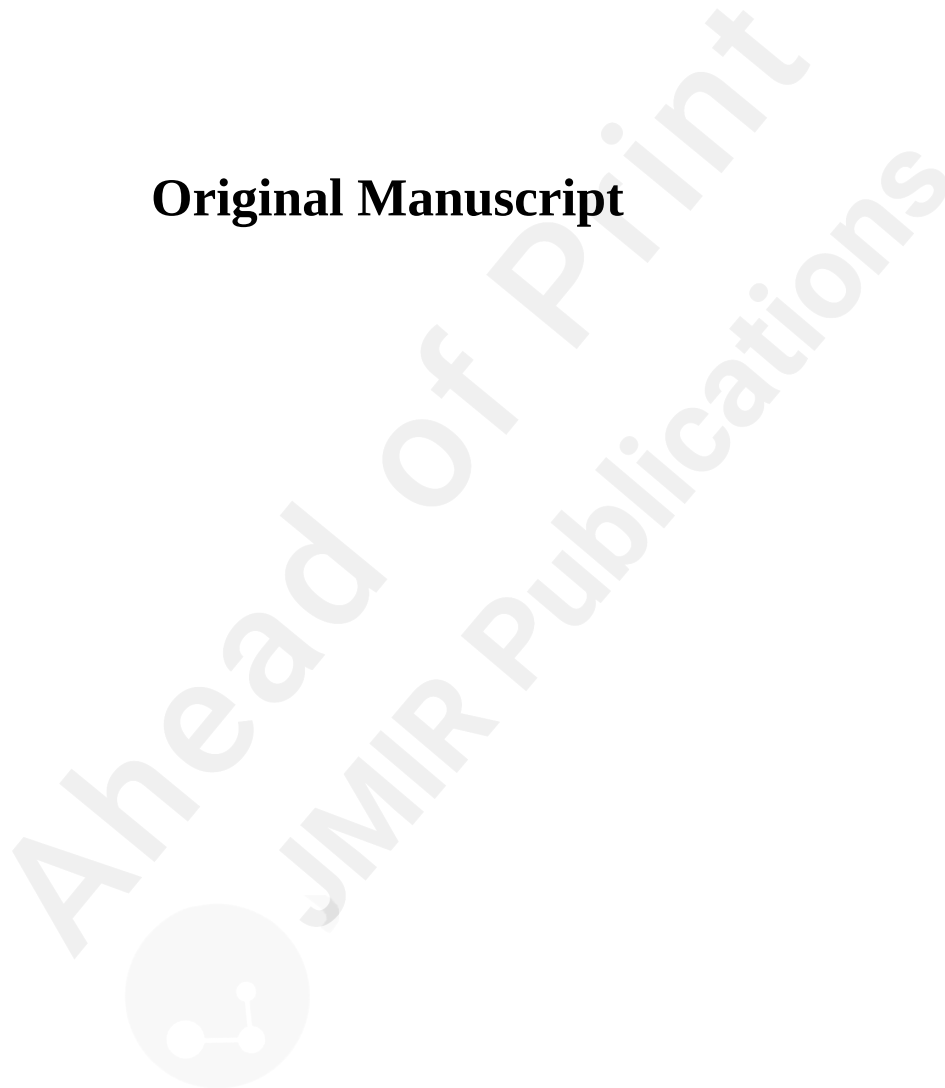
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Abstract

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Methods: We conducted a retrospective observational study of telemedicine sessions in the United States between Jan. 1, 2022 and Feb. 21, 2023, on the Doxy.me platform. Using google distance matrix, we determined the median travel distance between participating providers and patients for a proportional sample of sessions. Further, based on the best available public data, we estimated the total annual emissions costs and savings attributable to telemedicine in the U.S.

Results: The median round-trip travel distance between patients and providers was 49 miles. The median CO₂ emissions savings per telemedicine session was 19.81 kg CO₂. Accounting for the energy costs of telemedicine and U.S. transportation patterns, among other factors, we estimate that the use of telemedicine in the U.S. during the years 2021-2022 resulted in approximate annual CO₂ emissions savings of 1,443,800 metric tons.

Conclusions: These estimates of travel distance and telemedicine-associated CO₂ emissions costs and savings, based upon national data, indicate that telemedicine may be an important strategy in reducing the healthcare sector's carbon footprint.

Keywords

Air Pollution, Environmental Health, Telemedicine, Greenhouse Gases, Clinical Research Informatics, Informatics, Data Science

Introduction

Diminished air quality, marked by high levels of pollutants and particulate matter, has been associated with varied cardiovascular, respiratory, and other health issues and premature mortality.(1–12) Fossil-fuel-based transportation directly causes air pollution by releasing particulate matter, nitrogen oxides, and volatile organic compounds. Additionally, the emission of greenhouse gases, including CO₂ from fossil fuel consumption (including transportation-related consumption), contributes profoundly to climate change.(13) The heat-trapping properties of CO₂ and other greenhouse gases are considered primary drivers of global warming.(14) With climate change, we anticipate that air quality and human health will be further diminished by increased levels of ground-level ozone, particulate matter due to wildfires, and airborne allergens.(13) Beyond its effects on air quality, climate change is associated with varied additional health problems resulting in morbidity and mortality, ranging from heat-related illness to infectious disease transmission and food insecurity.(15) During the first year of the COVID-19 pandemic, we observed sharp decreases in atmospheric CO₂ worldwide, attributed to decreases in transportation and other CO₂-emitting human activities in compliance with public health orders.(16–18) However, atmospheric CO₂ has since increased and is forecasted to rise with fossil fuel consumption in the coming years, and there is a critical, global need to reduce emissions and mitigate impacts on human health.(18,19)

