RESEARCH ARTICLE

Mobile Phone GPS Data and Prevalence of COVID-19 Infections: Quantifying Parameters of Social Distancing in the U.S.

Nicholas N. DePhillipo, PhD, ATC[1,2]; Jorge Chahla, MD, PhD[3]; Michael Busler, PhD[4]; Robert F. LaPrade, MD, PhD[1]

Research performed at Twin Cities Orthopedics, Edina, MN, USA

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Abstract

Background: To evaluate the association between social distancing quantified by mobile phone data and the current prevalence of COVID-19 infections in the U.S. per capita.

Methods: Data were accessed on April 4, 2020, from Centers for Disease Control and Prevention, Google COVID-19 Community Mobility Report, and the United States Census Bureau to report prevalence of COVID-19 infections, mobility data, and population per state, respectively. Mobility data points were defined as daily length of visit or time spent in a single location based on mobile phone users shared locations from February 7 – March 29, 2020. Multivariable linear regression was used to evaluate relationships between normalized per capita infection prevalence and six parameters of social distancing.

Results: Mobility data indicated the following percent changes compared to median values of baseline activity: -50% in transit stations, -45% in retail/recreation, -36% in workplaces, -23% in grocery/pharmacy, -19% in parks, and +12% in residential living areas. Multivariable linear regression revealed significant correlation between prevalence of infection per capita and parameters of social distancing (*R*= 0.604, *P= 0.002*). Time at home was not an independent predictor for prevalence of infection per capita (beta= 0.016; 95% CI, -0.003 to 0.036; *P= 0.09*).

Conclusion: Based on mobility reports from mobile phone GPS data and six characteristics of social distancing, significant associations were identified between geographic activity and prevalence of COVID-19 infections in the U.S. per capita. Mobile phone data utilizing 'location history' may be warranted to monitor the effectiveness of social distancing parameters on reducing prevalence of COVID-19 in the U.S.

Level of evidence: IV

Keywords: Coronavirus, Contact tracing, Social distancing

Introduction

Since the novel coronavirus (COVID-19) was declared a global pandemic on March 11, 2020, public health officials have been feverishly working to monitor and reduce the exposure of persons to this virus (1-3). As communities strive to impart ways to control infectious outbreaks, the virus continues to cause significant economic, social, and political disruption. Social distancing has been identified as one of the main interventions to prevent the spread of global disease (4-7). As infection rates continue to rise in the United States (U.S.) for COVID-19, it is important to evaluate the real-time effects of social distancing as they relate to disease infection prevalence (8, 9).

Previous reports indicate that during the SARS (severe acute respiratory syndrome virus) epidemic in 2003, public health measures were critical in controlling the

Corresponding Author: Robert F. LaPrade, Adjunct Faculty University of Minnesota, Twin Cities Orthopedics, Edina, MN, USA
Email: Laprademdphd@gmail.com

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infectious outbreak (10). There are different methods of controlling infections by means of reducing human-to-human contact, which include isolation, quarantine, and community containment. Isolation is the separation of infected persons from non-infected persons, whereas quarantine is movement restriction of persons when it is not evident whether they have been infected but are not yet symptomatic or have not been infected (11). Community containment includes measures that range from increasing social distancing to community-wide quarantine. An important concept in evaluating successful interventions is the ability to analyze in real-time how infection rates change with containment strategies (9, 12, 13).

Recent research demonstrates the potential effectiveness of quarantine in controlling COVID-19 as seen in Wuhan, China; however it remains unclear if the current measures of community containment such as social distancing will be sufficient to control the spread of COVID-19 in the U.S (14, 15). Utilizing mobile phone data as a means of public monitoring has been recommended (9, 16). Yet, there is limited data to support validation of using mobile phone data to quantify social distancing parameters and its association on COVID-19 infection prevalence. Therefore, the purpose of this study was to evaluate the association between social distancing quantified by mobile phone data and the current prevalence of COVID-19 infections in the U.S. per capita.

Materials and Methods

Study Design & Data Extraction

This observational study was conducted utilizing publicly available records. Due to study design and lack of access to personally identifiable datasets, evaluation from an institutional review board committee was not warranted. Public data sources were screened to gather three key data points regarding U.S. populations: 1) current prevalence of COVID-19 infections per state, 2) current mobility data per state, and 3) current total living population per state. Data were accessed on April 4, 2020, from the Centers for Disease Control and Prevention (as of April 3, 2020), Google (Google LLC, Mountain View, CA, USA) Analytics COVID-19 Community Mobility Report (as of March 29, 2020; Supplement 1), and the United States Census Bureau (as of December 2019; Supplement 2), to report prevalence of COVID-19 infections, mobility data, and population per state, respectively (17).

