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Linking Self-Reported Social Distancing to Real-World Behavior During the COVID-19 Pandemic

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Abstract

In an effort to combat COVID-19 and future pandemics, researchers have attempted to identify the factors underlying social distancing. Yet, much of this research relies on self-report measures. In two studies, we examine whether self-reported social distancing predicts objective distancing behavior. In Study 1, individuals' self-reported social distancing predicted decreased mobility (assessed via smartphone step counts) during the COVID-19 pandemic. While participants high in self-reported distancing (+1 *SD*) exhibited a 33% reduction in daily step counts, those low in distancing (−1 *SD*) exhibited only a 3% reduction. Study 2 extended these findings to the group level. Self-reported social distancing at the U.S. state level accounted for 20% of the variance in states' objective reduction in overall movement and visiting nonessential services (calculated via the GPS coordinates of ∼15 million people). Collectively, our results indicate that self-reported social distancing tracks actual social distancing behavior.

Keywords

social distancing, COVID-19, coronavirus, self-report, physical distancing

During viral pandemics, public health officials strongly encourage people to socially distance (e.g., Strochlic & Champine, 2020; World Health Organization, 2020). Indeed, sustained social distancing helped contain the 1918 Influenza pandemic (e.g., Strochlic & Champine, 2020) and stopped exponential viral spread during the COVID-19 pandemic (e.g., Anderson et al., 2020; Kissler et al., 2020; McGrail et al., 2020). Despite its importance, however, variability in social distancing exists. For instance, at the start of COVID-19 (March 2020), while New Yorkers were sheltering-in-place, spring breakers in Florida enjoyed packed beaches (Dusenbury, 2020) and people in Chicago attended St. Patrick's Day celebrations (Rahman, 2020).

Researchers have thus scrambled to elucidate the individual- and group-level variables underlying social distancing. For instance, they have examined whether women social distance more than men (Olcaysoy Okten et al., 2020), how boredom proneness and self-control can impair distancing (Wolff et al., 2020), and whether political partisanship predicts distancing (Gollwitzer et al., 2020), among other predictors. Studies have also examined whether certain interventions can heighten people's distancing, including drawing attention to prosocial benefits (Jordan et al., 2020), eliciting feelings of empathy (Heffner et al., 2020; Pfattheicher et al., 2020), and introducing stay-at-home orders at the group level (Engle et al., 2020). These examples are merely a small portion of this research; however, ∼29,700 results were found when searching for "social distancing" + "COVID-19" on Google Scholar on March 26, 2020, and selecting "Since 2020" as the publication criteria. All these research efforts ideally should inform policy makers on how to motivate people (and *whom* to motivate) to engage in distancing during pandemics (Van Bavel et al., 2020).

However, due to the urgency of this line of work and the inability to perform in-person behavioral studies (in part due to distancing efforts themselves), much of this research relies on self-report measures.[1] This may be problematic for several reasons. For instance, individuals may overreport their distancing due to social desirability bias (Fisher, 1993; Maccoby & Maccoby, 1954), maintaining positive self-impressions (Leary & Kowalski, 1990), evaluating themselves more favorably than others (Alicke & Govorun, 2005), and not remembering distancing failures (Kouchaki & Gino, 2016). Indeed, a rich literature has documented gaps between self-reported judgments and

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actual behavior, including the intention–behavior gap (Sheeran & Webb, 2016), attitude–behavior gap (Ajzen & Fishbein, 1977), and knowledge–behavior gap (Hornik, 1989). Taken together, then, the COVID-19 pandemic provides a naturalistic test case of whether people's self-reported and actual behavior aligns in the midst of a worldwide emergency in which the behavior in question (distancing) has serious consequences (infection and death).

In two studies, we tested whether self-reported and objective distancing overlapped during the COVID-19 pandemic. In Study 1, we assessed this link at the individual level. Because a core component of social distancing involves staying home (e.g., sheltering-in-place, avoiding travel), individuals who are distancing should exhibit reduced mobility from before to during COVID-19. To test this possibility, we examined whether participants' self-reported distancing predicted a greater reduction in average daily step count from before to during COVID-19 as assessed by participants' smartphone pedometers.

Notably, Study 1 provides a conservative test of our hypotheses. Although researchers have validated and used smartphone step counters to quantify health behaviors (Duncan et al., 2018; Larson et al., 2004), this data source remains noisy (Ata et al., 2018). For instance, step count presumably captures variance alternate to distancing as well (e.g., exercise). To control for such third variables, in Study 1, we adjusted for participants' step counts before COVID-19 (which should account for general individual differences in step count) and included specific control variables (e.g., jogging or hiking in a distanced manner during COVID-19).

Social distancing varies not only among individuals but also among groups. As illustrated by GPS mobility data (e.g., Barrios et al., 2021; Gollwitzer et al., 2020), fluctuating stay-at-home orders, and patchwork business reopenings (Healy et al., 2020), U.S. states and counties embraced social distancing during COVID-19 at strikingly different degrees. Building on these differences, Study 2 examined whether self-reported and objective distancing during the COVID-19 pandemic overlapped at the U.S. state level. Specifically, we tested whether states' self-reported distancing predicted a greater reduction in states' overall movement and visiting nonessential services from before to during COVID-19 (assessed via the daily GPS coordinates of $\sim$15 million smartphones). Notably, doing so not only sheds light on group-level distancing but also provides insight into cultural variation within a nation (the United States) during a national emergency, an analysis level left unexplored by psychologists (see Harrington & Gelfand, 2014; Vandello & Cohen, 1999; Varnum & Kitayama, 2011).