Ironically, hospitals and healthcare organizations are major contributors to CO₂ emissions. These emissions relate to both direct and indirect energy expenditures of health care facilities, many of which operate 24 hours per day, seven days per week. Emissions also result from transportation of health care providers, and other employees who provide services, and the transportation of patients and other visitors traveling to facilities. Most health care emissions result from the supply chain, which is dependent upon fossil fuels

and includes the production, transportation and operation of equipment, devices, and material supplies.(20) In a 2016 economic input-output life cycle assessment (EIO-LCA) modeling analysis, Eckelman & Sherman estimated that 10% of U.S. CO₂ emissions are attributable to the healthcare sector in 2013, prompting a re-examination of health care delivery practices in light of environmental impact.(21) In a 2020 update to the original analysis, the authors analyzed more recent data and incorporated additional state-level analyses of access and quality.(22) They determined that the U.S. national healthcare greenhouse gas (GHG) emissions increased by 6% from 2010 to 2018, and that electricity is the largest contributor to GHG emissions from the healthcare sector.(22) Healthcare pollution is a growing global concern. It is estimated that the health care sector is responsible for 4.4% of global GHG emissions and the U.S. appears particularly culpable. (20) In an international comparison of health carbon footprints, defined as global supply chain CO₂ emissions related to health care expenditures and investments, the U.S. was the second largest emitter of health care related CO₂ emissions. (23)

Telemedicine is one potentially important strategy for mitigating health care related GHG emissions, and numerous studies have examined the GHG emissions attributable to telemedicine. A 2022 systematic review of 31 studies conducted between 2000-2021 by Donald and Irurra found that telemedicine is associated with substantial CO₂ emission savings.(24) However, previously conducted U.S. studies that examined telemedicine-associated CO₂ emissions savings were conducted entirely in local or regional settings.(24) For example, a 2021 study by Jiang et al examined travel-related emissions savings in a convenience sample of 100 veterans receiving teleoncology care at a single site.(25) They estimated that there was a savings of 35.5 metric tons CO₂ with 560 sessions. In a recent, larger study conducted at Stanford Health Care in California, researchers estimated a savings of 17,000 metric tons in 2021 due to telemedicine use.(26)

However, specific estimates of CO₂ emissions savings from prior research vary widely, as they are based upon varied assumptions, regions, and medical specialties. Among U.S. studies, estimates of the CO₂ emissions savings per telemedicine session range from 11.2 kg CO₂ (vascular surgery, Michigan) to 893 kg CO₂ (Otorhinolaryngology head and neck surgery, New Mexico).(24,27,28) Additionally, most estimates are based upon fairly small regional samples with under 500 participants. In the Donald and Irukurra review, only two U.S. studies, one conducted in California and one conducted in Utah, had more than 1,000 participants.(29,30) Consequently, the overall extent of telemedicine's contribution to CO₂ emissions savings in the U.S. is unknown.

Health care pollution is a critical concern, and we must consider environmental impacts including GHG emissions when designing healthcare programs, services, and facilities to avoid unintended adverse consequences on human health. Digital health and telemedicine are potentially important strategies to decrease the health care sector's adverse environmental health impacts. However, we currently lack robust national estimates of emissions savings attributable to telemedicine that would enable the quantification of telemedicine's emissions savings in modeling efforts. This study aimed to (1) determine the travel distance between participants in U.S. telemedicine sessions, and (2) estimate the net reduction in CO₂ emissions attributable to telemedicine in the United States, based on national, observational data describing the geographical characteristics of telemedicine session participants.

Methods

We conducted a retrospective observational study of telemedicine sessions in the United States between Jan. 1. 2022 and Feb. 21, 2023 on the Doxy.me platform. We calculated

the approximate travel distance between providers and patients for a proportional sample of sessions, including estimated emissions savings and expenditures. Further, based on the best available public data, we calculated the emissions savings attributable to telemedicine in the U.S.

Ethical Review and Approval. The data used in this study were determined HIPAA de-identified using the expert determination method. All study procedures were reviewed by the University of Utah Institutional Review Board and determined to be non-human subjects research.

Doxy.me Session Data. Doxy.me is a commercial telemedicine platform commonly used by individual providers, clinics, and healthcare organizations.(31) Based on third-party survey research and other estimates, doxy.me is used in 8-30% of telemedicine sessions in the U.S. daily.(32–34) A HIPAA-compliant platform, it does not store patient names, addresses, or medical information. For operational purposes, Doxy.me stores I.P. addresses of session participants and limited account information about providers. For this study, we defined a telemedicine session as any session between one patient and one provider, with a duration between 5-120 minutes. Doxy.me assigned approximate locations (geospatial coordinates) to the telemedicine sessions based upon I.P. address using a free I.P. geolocation service, ipstack.(35)

Sampling and Time Frame. We analyzed a proportional sample of 79,904 sessions, drawn from a randomized sample of 8,000,000 doxy.me telemedicine sessions that occurred in the U.S., between two participants (one patient and one provider), between Jan. 1, 2022 and Feb. 21, 2023, meeting inclusion criteria and less than 400 miles geodesic distance. The strata used for proportions were: call region (Northeast, Southeast, West, Midwest, and Southwest); session length (5-30 minutes, or greater than 30 minutes); day of the week (Monday thru Friday or weekend); the hour of the day (13:00 thru 23:00 UTC, or

all other hours). Then, we calculated travel distance and time using Google Distance Matrix API for car travel.(36)

Inclusion Criteria: Telemedicine sessions occurring between dyads (one provider and one patient), using any device, between Jan. 1, 2022, and Feb. 21, 2023.