According to Google LLC, all geographical data input from mobile phone users is aggregated and anonymized including publicly accessible records such as Google's COVID-19 Community Mobility Report. Mobility data was determined from users who have actively turned on their 'Location History' setting in correspondence with their mobile phones global positioning system (GPS) (i.e. Google Maps, Google LLC, Mountain View, CA, USA). These Community Mobility Reports chart movements over time by geography and across different categories of places which aim to provide insight to how visits and length of stay at different places change compared to a previous time period.

Outcomes Measures

For mobility data, six parameters of social distancing were defined and used in the analysis: 1) retail and recreation, 2) grocery and pharmacy, 3) parks, 4) transit stations, 5) workplaces, and 6) residential areas. Mobility data points were defined as daily length of visit or time spent in a single location based on Google users shared locations from February 7 – March 29, 2020 (experiment period). Parameters of mobility were expressed as a percent change in the median value in comparison to the baseline activity. Baseline activity was defined as the median value for the corresponding day of the week during a 5-week period of January 3 – February 6, 2020.

Statistical Analysis

Descriptive statistics were gathered and reported for COVID-19 infection prevalence and populace per state in the U.S. Infection rates were normalized for each state according to total current living population and expressed as a percentage. For social distancing parameters, the median values of mobility data were used to determine a percent change from baseline and expressed as either positive activity (increase time spent) or negative activity (decrease time spent). Multivariable linear regression modelling was used to evaluate associations between normalized per capita infection prevalence and geographic mobility. For the multivariable regression model, the previously mentioned six parameters of social distancing were entered with an alpha level set at $P < 0.05$ for statistical significance. Due to the fixed sample size (n=51) and unknown aggregate data from public sources, a power analysis was not calculated and additional confounders (e.g. age, sex, comorbidities) were unable to be entered to adjust the model. Residual diagnostics were performed to assess whether model assumptions were satisfactorily met. Unless otherwise noted, data were reported as median (first and third quartiles). Data were analyzed using SPSS statistical software version 22.0 (IBM Corp).

Results

Infection Prevalence

As of April 4, 2020, the total number of COVID-19 infections in the U.S. was 238836, which corresponds to 0.07% of the total U.S. population. The median number of infections per state was 1358 [479, 3824] (0.03% per capita). The highest numbers of COVID-19 infections were 90279, 25590, and 10791 for New York, New Jersey, and Michigan, respectively. Per capita, New York (0.46%), New Jersey (0.29%), and Louisiana (0.20%) had the highest infection prevalence. The lowest number of COVID-19 infections were 147, 150, and 159 for Alaska, Wyoming, and North Dakota, respectively. Per capita, West Virginia (0.01%), Nebraska (0.01%), and Minnesota (0.01%) had the lowest infection prevalence [Table 1].

Social Distancing

During the experiment period from February 7 to March 29, 2020, mobility data across 51 states indicated the following percent changes compared to baseline activity: -50% [-60, -34] activity in transit stations, -45% [-53, -39] activity in retail/recreation, -36% [-39, -33] activity in

Table 1. Prevalence of COVID-19 infections in U.S. and percent change in six domains of social distancing[a,b]