Before continuing, we note two caveats.[2] First, self-reported and objective distancing may overlap due to a third variable: COVID-19 severity. Participants living in places experiencing severe COVID-19 outbreaks may exhibit higher self-reported distancing for biased reasons (e.g., social norm pressure). And, these participants may also exhibit reduced step counts due to local distancing restrictions. To account for this possibility, in Studies 1 and 2, we controlled for the COVID-19 severity in participants' locations.

Second, in our analyses, we tested two subtypes of self-reported distancing: personal distancing (participants' own reported distancing) and community distancing (participants' judgments of their communities' distancing). Doing so allowed us to test whether these subtypes differentially predict objective distancing. For instance, one might expect a clearer link between personal and objective distancing at the individual level (Study 1) and a clearer link between community and objective distancing at the group level (Study 2).

Study 1

Method

Participants

A sensitivity power analysis indicated that with 258 participants we would have 90% power to find a small effect ($r = .20$; see preregistration).[3] We preregistered to recruit 300 participants on MTurk (to account for exclusion); 302 participants were recruited (126 female; $M_{\text{age}} = 35.26$, $SD_{\text{age}} = 10.83$);[4] 21 participants were excluded for attention failure. We only recruited iPhone users. For detailed materials and additional analyses, see Supplements, Appendix, and Verbatim Materials on Open Science Framework (OSF; https://osf.io/gtjur/?view_only=baafb4c672f54bd2ac38026d7a431831).

Self-Reported Distancing

We included four self-reported distancing measures: an abbreviated measure from political science (Wu & Huber, 2020), a measure from intervention work in psychology (Jordan et al., 2020), a six-item scale out of our own research group, and a two-item face-valid measure. These measures assessed personal (e.g., "I have almost zero in-person social interactions with people I am not living with") and community social distancing (e.g., "People in my community are social distancing"). The measures included general items (e.g., "I am social distancing") and concrete items (e.g., "I am avoiding small gatherings") For verbatim measures see Supplements or Verbatim Material files on OSF (link above). For verbatim measures see Supplements or Verbatim Material files on OSF (link above).

Step Count

Participants reported their average daily step count in the week before participation (April 3–9, 2020) as indicated by their iPhone Health App. Participants also reported their average daily step count before COVID-19: in February 2020, March 2019, and April 3–9, 2019.[5,6]

COVID-19 Severity

We included COVID-19 infections-per-capita in the county in which participants were located on the date of participation (*New York Times*, 2020).

Table 1. Study 1: Output of GLM Models 1 Through 3.

		Predicting Average Daily Step Count Between April 3 and 9, 2020		
Models	Coefficient	Test Statistic	*p* Value	Effect Size
Model #1				
Personal social distancing	$\mathbf{B = -.231}$	$\boldsymbol{\chi^2(1, N = 220) = 11.89}$	$\boldsymbol{p = .001}$	**Exp(*B*) = 0.794, 95% [0.696, 0.905]**
Step count before COVID-19	$B = .742$	$\chi^2(1, N = 220) = 74.05$	$p < .001$	Exp(*B*) = 2.100, 95% [1.774, 2.487]
Jogging/hiking [a]	$B = .041$	$\chi^2(1, N = 220) = 0.28$	$p = .594$	Exp(*B*) = 1.042, 95% [0.897, 1.210]
COVID-19 severity	$B = -.139$	$\chi^2(1, N = 220) = 4.04$	$p = .044$	Exp(*B*) = 0.870, 95% [0.759, 0.997]
Model #2				
Community social distancing	$\mathbf{B = -.106}$	$\boldsymbol{\chi^2(1, N = 220) = 2.40}$	$\boldsymbol{p = .121}$	**Exp(*B*) = 0.899, 95% [0.786, 1.029]**
Step count before COVID-19	$B = .713$	$\chi^2(1, N = 220) = 67.34$	$p < .001$	Exp(*B*) = 2.039, 95% [1.720, 2.418]
Jogging/hiking	$B = .064$	$\chi^2(1, N = 220) = 0.65$	$p = .419$	Exp(*B*) = 1.066, 95% [0.913, 1.244]
COVID-19 severity	$B = -.163$	$\chi^2(1, N = 220) = 5.48$	$p = .019$	Exp(*B*) = 0.850, 95% [0.741, 0.974]
Model #3				
Personal social distancing	$\mathbf{B = -.228}$	$\boldsymbol{\chi^2(1, N = 220) = 10.20}$	$\boldsymbol{p = .001}$	**Exp(*B*) = 0.796, 95% [0.692, 0.916]**
Community social distancing	$\mathbf{B = -.007}$	$\boldsymbol{\chi^2(1, N = 220) = 0.01}$	$\boldsymbol{p = .918}$	**Exp(*B*) = 0.993, 95% [0.864, 1.141]**
Step count before COVID-19	$B = .743$	$\chi^2(1, N = 220) = 73.48$	$p < .001$	Exp(*B*) = 2.102, 95% [1.774, 2.492]
Jogging/hiking	$B = .041$	$\chi^2(1, N = 220) = 0.29$	$p = .590$	Exp(*B*) = 1.042, 95% [0.897, 1.212]
COVID-19 severity	$B = -.140$	$\chi^2(1, N = 220) = 4.04$	$p = .044$	Exp(*B*) = 0.870, 95% [0.759, 0.996]

Note. *B* is the log coefficient (ln transformed). Exp(*B*) is an odds ratio (transformed back from log). Exp(*B*) below one indicates decreased step count. Exp(*B*) above one indicates increased step count. Model 1: A GLM (negative binomial distribution) with personal distancing, average step count before COVID-19, jogging/hiking between April 3 and 9, 2020, and COVID-19 severity in participants' locations as predictors (all z-scored). Model 2: Identical to Model 1 except personal distancing replaced by community distancing. Model 3: Identical to Models 1 and 2 except both personal and community distancing were included as predictors. Self-reported personal distancing predicted lower average daily step count between April 3 and 9, 2020 in Models 1 and 3. Self-reported community distancing neither predicted reduced average daily step count in Model 2 nor in Model 3 (key findings are given in bold). GLM = generalized linear model.
[a]We altered the scale points of this measure and found it to predict greater step-count as expected in Study S1.