Exclusion Criteria: We excluded calls less than five minutes, as calls of this duration generally do not represent actual clinical encounters. Rather, they are attributable to changes in equipment/ devices or a need to adjust settings. We also excluded group sessions and sessions longer than 2 hours, which likely represent the use of doxy.me for remote monitoring. We excluded sessions with >400 miles geodesic distance in order to mitigate bias related to extreme distances and based on the conservative assumption that most patients receiving care from a highly distant health care provider, should they need to see that provider in-person, would seek alternative local care or not seek care at all.

Analysis. For the proportional sample of 79,904 sessions, we first geocoded the location of healthcare seekers and providers based on the coordinates derived from IP addresses, then calculated car travel time and distance using the Google Distance Matrix API.(36) We calculated descriptive statistics and box plots to describe session characteristics, including duration, specialty, patient travel time, and travel distance (round-trip). Then we adjusted the travel distance for a more realistic approximation of travel savings due to telemedicine. We multiplied by 0.848, based on the assumption that approximately 84.8% of travel was car travel, consistent with American Community Survey data on adult commuting patterns in the U.S.(37)

CO₂ emission savings. We calculated the tailpipe carbon dioxide (CO₂) emission savings associated with the telemedicine sessions by multiplying the total adjusted travel distance in miles by 404 grams, which is the 2022 EPA estimate of CO₂ emissions per mile

for an average passenger vehicle, assuming an average fuel economy of 22.0 miles per gallon.(38)

CO₂ expenditure. To approximate the CO₂ expenditure associated with each telemedicine session, we first calculated the energy expenditure associated with videoconferencing using the estimates and methods described by Blenkinsop and colleagues and Mytton, corresponding to the use of 720p HD video by two participants. (39,40) Following that approach, we calculated the total amount of data transferred during each session using a rate of 0.036 GB per minute.(39) We assumed electricity use of 0.015kWh/GB, based upon fixed line energy transmission estimates.(41) Using the U.S. EPA conversion rate of 4.33×10^{-4} metric tons CO₂/kWh, we estimated the CO₂ emissions expenditure in metric tons. Then, we subtracted the CO₂ expenditure from CO₂ savings to calculate the net CO₂ savings per session.

No publicly available data describes the total number of telemedicine sessions that took place in the U.S. during the dates of this study. To obtain an approximate estimate of annual U.S. telemedicine sessions, we used publicly reported data on the number of telemedicine sessions reimbursed via the U.S. Medicare and Medicaid programs. Centers for Medicare and Medicaid Services (CMS) spending accounted for 38% of National Health Expenditures in 2021. CMS reimbursed for 27,691,878 telemedicine sessions during one year, Mar. 1, 2020 to Feb. 28, 2021.(42) While expenditures do not translate directly to the volume of health care delivery or the number of telemedicine sessions that take place, we used it as a best-available approximate overall volume of health care delivered using telemedicine. Based upon these figures, we estimate that CMS-reimbursed telemedicine sessions represented 38% of a total of 72,873,363 telemedicine sessions that occurred in the U.S. in 2021, and we base our estimate of CO₂ emissions savings on this number of sessions and the post-pandemic policy environment of 2021 and 2022.

Representativeness of Doxy.me session data. We used multiple data sources describing national telemedicine utilization patterns to assess the representativeness of doxy.me data for national patterns of use.(42–45) We calculated descriptive statistics for two points of comparability, the regional distribution of sessions and the specialty of providers, and compared the observed distributions with that reported nationally for Medicare claims. See appendix 1 for a detailed comparison.

Geographic distribution of CO₂ emissions savings. Using ArcGIS, we created two maps that visualize CO₂ emissions savings at the zip code level. The first map shows the overall pattern of CO₂ savings. The second map shows the ratio of CO₂ savings to population size.

Results

A random sample of 8,000,000 telemedicine sessions, hosted by doxy.me, between Jan. 1, 2022 and Feb. 21, 2023 were examined. Of the sample, 6,231,614 sessions met our inclusion and exclusion criteria. After proportional sampling, the analytic data set consisted of 79,904 sessions.

Session Characteristics. The duration of sessions was bimodal in distribution. We dichotomized sessions to be 5 - 30 minutes in length (44%), or > 30 - 120 minutes (56%). The Northeast region had the most sessions (34%), followed by Southeast (20%), West (19%), Midwest (17%), and finally Southwest (9%). Tuesday, Wednesday, and Thursday were most frequent (22.7%, 22.2%, 21.3%, respectively). 2pm – 5pm Eastern (11am – 2pm Pacific) were the most common hours (each at 10.2%). The geographic distribution of the sessions by region is described in table 1 and depicted in figures 1 and 2. Comparisons of the doxy.me data to reference data sources, by state and by specialty is provided in appendix A.

Table 1. Session characteristics including duration, and geographic distribution.