State	Number of †Infections	††State Population	Infections Per *Capita	Retail & Recreation	Transit	Grocery & Pharmacy	Workplace	Parks	Residential
AL	1270	4903185	0.03	-41	-30	-13	-32	19	9
AK	147	731545	0.02	-48	-55	-27	-33	18	10
AZ	1598	7278717	0.02	-40	-41	-17	-33	-7	10
AR	679	3017804	0.02	-29	-22	-7	-27	81	7
CA	9191	39512223	0.02	-50	-54	-24	-39	-38	15
CO	3728	5758736	0.06	-51	-60	-27	-40	-12	13
CT	3824	3565287	0.11	-56	-64	-32	-38	-52	15
DE	393	973764	0.04	-47	-57	-28	-37	-6	12
DC	653	705749	0.09	-64	-68	-30	-47	-41	14
FL	8694	21477737	0.04	-50	-63	-26	-41	-48	13
GA	5486	10617423	0.05	-42	-52	-17	-37	-2	11
HI	225	1415872	0.02	-56	-72	-36	-45	-65	16
ID	891	1787065	0.05	-42	-34	-18	-38	25	10
IL	7695	12671821	0.06	-53	-55	-24	-39	-29	13
IN	3039	6732219	0.05	-48	-34	-25	-36	24	11
IA	614	3155070	0.02	-43	-28	-10	-29	41	10
KS	552	2913314	0.02	-36	-20	-14	-30	72	9
KT	770	4467673	0.02	-37	-34	-11	-34	68	9
LA	9150	4648794	0.20	-45	-49	-16	-35	-18	11
ME	376	1344212	0.03	-50	-56	-22	-31	-24	10
MD	2331	6045680	0.04	-45	-51	-25	-39	29	13
MA	8966	6892503	0.13	-59	-73	-36	-42	-56	16
MI	10791	9986857	0.11	-58	-55	-28	-43	15	12
MN	789	5639632	0.01	-58	-64	-35	-38	-16	14
MS	1358	2976149	0.05	-32	-29	-7	-30	27	9
MO	1834	6137428	0.03	-38	-34	-12	-32	73	9
MT	244	1068778	0.02	-51	-37	-25	-37	28	10
NE	255	1934408	0.01	-34	-18	-9	-24	109	8
NV	1458	3080156	0.05	-47	-62	-23	-52	-38	14
NH	479	1359711	0.04	-58	-63	-35	-38	-63	13
NJ	25590	8882190	0.29	-59	-70	-33	-44	-36	16
NM	403	2096829	0.02	-44	-31	-18	-34	-12	11
NY	90279	19453561	0.46	-62	-68	-32	-46	-47	16
NC	2093	10488084	0.02	-40	-51	-15	-35	13	10
ND	159	762062	0.02	-44	-36	-13	-24	73	9
OH	2902	11689100	0.02	-43	-33	-19	-35	117	10
OK	879	3956971	0.02	-36	-23	-12	-32	29	9
OR	826	4217737	0.02	-51	-47	-25	-38	-22	12
PA	7016	12801989	0.05	-50	-52	-27	-38	7	12
RI	681	1059361	0.06	-55	-67	-30	-37	-50	14

Table 1. Continued

SC	1554	5148714	0.03	-38	-34	-11	-34	-4	9
SD	165	884659	0.02	-35	-31	-3	-25	126	8
TN	2845	6829174	0.04	-35	-35	-9	-34	35	8
TX	4669	28995881	0.02	-45	-47	-23	-36	-27	13
UT	1165	3205958	0.04	-41	-44	-14	-40	26	10
VT	338	623989	0.05	-62	-71	-42	-43	-55	13
VA	2012	8535519	0.02	-39	-50	-16	-36	46	11
WA	5683	7614893	0.07	-48	-56	-26	-41	-11	13
WV	217	1792147	0.01	-38	-31	-16	-33	52	8
WI	1730	5822434	0.03	-55	-50	-30	-34	-12	13
WY	150	578759	0.03	-37	-14	-13	-29	29	8

†As reported by Centers for Disease Control and Prevention on April 3, 2020.
††As reported by United States Census Bureau on December 31, 2019.
*Value: (number of infections / total living population) = percentage of infections per capita
aParameters of mobility are expressed as percent change in comparison to baseline activity. Baseline activity is defined as the median value for the corresponding day of the week during 5-week period of January 3 – February 6, 2020.
bValues: negative values indicate percent decrease in time spent in location compared to baseline; positive values indicate percent increase in time spent in location compared to baseline.

workplaces, -23% [-28, -13] activity in grocery/pharmacy, -19% [-29, 9] activity in parks, and +12% [9, 13] activity in residential living areas. Multivariable linear regression revealed significant correlation between prevalence of infection per capita and parameters of social distancing (R^2= 0.365, *R*= 0.604, *P= 0.002*); specifically, as geographic mobility increased, infection prevalence increased [Figure 1]. Independent predictors of lower prevalence of infection per capita were decreased retail/recreation activity (beta= -0.007; 95% CI, -0.013 to -0.001; *P= 0.02*) and decreased grocery/pharmacy activity (beta= 0.008; 95% CI, 0.002 to 0.014; *P= 0.01*). Despite the overall increase in residential activity compared to baseline (range, 7-16%), time at home was not an independent predictor for prevalence of infection per capita (beta= 0.016; 95% CI, -0.003 to 0.036; *P= 0.09*) [Table 2].