Additional Measures

For validation purposes, we assessed participants' perceived control over COVID-19 spread, whether they were traveling for work, and potential comorbidities (e.g., diabetes). We also included a COVID-19 knowledge test.

Procedure

Participants completed the self-reported distancing measures (randomized, clustered together, including the COVID-19 knowledge test) and the step count items (clustered together) in random order. Participants then completed the additional measures and the attention check.

Results

Analyses in Studies 1, 2, and S1 were conducted in SPSS, R, and Python. All data files and code are hosted on OSF (https://osf.io/gtjur/?view_only=baafb4c672f54bd2ac3802 6d7a431831).

Analysis Plan

Our analyses involved four steps: (1) calculating self-reported distancing scores, (2) linking self-reported distancing to reduced step counts during COVID-19, (3) linking self-reported distancing to a greater *reduction* in step counts from before to during COVID-19, and (4) analyzing a replication study (Study S1).

Calculating Self-Reported Distancing

A principal component analysis revealed two factors underlying self-reported distancing: personal distancing (how much participants reported distancing themselves; *eigenvalue* = 2.96) and community distancing (how much participants reported their community as distancing; *eigenvalue* = 1.22). Personal distancing was calculated by z-scoring participants' scores on the personal items of the four distancing measures, respectively, and then averaging these z-scores, $\omega_t = .84$. Community distancing was calculated in the same manner but using the community distancing items. The two types of distancing were weakly-to-moderately correlated, $r = .34$. In line with self-enhancement motives (e.g., Alicke & Govorun, 2005; O'Mara & Gaertner, 2017), participants rated themselves as better distancers than their community (personal vs. community distancing), $t(278) = 12.93$, $p < .001$, $d = .97$. See Supplements.[7,8]

Linking Self-Reported Distancing to Step Count

We conducted three generalized linear models (GLMs) each fit on a negative binomial distribution (given the count outcome variable) to test whether self-reported personal and community distancing predicted step counts during COVID-19. Model 1 included self-reported personal distancing as the main predictor. Model 2 included self-reported community distancing. Model 3 included both types of distancing.[9]

The three models also included control predictors (all z-scored): (1) average daily step count before COVID-19 (collapsed across February 2020, March 2019, and April 3–9, 2019); (2) going jogging, hiking, or on long walks in a distanced manner between April 3 and 9, 2020; and (3) COVID-19 cases-per-capita in participants' location (U.S. county) on the date of participation. Participants' average daily step count between April 3 and 9, 2020, $M = 3{,}916.23$, $SD = 4{,}218.21$, functioned as the outcome variable.[10]

In Model 1, self-reported personal distancing predicted lower average daily step counts between April 3 and 9, 2020, $p = .001$ (Table 1). For every $+1$ SD in personal distancing ($SD = 0.85$), individuals' average daily steps were approximately 20.6% lower (odds ratio = .794). Said another way, participants $+1$ SD in personal distancing exhibited $\sim$3,109 daily steps between April 3 and 9, 2020 ($\sim$807 less steps per day).[11,12,13]

In Model 2, participants' community distancing did not predict average daily step count, $p = .121$ (Table 1). Finally, in Model 3, personal distancing still predicted reduced step count, $p = .001$, while community distancing still did not, $p = .918$ (Table 1).[14] These findings align with the individual level of the study; while participants' own reported distancing predicted reductions in their step count, their judgments of their communities' distancing did not.

Linking Self-Reported Distancing to Change in Step Count

We conducted generalized estimating equations (GEEs) to examine whether self-reported distancing predicted a greater reduction in step count from before to during COVID-19. The conducted GEEs were identical to Models 1–3 except time was entered as a within-subjects factor (1 = April 3–9, 2020, 2 = February 2020, 3 = April 3–9, 2019, and 4 = March 2019). The interaction between self-reported distancing and

Table 2. Participants Higher in Self-Reported Personal Distancing Exhibited a Reduction in Average Daily Step-Count From Before to During COVID-19 and Those Low in Personal Distancing Did Not Exhibit a Step-Count Change.