	No.(%) of Sessions	
	Full Dataset (N=6,231,614)	Proportional Sample (N=79,904)
Duration (minutes)		
5 – 30	2,747,610 (44)	35,204 (44)
30 – 120	3,484,004 (56)	44,700 (56)
Geographical Location (by region)		
Northeast	2,125,693 (34)	27,311 (34)
Southeast	1,272,704 (20)	16,318 (20)
West	1,183,814 (19)	15,179 (19)
Midwest	1,076,509 (17)	13,788 (17)
Southwest	572,884 (9)	7,308 (9)
Missing	10 (0)	0 (0)

Figure 1. Geographical distribution of telemedicine sessions, total number of sessions for each county

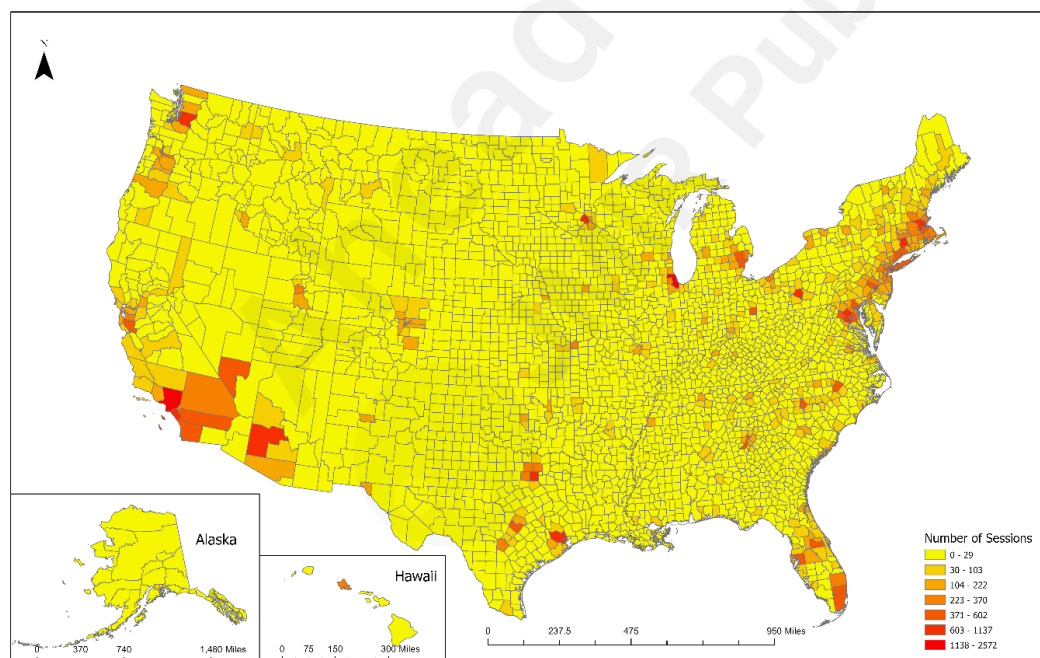
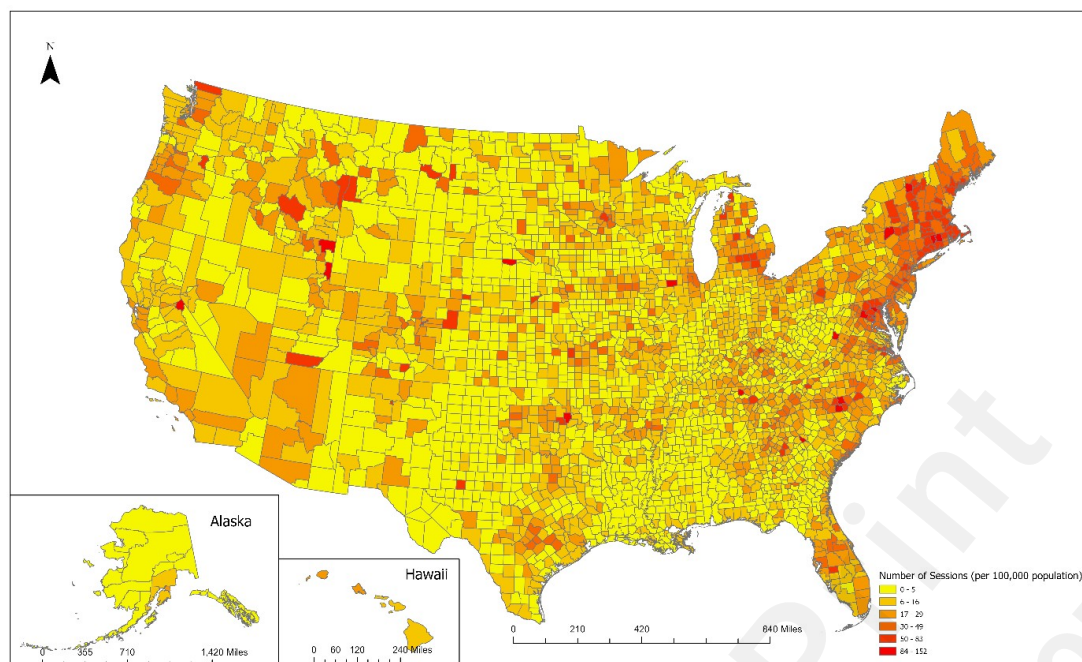


Figure 2. Geographical distribution of telemedicine sessions, number of sessions per 100,000 population for each county