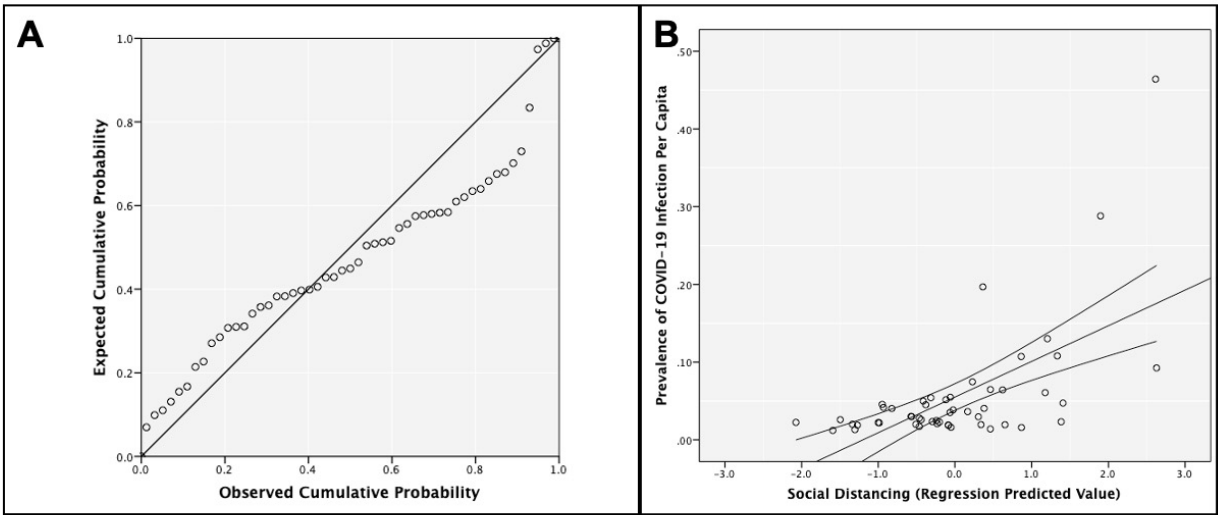

Figure 1. A) Normal P-P plot of standardized residuals demonstrating normal distribution of data. B) Scatterplot of multivariable linear regression between social distancing parameters and prevalence of COVID-19 infections per capita in the U.S. Lines above and below center line represents 95% confidence intervals. There was a significant positive correlation between mobility activity and prevalence of COVID-19 infections (R= 0.604, *P= 0.002*).

Table 2. Multivariable linear regression model for social distancing parameters and prevalence of COVID-19 infections per capita

	Beta[a]	95% CI	SE	*t Value*	*P Value**
(Intercept)	-0.390	-0.628 to -0.152	0.118	-3.30	0.002
Retail & Recreation	-0.007	-0.013 to -0.001	0.003	-2.36	0.023
Transit	0.000	-0.003 to 0.003	0.001	0.12	0.900
Grocery & Pharmacy	0.008	0.002 to 0.014	0.003	2.56	0.014
Workplace	-0.003	-0.008 to 0.003	0.003	-0.91	0.364
Parks	0.000	-0.001 to 0.001	0.000	0.49	0.625
Residential	0.016	-0.003 to 0.036	0.010	1.68	0.099

*Statistical significance considered *P<0.05*.
aBeta values are the expected change in infection prevalence given a 1-unit decrease in that covariate, holding all other variables constant.

Discussion

The most important finding of this study was the validation of using mobile phone GPS data to evaluate social distancing efforts which were associated with COVID-19 infection prevalence in the U.S. per capita. Based on this current study, mobility habits including time spent at home and in public areas have changed dramatically in the past two months due to the COVID-19 pandemic, corresponding with local quarantine and governmental mandates of social distancing. However, regression analysis failed to demonstrate association between increased residential time (during February 7 to March 29, 2020) and decreased prevalence of COVID-19 infections per capita. This mobility data can provide insight to potential social distancing effectiveness and it can be recommended to share mobile phone data for monitoring and tracking of infection prevalence in the U.S.

In the current study, there was a significant positive correlation between geographic activity and COVID-19 infection prevalence, providing justification for social distancing for virus containment. The positive association is best related to the ongoing and current infection prevalence of CVOID-19 in the U.S. As infection rates continue to rise, it appears community's movement patterns and geographic exposure may directly influence prevalence. However, because of the study methodology and data collection procedures, this study is unable to evaluate the effectiveness in reducing COVID-19 prevalence by means of social distancing. Recently, Hou et al. evaluated containment strategies for COVID-19 in Wuhan City, China, and demonstrated effectiveness of quarantine and isolation in reducing the potential peak number of COVID-19 infections (14). Similarly, others have reported the tremendous potential of social distancing in controlling disease transmission for influenza and the current novel coronavirus (4, 5, 8, 18-20). Therefore, continued intervention strategies of social distancing in the U.S. are warranted in an effort to prevent the spread of COVID-19 (11, 21, 22).