	Average Daily Steps *Before* COVID-19: March, 2019	Average Daily Steps *Before* COVID-19: April 3–9, 2019	Average Daily Steps *Before* COVID-19: February, 2020	Average Daily Steps *During* COVID-19: April 3–9, 2020
Model #1				
		Contrast: $B = -1577.41$, $\chi^2 = 23.95$, $p < .001$		
High personal distancing (+1 *SD*)	$M = 4{,}816.84$, $SE = 306.51$	$M = 4{,}727.39$, $SE = 294.23$	$M = 4{,}958.63$, $SE = 350.27$	$M = 3{,}256.88$, $SE = 335.78$
		Contrast: $B = -123.74$, $\chi^2 = 0.09$, $p = .768$		
Low personal distancing (−1 *SD*)	$M = 4{,}219.41$, $SE = 286.78$	$M = 4{,}451.08$, $SE = 297.98$	$M = 4{,}792.62$, $SE = 324.13$	$M = 4{,}363.97$, $SE = 428.09$
Model #2				
		Contrast: $B = -1056.21$, $\chi^2 = 9.30$, $p = .002$		
High community distancing (+1 *SD*)	$M = 4{,}737.64$, $SE = 302.72$	$M = 4{,}986.00$, $SE = 322.95$	$M = 4{,}951.43$, $SE = 392.01$	$M = 3{,}835.48$, $SE = 404.41$
		Contrast: $B = -628.67$, $\chi^2 = 2.87$, $p = .090$		
Low community distancing (−1 *SD*)	$M = 4{,}297.03$, $SE = 292.69$	$M = 4{,}194.61$, $SE = 282.61$	$M = 4{,}797.49$, $SE = 385.21$	$M = 3{,}801.04$, $SE = 382.23$
Model #3				
		Contrast: $B = -1613.45$, $\chi^2 = 25.32$, $p < .001$		
High personal distancing (+1 *SD*)	$M = 4{,}766.68$, $SE = 318.61$	$M = 4{,}565.90$, $SE = 301.92$	$M = 4{,}937.95$, $SE = 370.28$	$M = 3{,}143.39$, $SE = 313.07$
		Contrast: $B = -48.96$, $\chi^2 = 0.01$, $p = .912$		
Low personal distancing (−1 *SD*)	$M = 4{,}258.40$, $SE = 297.48$	$M = 4{,}578.90$, $SE = 317.64$	$M = 4{,}810.74$, $SE = 342.85$	$M = 4{,}500.39$, $SE = 454.20$
		Contrast: $B = -768.69$, $\chi^2 = 3.95$, $p = .047$		
High community distancing (+1 *SD*)	$M = 4{,}637.11$, $SE = 311.32$	$M = 4{,}989.43$, $SE = 346.50$	$M = 4{,}933.25$, $SE = 413.24$	$M = 4{,}084.58$, $SE = 445.17$
		Contrast: $B = -997.59$, $\chi^2 = 9.95$, $p = .002$		
Low community distancing (−1 *SD*)	$M = 4{,}377.39$, $SE = 305.54$	$M = 4{,}190.23$, $SE = 296.34$	$M = 4{,}815.32$, $SE = 412.13$	$M = 3{,}463.39$, $SE = 328.51$

Note. Participants' self-reported community distancing did not predict differential changes in step-count.

time functioned as the main predictor. The outcome variable was average daily step count for each of the four time points.

In Model 1, an interaction between personal distancing and time was observed, χ^2 (3, $N_{between} = 219$; $N_{within} = 876$) $= 9.07$, $p = .028$. Unpacking this interaction, participants high in personal distancing (+1 *SD*) exhibited a reduction in daily step count from before to during COVID-19, $p < .001$ (Table 2; Helmert-contrasts applied). Specifically, they exhibited a decrease from 4,834.29 to 3,256.88 daily steps (a ~33% decrease). In contrast, the daily step count of participants low in personal distancing (−1 *SD*) did not change from before to during COVID-19, $p = .768$.[15] They exhibited a change from 4,487.70 to 4,363.97 daily steps (a ~3% decrease; Table 2). In contrast, and consistent with the previous GLM findings, a significant interaction between community distancing and time was not observed in Model 2, χ^2 (3, $N_{between} = 219$; $N_{within} = 876$) $= 2.38$, $p = .497$ (Table 2). Finally, personal distancing still interacted with time to predict a reduction in step count in Model 3, χ^2 (3, $N_{between} = 219$; $N_{within} = 876$) $= 11.38$, $p = .010$, while the interaction between community distancing and time remained nonsignificant, χ^2 (3, $N_{between} = 219$; $N_{within} = 876$) $= 3.34$, $p = .342$ (Table 2).

Replication

In Study S1 ($N = 271$), we replicated the findings of Study 1 when verifying participants' step counts via uploaded screenshots, changing the step count time frame to April 2020, controlling for additional third variables, for instance, exercising indoors, and when including Android users[16] (see Supplements).

Study 2

Study 1 was limited to the individual level. Given the community-based nature of viral pandemics (e.g., community spread, location-based ICU shortages), distancing at the group level should also play a role in understanding and combating pandemics. Indeed, during the COVID-19 pandemic (and the 1918 Influenza Pandemic), stark differences in distancing were observed at the region and community level (Bosman & Mervosh, 2020; Engle et al., 2020; Strochlic & Champine, 2020), and these differences resulted in differential health outcomes (e.g., Gollwitzer et al., 2020; Johnson & Thompson, 2020). In Study 2, we thus tested whether self-reported and objective distancing overlap at the group level (U.S. states). Specifically, we tested whether states' self-reported distancing predicted a greater reduction in general movement and visiting nonessential services (e.g., barbers, clothing stores) from before to during COVID-19 in those states (as calculated by the daily GPS mobility data of ~15 million people).

Participants

We aimed to recruit 50–115 participants in each of the 35 most populous U.S. states (Mechanical Turk [MTurk]; the study was preregistered[17]); 2,922 participants were recruited (1,527 female; $M_{age} = 40.41$, $SD_{age} = 13.10$). Participation occurred between April 10 and 14, 2020; 71 participants were excluded for attention failure and eight for repeat submissions (identified via MTurk-ID). Our final sample included 50 participants or more for 29 of the 35 included states, resulting in a sample size of 29 states ($M_{Sample\ Size} \sim 88$ per state; $N_{individual\ level} = 2{,}566$). With this sample, we had 80% power to observe a large effect ($r \sim .5$). Detailed analysis outputs, additional analyses, and all code files of Study 2 can be found in the Supplements and R Markdown files on OSF (see link above).