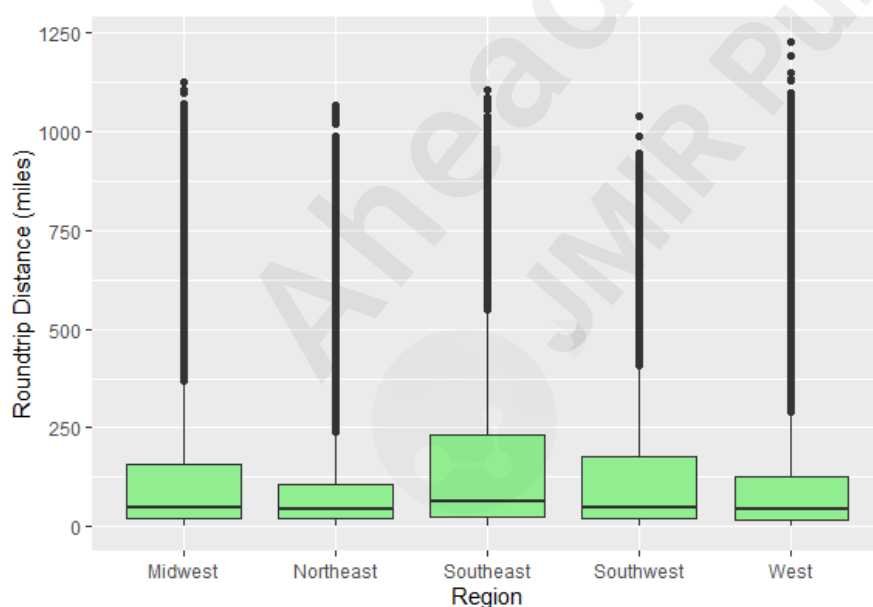
Travel Distance. Travel distance was not normally distributed. Overall, the median roundtrip distance was 49 miles; the mean roundtrip travel distance was 134 miles (SD = 196). Descriptive statistics for roundtrip travel distance (in miles) grouped by day of week, region, and telehealth session length is presented in Table 2. Weekends show the highest roundtrip distance (mean = 150, median = 52). The Southeast region showed the highest distance of travel (mean = 167, median = 63). Telemedicine sessions of 5-30 minutes duration showed highest travel distance (mean = 144, median = 54). Figure 3 shows boxplots of roundtrip travel distance, by region. The boxplots illustrate regional variation, the skewed distribution of distance across all regions, and the presence of high distance outliers.

Table 2. Roundtrip travel distance (miles), for proportional sample (n=79,904).

	n	Mean	Media	SD	Minimu	Maximu
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			n		m	m
Day of Week						
Monday	13777	131	49	194	0	1228
Tuesday	18134	132	49	195	0	1191
Wednesday	17751	135	49	198	0	1130
Thursday	17052	133	49	195	0	1098
Friday	10711	136	50	198	0	1065
Sat-Sun	2479	150	52	210	0	1065
Region						
Midwest	13788	143	48	209	0	1127
Northeast	27311	106	46	157	0	1065
Southeast	16318	167	63	214	0	1104
Southwest	7308	145	49	205	0	1040
West	15179	136	44	217	0	1228
Session Length						
30-120 mins	44700	126	46	190	0	1228
5-30 mins	35204	144	54	204	0	1130

Figure 3. Boxplots of roundtrip travel distance (miles) by U.S. region, for proportional sample ($n=79,904$).



Emissions Savings and Expenditures. The emissions savings and expenditures are detailed in Table 3. The mean CO₂ savings per telemedicine session was 54,077 (grams), median = 19,812 (grams). The mean CO₂ savings per minute of telemedicine care was 2896 (grams), median = 723 (grams). For the 6,231,614 doxy.me telemedicine sessions,

we estimate a savings of 123,461 metric tons of CO₂ (calculated with median). Further, we estimate that nationally, the use of telemedicine in the U.S. during the years 2021- 2022 resulted in approximate annual CO₂ emissions savings of 1,443,800 metric tons (calculated with median).

Table 3. Travel and emissions calculations per session, for proportional sample (n=79,904).

	Mean	Median	SD	Minimum	Maximum
Travel time, round-trip, automobile* (hours)	2.38	1.15	3.01	0.00	22.94
Travel distance, round-trip, automobile* (miles)	133.87	49.05	196.44	0.00	1227.55
Transportation-related CO ₂ emissions savings (grams)	54085.06	19818.13	79362.04	0.00	495928.64
Duration (minutes)	34.53	36.73	20.03	5.00	119.83
CO ₂ emissions equivalent of telemedicine energy use (grams)	8.07	8.59	4.68	1.17	28.02
Net emissions savings per telemedicine session (grams)	54076.99	19812.45	79362.26	-27.89	495921.13
Net emissions savings per minute of session length (grams)	2896.17	722.99	6258.47	-0.23	79230.29

*Calculated using Google Distance Matrix API

Discussion

We used national, observational data to determine the travel distance between patients and providers participating in telemedicine sessions. Further, we used our findings to generate national estimates of CO₂ emissions costs and savings. Under the relatively stable relevant policy conditions of the years 2021 and 2022, we estimate the annual emissions savings

associated with U.S. telemedicine in as 1,462,932 metric tons, or nearly 1.5 million metric tons. This is the equivalent to the CO₂ emissions from approximately 3.4 million barrels of oil or 165 million gallons of gasoline.(46) This estimate is unique in that it was based upon a large national set of observational data, calculation of travel distance using Google Distance Matrix, and a set of conservative assumptions related to telemedicine connections and behavior. Further, we estimated emissions savings per telemedicine session and per minute of telemedicine care delivery, potentially useful estimates for modeling the environmental impact of healthcare programs and services. Previously published estimates of emissions savings were based on regional or local telemedicine utilization and are not directly comparable. Here, we generated estimates based on a large national sample of U.S. telemedicine sessions conducted in varied geographic areas by healthcare providers of varied specialties.