According to mobility reports using GPS 'Location History' of mobile phone users (Google LLC) in the U.S., the largest overall changes in mobility areas since February 7, 2020 were seen in transit stations, with a decrease of 50% activity reported compared to baseline activity. However, decreased activity reported in retail/recreational areas and grocery/pharmacy areas were found to independently predict COVID-19 infection prevalence per capita. Despite the increased time seen in residential locations, identifying with current mass social distancing, there was no association with decreased infection prevalence. However, this parameter of social distancing had the lowest range (7-16%) and smallest overall percent change (+12%) compared to baseline values and in comparison to the other five parameters of social distancing. This finding may help guide public health officials on future recommendations of implementing wider forms of community containment for controlling COVID-19 in the U.S (2, 23, 24).

In the current multivariable regression model, a significant linear relationship was identified— indicating lower infection prevalence with lower activity in community areas and higher prevalence with higher activity in community areas. Using mobile phone data from GPS tracking systems is an imperfect science, yet this can serve as an accessible form of global monitoring of human movement patterns in real-time by potentially less invasive means in comparison to mass monitoring strategies. Thus, maintaining user privacy is a major concern. Reports by Google LLC indicate that all data is aggregated and anonymized and based on user consent of agreeing to monitor 'Location History', therefore ensuring privacy protection and complying with ethical policies. Strict large-scale data monitoring as seen in China has illustrated success in mitigating and reducing virus transmission (9, 14, 15, 24). However, this type of mass surveillance may be contraindicated in the U.S. as it violates freedom policies and privacy laws. Therefore, further planning of mobile phone data collection and analysis is needed in order to ensure user privacy and that ethical standards are not compromised (4, 25, 26).

The present study is a small-scale attempt to validate the use of mobile phone data to quantify current social distancing parameters and their association with prevalence of COVID-19. However, further information is needed to apply large-scale statistical modelling in order to adjust for all potential confounding variables such as age, sex, comorbidities, and exposure risk. Also, implementation of enhanced technologies may increase efficiency of data collection and reporting during the current pandemic. This has been reinforced by previous authors who recommend the use of machine learning algorithms and artificial intelligence to rapidly identify infectious contacts and more efficiently reduce the spread of COVID-19 infections (9). Utilizing immediately available data that allows for analyzing the effectiveness of community containments in real-time can ultimately guide government policy on when to resume normal ways of living (22, 24, 27, 28). With the current state of economic turmoil, it is vitally important to understand the effects of social distancing and community containment in real-time as the infrastructure of the global economy is at risk with prolonged quarantine (4, 15, 29).

Based on mobility reports from mobile phone GPS data and six characteristics of social distancing, significant associations were identified between geographic activity and prevalence of COVID-19 infections in the U.S. per capita. Mobile phone data utilizing 'location history' may be warranted to monitor the effectiveness of social distancing parameters on reducing prevalence of COVID-19 in the U.S.

Limitations

This study is not without limitations. First, there was inherent selection bias based on the data collection methods because social distancing outcomes represent a sample of mobile phone users of Google applications, limiting the external validity and generalizability of the current sample to the entire U.S. population. Second, the unknown number of observations limits the ability to conduct sensitivity testing as well as calculation of odds ratios for determining relative risk of disease transmission. Third, due to study design, this study was unable to demonstrate causal inference as relates to social distancing and COVID-19 infection rates. Rather the intention of this study was to report relationships and demonstrate proof-of-concept for large-scale interventions. Prospective studies and long-term follow-up are needed to assess the accuracy of mobile phone data and its ability to monitor social distancing intervention strategies on COVID-19 containment.

Nicholas N. DePhillipo PhD ATC[1, 2]
Jorge Chahla MD PhD[3]
Michael Busler PhD[4]
Robert F. LaPrade MD PhD[1]
1 Adjunct Faculty University of Minnesota, Twin Cities Orthopedics, Edina, MN, USA
2 Oslo Sports Trauma Research Institute, Oslo, Norway
3 Midwest Orthopaedics at Rush, Chicago, IL, USA
4 Stockton University, Galloway, NJ, USA

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