Self-Reported Distancing

Unlike Study 1, we measured distancing specifically in the week before participation ("In the last week . . . ").[18] We collapsed across participants in each of the included states to create state-level distancing scores. See Supplements and Verbatim Materials.

Distancing Behavior

States' objective distancing was provided by the software company Unacast (2020) using ~15 million daily smartphone GPS coordinates. Unacast provided states' percentage reduction in overall movement and visiting nonessential services (e.g., barbers, restaurants) from before COVID-19 struck the United States (pre-March 9) to during COVID-19 (daily scores after March 8, 2020).[19,20] Past research has documented the validity of the utilized Unacast dataset (e.g., Gatalo et al., 2020; Gollwitzer et al., 2020). See Supplements.

COVID-19 Severity

We assessed COVID-19 severity via (1) states' cumulative cases-per-capita and (2) states' infection and fatality growth rates (daily change in cumulative infections and fatalities; *New York Times*, 2020; e.g., Courtemanche et al., 2020; Gollwitzer et al., 2020). See Supplements.

Procedure

Participants completed the self-reported distancing measures (randomized, clustered together) followed by the attention check and demographics. Participants did not complete objective distancing measures (data were provided by Unacast).

Results

Analysis Plan

Analyses were separated into three sections: (1) calculation of self-reported and objective distancing, (2) linking states' self-reported personal and community distancing to states' objective distancing, and (3) robustness checks. Again, we examined states' personal- and community distancing separately.

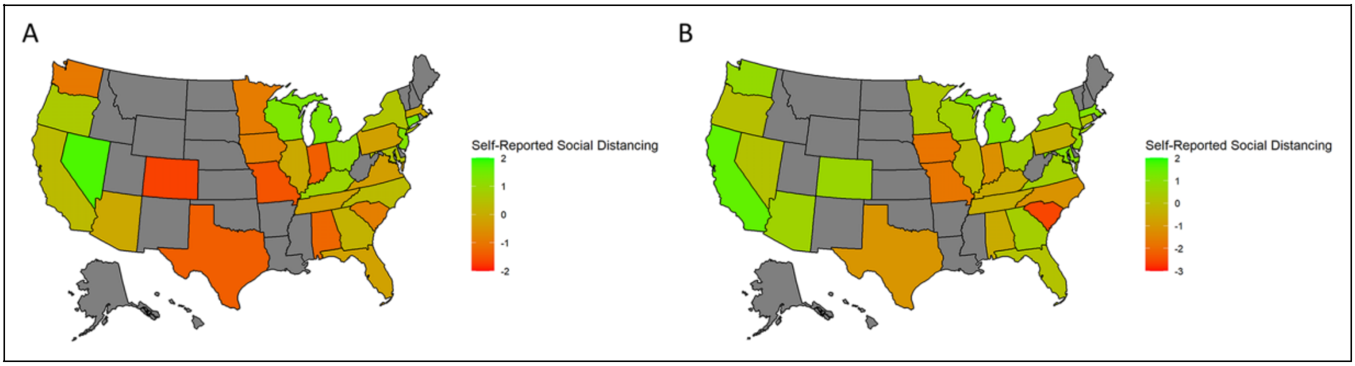

Figure 1. (A) Self-reported personal distancing in the week prior to participation. (B) Self-reported community distancing in the week prior to participation. Participation date varied between April 10 and 15, 2020. All *z*-scored.

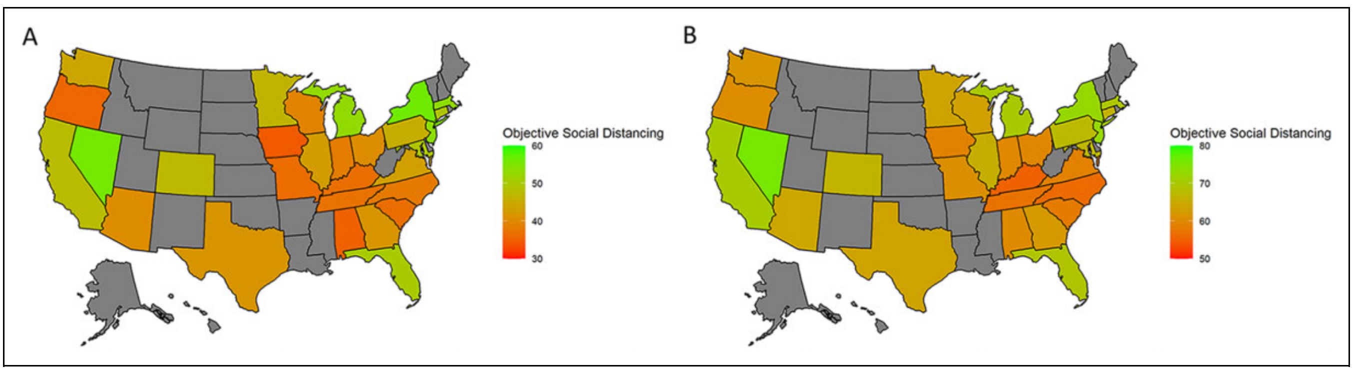

Figure 2. (A) Objective distancing: Percent reduction in general movement from before COVID-19 to the week prior to participation. B) Objective distancing: Percent reduction in visiting non-essential retail and services from before COVID-19 to the week prior to participation. Participation date varied between April 10th and 15th, 2020.

Table 3. Study 1: Output of LME Models 1 Through 8.