We used round-trip travel distance determined using Google Distance Matrix rather than geodesic distance as the basis for emissions savings estimates. With geodesic distance ≤ 400 , travel distance by car still exceeded 1000 miles in some rare cases, particularly in the West, but was typically much lower. We found that travel distance varied according to region and day of the week. On weekends, there were fewer telemedicine sessions, but the travel distance between providers and patients was greater. This may reflect weekend telemedicine staffing patterns that utilize more distant health care providers, or the use of telemedicine services based in more distant geographical areas, when local, in-person health care services are closed over a weekend. Additionally, we observed some regional variation in the distribution of travel distance. We observed the highest median travel distance between patients and providers in the southeastern U.S., and the lowest median distance in the West. Additionally, shorter sessions were characterized by greater distances, which could reflect decisions to manage brief

encounters such as follow-up visits by telemedicine when patients are particularly distant from the health care provider.

We found a median round-trip travel distance by automobile of 49.05 miles, based upon the approximate locations of patients and providers participating in telemedicine sessions. This estimate is far lower than the travel distance savings found in larger pre-pandemic research studies.(24) For example, Thota et al found a mean round-trip distance savings of 332 miles per encounter for virtual cancer care in rural Utah.(29) A pre-pandemic study of telemedicine consultations in the UC Davis system found a mean round-trip distance savings of 278 miles.(30) A larger and more recent pandemic era study of telemedicine in five UC health systems showed a substantially lower round-trip travel distance savings of 17.6 miles, likely reflecting widespread pandemic-era telemedicine adoption and increased use of telemedicine in urban areas of the U.S.(47) Our results align most closely with those of Sharma and colleagues(47), consistent with the similar timeframe and pandemic-era telemedicine use patterns. Our results likely differ because we used an entirely different approach to calculating travel distance; we used google distance matrix to calculate automobile travel distance based on observational data describing the approximate actual location of patients and providers during telemedicine sessions, rather than geodesic (point-to-point) distance and historical street address data as in most previous studies. Further, our analysis was based on national data that reflects greater geographical diversity and diversity in patterns of telemedicine use.

To slow global warming and climate change, we must reduce CO₂ emissions in the health care sector. Though we estimate a substantial net savings of CO₂ emissions through telemedicine, these savings are equivalent to merely .02% of the total U.S. CO₂ emissions in 2021 (6,340.2 million metric tons).(48) Telemedicine is clearly important in reducing GHG, but must combined with other innovative programs, services, and changes in

behavior within and beyond the health care sector. An increasing number of health care organizations in the United States have committed to reducing their carbon footprint. For example, Kaiser Permanente achieved carbon neutrality in 2020, and University of California San Francisco is working toward carbon neutrality by 2025.(49) Given our findings, the environmental impact of telemedicine should be duly considered in designing programs and services, as part of the effort to reduce health care's carbon footprint.

Limitations and Considerations. The estimates in this study depend upon a series of assumptions related to energy-consuming human behaviors. However, many of the assumptions are conservative and, if erroneous, would underestimate rather than overestimate CO₂ emissions savings. For example, we used adult commuting patterns to determine the percentage of travel occurring by car. However, patients who use alternative transportation to work (e.g., public transportation, biking, walking) may still travel by car to health care appointments. Also, the use of cars for travel to health care appointments may differ for children, retired, elderly or disabled persons.

Similarly, we assumed patients would not travel to in-person appointments in place of telemedicine when the geodesic distance exceeds 400 miles and excluded sessions with a geodesic distance > 400 from the analysis. Given this distance, if telemedicine was not an option, we reason that patients would have sought alternative local care or missed care. In reality, a certain proportion of these patients may travel unusually long distances, especially those seeking specialty care (e.g., care at a cancer center) and patients in frontier areas. However, we made the decision to exclude high-distance telemedicine sessions to avoid inflated estimates.

Another critical assumption is that doxy.me data are nationally representative of patients and providers participating in telemedicine. We compared the geographic distribution of doxy.me session data to that reported for Medicare fee-for-service payments

in Grace (2020) by state. (45) We found them to be highly similar (see *appendix 1*). States with higher dense populations, such as California, New York, and Texas, are consistent in higher telemedicine session use in both sources. In contrast, more rural states like Wyoming have consistently low utilization (*Appendix A*). The overall market share of the doxy.me platform has been estimated by third parties as between 7-30% of U.S. telemedicine.(32–34,50–52)

For doxy.me specialty data, we were limited to the data available through deterministic linkage of doxy.me provider accounts to NPPES, which was available for only 43.55% of the sessions. To gain insight into whether the doxy.me data is nationally representative in terms of specialty, we compared the distribution of specialty in the doxy.me data to that of the Medicare fee-for-payment data described by Grace (2020).(45) There were marked differences in the distribution of specialties, which may or may not be attributable to quality issues in the linked specialty data (see Appendix 1). However, mental health services, psychiatry, and social work were consistent and frequent specialties in both doxy.me and the Medicare data. The types of telemedicine supported by the doxy.me telemedicine platform may differ somewhat from those of other platform providers. Doxy.me has a firm market share among mental health providers, offering integrated digital health functionality for mental health care. Thus, the sample that we analyzed may over-represent mental health services and under-represent other health care specialties.(53) Given the large amount of missing data for specialty, and substantial differences compared to Medicare claims data, we did not estimate telemedicine emissions savings by provider specialty.