Models	Coefficient	*p* Value	95% Confidence Interval (CI)
Model #1: Reduction in general movement, $R^2_{\text{Marginal}} = .12$			
Personal social distancing	$B = 2.82$	$p = .022$	95% CI [0.44, 5.20]
Model #2: Reduction in visiting nonessential services, $R^2_{\text{Marginal}} = .11$			
Personal social distancing	$B = 2.02$	$p = .042$	95% CI [0.08, 3.96]
Model #3: Reduction in general movement, $R^2_{\text{Marginal}} = .29$			
Community social distancing	$B = 4.40$	$p < .001$	95% CI [2.42, 6.37]
Model #4: Reduction in visiting nonessential services, $R^2_{\text{Marginal}} = .27$			
Community social distancing	$B = 3.10$	$p = .001$	95% CI [1.40, 4.80]
Model #5: Reduction in general movement, $R^2_{\text{Marginal}} = .30$			
Personal social distancing	$B = 0.98$	$p = .378$	95% CI [−1.26, 3.22]
Community social distancing	$B = 3.94$	$p = .001$	95% CI [1.69, 6.18]
Model #6: Reduction in visiting nonessential services, $R^2_{\text{Marginal}} = .28$			
Personal social distancing	$B = 0.73$	$p = .449$	95% CI [−1.22, 2.67]
Community social distancing	$B = 2.76$	$p = .007$	95% CI [0.81, 4.70]

Note. Self-reported distancing measures were *z*-scored. Descriptive statistics of the outcome variables: Percentage reduction in general movement, $M = 43.77$, $SD = 6.76$. Percentage reduction in visiting nonessential services, $M = 63.99$, $SD = 5.39$. Ranges: Percentage reduction in general movement, min. = 34.39, max. = 56.25. Percentage reduction in visiting nonessential services, min. = 55.11, max. = 75.62. LME = linear mixed effect.

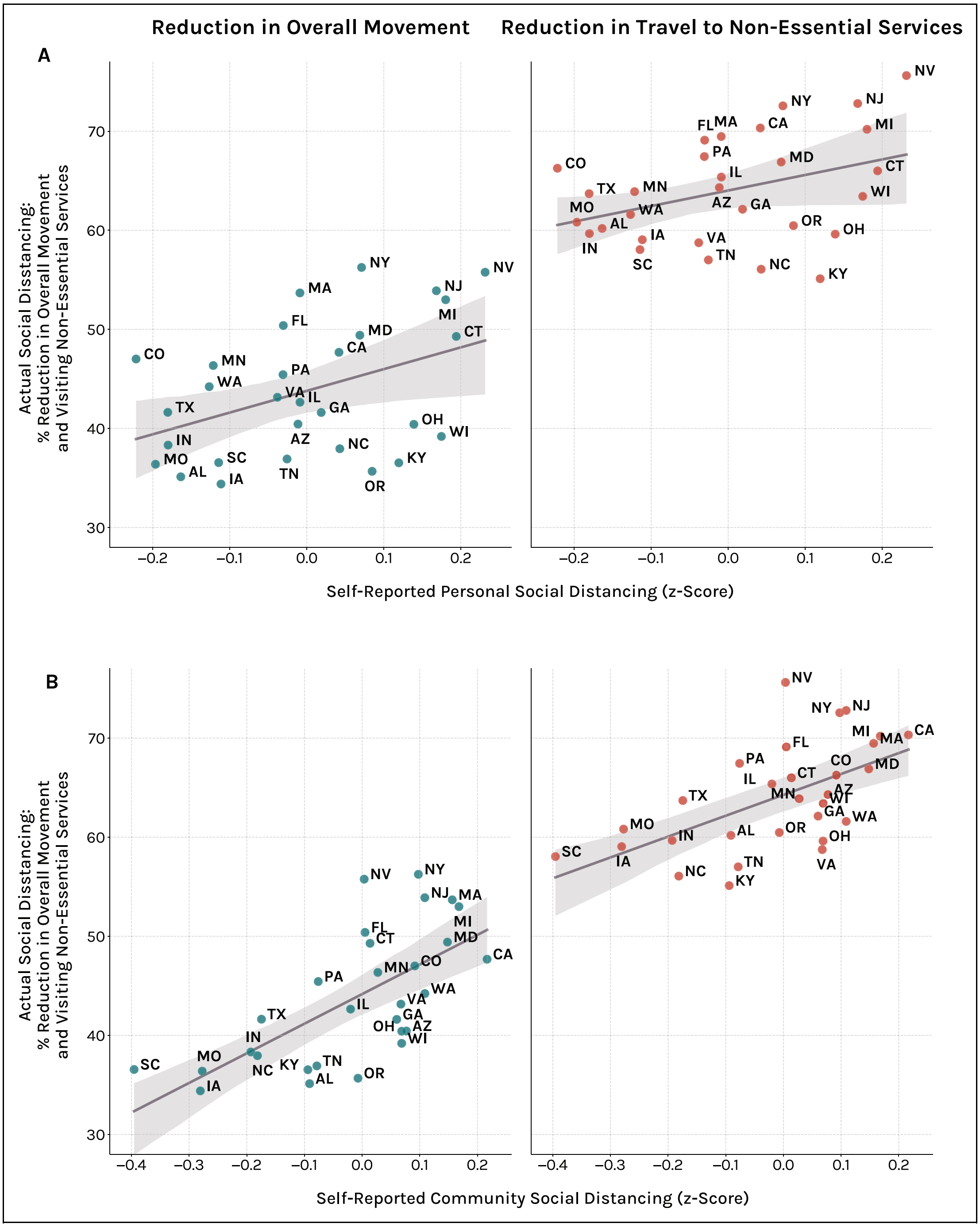

Figure 3. (A) The raw linear trends between U.S. states' self-reported personal distancing (z-scored) and objective distancing behavior, as measured via states' percentage reduction in overall movement (left) and visiting nonessential services and retail (right) from before to during COVID-19. (B) The same raw linear trends but for self-reported community distancing rather than personal distancing (z-scored). Error bands: ± 1 *SE*.

Calculating Self-Reported Distancing

As in Study 1, we observed two factors underlying self-reported distancing: personal (*eigenvalue* = 2.24) and community (*eigenvalue* = 1.27). Personal and community distancing in the past week were calculated as in Study 1 ($\omega_t = .92$, $\omega_t = .71$). These scores were then collapsed at the state level (Figure 1; see Supplements).

Calculating Objective Distancing

States' objective distancing values were available for each of the 7 days (1 week) prior to participants' study participation. As such, we assigned objective distancing scores for each of the included 7 days to each participant based on participants' location and participation date (see Supplements). We then collapsed across these scores within each state for

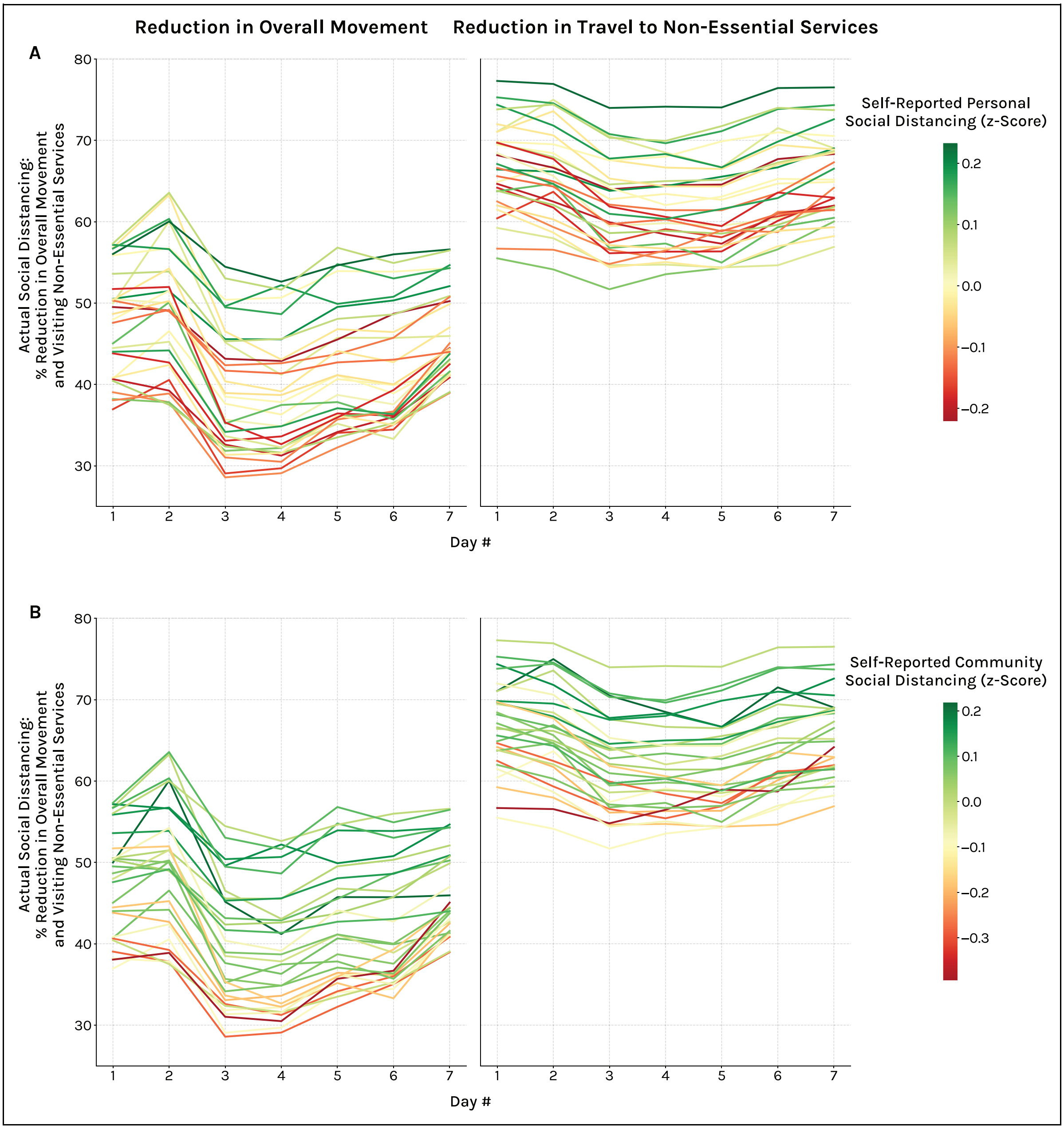

Figure 4. States' objective distancing as a function of time (Day 7 on the *x*-axis indicates one day before participants completed the study; Day 1 indicates 7 days before participants completed the study) and self-reported (A) personal distancing and (B) community distancing in that week (*z*-scored). Each line represents a U.S. state.

each of the 7 days, respectively, to create state-level estimates (Figure 2).

Linking Self-Reported and Objective Distancing

All analyses were conducted at the state level. Six linear mixed effects models examined whether states' self-reported and objective distancing overlapped. Personal distancing (Models 1 and 2), community distancing (Models 3 and 4), and personal and community distancing (Models 5 and 6) functioned as the predictors (all *z*-scored). States' objective distancing—percentage reduction in movement (Models 1, 3, and 5) and visiting nonessential services (Models 2, 4, and 6)—in the week prior to participation functioned as the outcome variables. Time, in terms of day, was included as a repeated-measures fixed factor (seven levels given the 7 days prior to participation). State and time (crossed factors) were included as random intercepts.