The total number of telemedicine sessions that occur in the U.S. during a given year is unknown. We based our estimate on actual CMS reimbursement for telemedicine during 2021, and the proportion of U.S. healthcare expenditures funded by CMS. Both 2021 and

2022 were years during the federal health emergency declaration related to the COVID-19 pandemic. Federal and state policy related to reimbursement and licensing can substantially affect telemedicine utilization patterns. However, policy was relatively stable during the years 2021-2022.

In future work, we plan to update and refine these estimates based on observational data describing real-world telemedicine connection characteristics and the type of devices used to connect, which affect the energy costs associated with telemedicine. We also plan to incorporate energy costs associated with standard, in-person care delivery including built infrastructure and personnel transportation. More robust specialty data would enable additional insights into potential variation in CO₂ emissions costs and savings across different types of healthcare. Additionally, future efforts could refine model assumptions based upon observed health care utilization behavior patterns and regional differences in health care service delivery, as the body of evidence describing telemedicine utilization grows.

Conclusion. U.S. healthcare is under increasing scrutiny for contributing to air pollution, climate change, and related adverse health outcomes. To duly consider environmental impacts in decision-making related to healthcare facilities, programs, and services, we must be able to quantify and compare the environmental effects of varied approaches to healthcare delivery. Here, we determined the travel distance between participants in U.S. telemedicine sessions and on that basis, estimated the associated annual CO₂ emissions savings for U.S. telemedicine in 2021-2022 as nearly 1.5 million tons. Further, we estimated emissions savings per telemedicine session, and per minute of telemedicine care delivery based upon a large, national sample of telemedicine sessions. In doing so, we adopted conservative assumptions related to patient behavior and transportation and considered both energy savings and expenditures of telemedicine. The

results indicate that telemedicine is an important strategy in reducing the healthcare sector's carbon footprint. Additionally, the findings enable quantification of telemedicine-associated CO₂ emissions savings.

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Conflicts of Interest. Author Welch is the founder, CEO, and shareholder of Doxy.me Inc, a commercial telemedicine company. Authors Cummins, Ivanova, Ong, Soni, Barrera, Wilczewski & Bunnell are employees of the same company. The authors declare no other conflicts of interest.

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List of Abbreviations

U.S. = United States

CMS = Centers for Medicare & Medicaid Services

CO₂ = carbon dioxide

EIOLCA = economic input-output lifecycle assessment

GHG = greenhouse gas

kWh = kilowatt hours

GB = gigabyte

HIPAA = Health Insurance Portability and Accountability Act of 1996

IP = Internet Protocol

UTC = coordinated universal time

API = application programming interface

EPA = U.S. Environmental Protection Agency

HD = High Definition



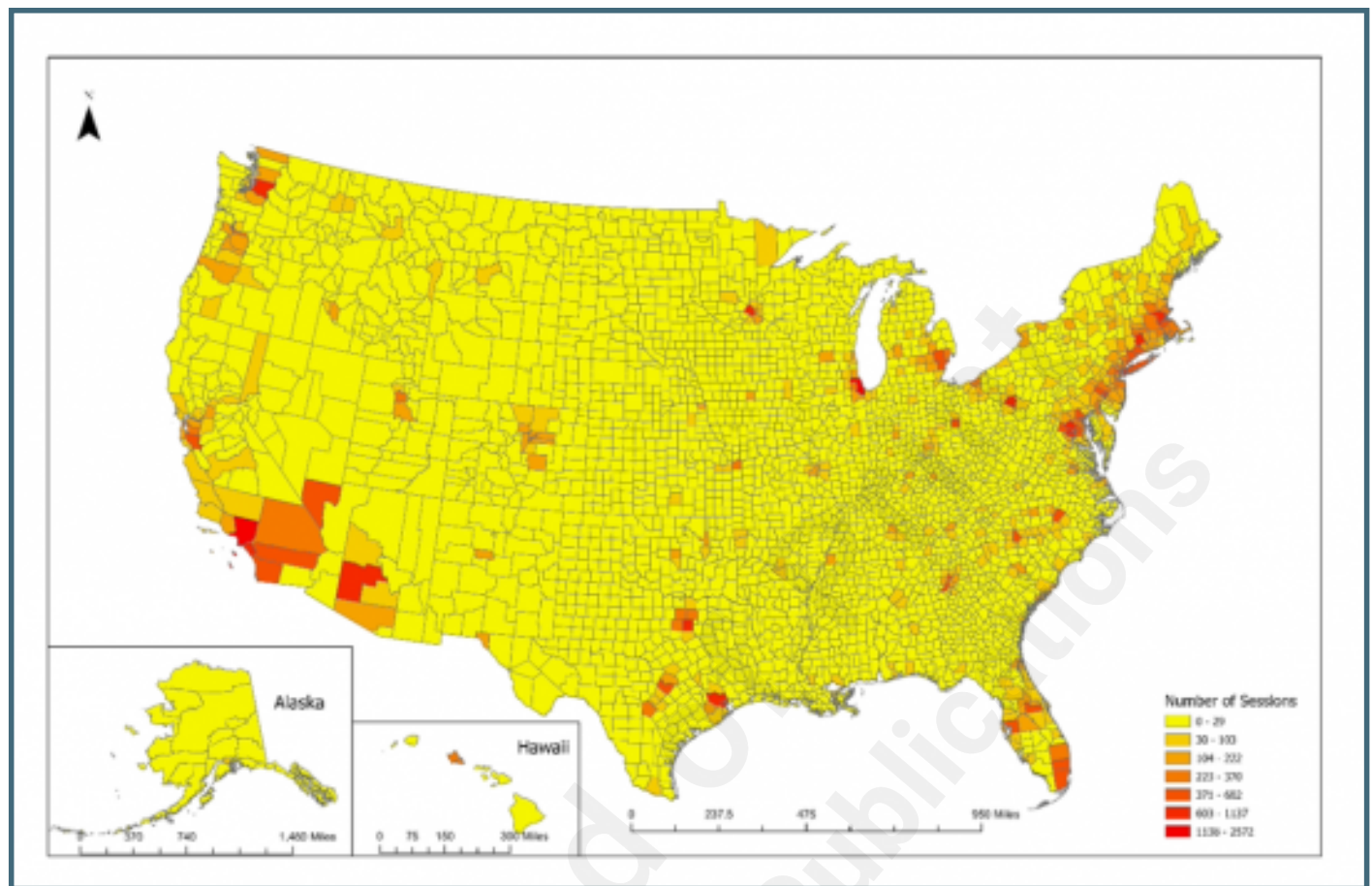
Supplementary Files

Comparison of doxy.me session characteristics to other national data (state, specialty).

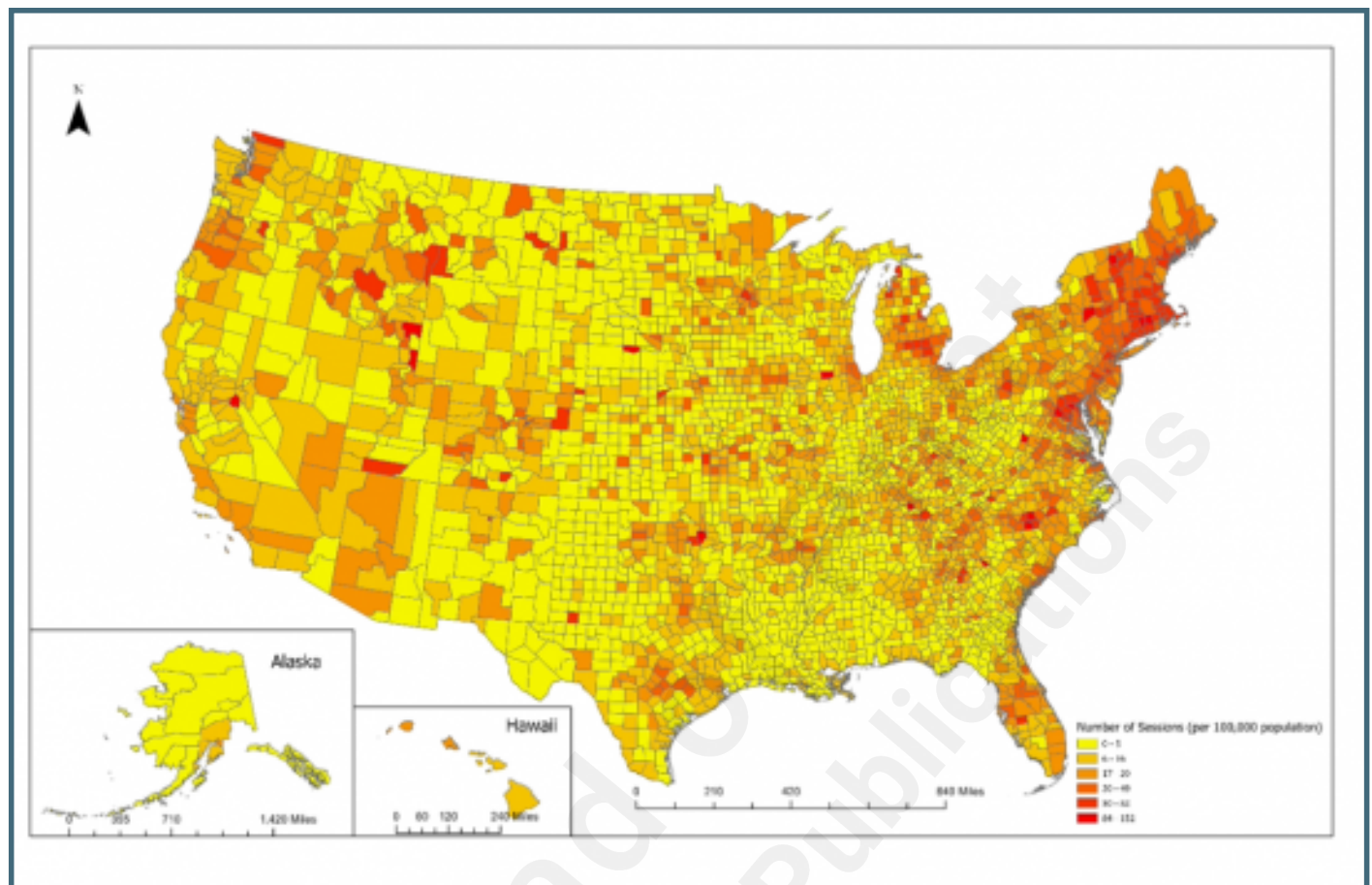
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Figures

Geographical distribution of telemedicine sessions, total number of sessions for each county.



Geographical distribution of telemedicine sessions, number of sessions per 100,000 population for each county.



Boxplots of roundtrip travel distance (miles) by U.S. region, for proportional sample (n=79,904).