In Models 1 and 2, states' self-reported personal distancing in the past week positively predicted states' actual social distancing in that week, both in terms of reduction in movement, $p_{\text{movement}} = .022$, and visiting nonessential services, $p_{\text{visitation}} = .042$. Similarly, and unlike in Study 1, in Models 3 and 4, states' community distancing also positively predicted objective distancing, $p_{\text{movement}} < .001$, $p_{\text{visitation}} < .001$ (Table 3 and Figure 3). The observed coefficients indicate that a U.S. state $+1$ *SD* versus -1 *SD* in personal and community distancing (collapsed) exhibited a 56.97 versus 50.80 percentage-point reduction in movement and visitation (collapsed) from pre- to during COVID-19 (between April 4 and 13, 2020), equivalent to a $\sim$12.15% greater increase in social distancing. When accounting for the range of the objective distancing measures (see Table 3 footnote), however, this percentage increase rose to 29.12%. Finally, considering the observed marginal R^2 values, self-reported distancing accounted for $\sim$19.75% of the variance in objective distancing.

Notably, unlike Study 1, community distancing explained more variance than personal distancing in Models 1–4 (see marginal R^2 values, Table 3) and fit the data better in terms of AIC (see Supplements). In line with these findings, adding community distancing to Models 1 and 2 improved model fit, $\chi^2 = 11.50$, $p_{\text{movement}} < .001$, and, $\chi^2 = 8.08$, $p_{\text{visitation}} < .001$, and in Models 5 and 6, personal distancing no longer predicted objective distancing, *p*s > .378, while community distancing still did, *p*s < .007 (Table 3).

Robustness Checks

We conducted four robustness checks. First, our findings appeared relatively stable across time. That is, except for in one model,[21] we did not observe significant two-way interactions between self-reported distancing and time (Day 1 to Day 7 before participants completed the study; categorical factor) when adding these interactions terms to Models 1–4, *ps* > .115 (Figure 4).

Second, our findings remained consistent across the four individual self-reported distancing submeasures (Wu & Huber measure, Jordan measure, our measure, and the face-valid measure). We did not observe significant two-way interactions between self-reported distancing and a within-participants factor capturing the different submeasures when adding these interactions to Models 1–4, *p*s > .541.

Third, our results remained consistent when adding states' COVID-19 infection and fatality growth rates (single day and moving averages) as predictors to Models 1–4, .043 > *ps* > .001. Additionally, significant interactions between self-reported distancing and infection and fatality growth rates were not observed, .831 > *ps* > .156. Finally, the observed estimates decreased, but only slightly, when entering COVID-19 cases-per-capita instead of growth rates to the models, .087 > *ps* > .001; see Supplements).

Fourth, by collapsing across self-reported distancing at the state level, we neglected to consider variance in self-reported distancing within states (individual-level variance).[22] Demonstrating that our results are robust to this error variance, applying White's correction to Models 1–4 (which accounts for bias in micro-to-macro analyses; Foster-Johnson & Kromrey, 2018) did not meaningfully change significance, .032 > *ps* > .001. Furthermore, when we conducted 10,000 simulations of Models 1–4 in which states' self-reported distancing scores were allowed to vary within the 95% confidence intervals of the estimated state means, the error-corrected *p* values aligned with our original models, .050 > *ps* > .001 (see Supplements).

General Discussion

Across two studies, we demonstrated a consistent link between self-reported and objective social distancing. In Study 1, participants who reported greater social distancing exhibited lower average daily step counts during COVID-19. Additionally, participants high ($+1$ *SD*) versus low (-1 *SD*) in self-reported personal distancing exhibited a 33% versus 3% decrease in step counts from before to during COVID-19. Notably, these links were observed while controlling for alternate predictors, for instance, going jogging in a distanced manner and the severity of COVID-19 in participants' locations.

While Study 1 considered the individual level, Study 2 examined the group level. Communities have played a major role in how people approach COVID-19 and distancing. For instance, stay-at-home-orders at the U.S. state level, states' political partisanship, and countries' initial responses greatly influenced the spread of COVID-19 (Allcott et al., 2020; Anderson et al., 2020; Engle et al., 2020; McGrail et al., 2020). Informing these group-level differences, in Study 2, U.S. states' self-reported distancing predicted $\sim$20% of the variance in states' objective distancing, as assessed by reductions in overall movement and visiting nonessential services from before to during COVID-19 (quantified via $\sim$15 million daily smartphone GPS-point coordinates).

Collectively, our findings indicate that self-reported distancing does not suffer from self-report biases to the extent that it no longer predicts actual behavior. As such, self-reported distancing measures may be appropriate when in-person behavioral measures are infeasible. Nonetheless, we note that behavioral measures should be prioritized; indeed, our article raises two widely accessible indicators of objective distancing (step count and GPS mobility data).

Personal Versus Community Distancing

Our results indicate that researchers and public officials should differentiate between personal and community distancing. In Study 1, participants' judgments of their own distancing predicted reduced step count, whereas their judgments of their communities' distancing did not. In contrast, in Study 2, states' degree of community distancing was a better predictor of objective distancing than states' degree of personal distancing. For one, these results support validity in that the observed links match the levels of analysis of the two studies: individual level (Study 1) and group level (Study 2). For another, they indicate that people's estimations of the social distancing of their communities may be surprisingly accurate.

GPS Mobility Data

Numerous studies have utilized GPS data as a proxy for objective distancing and predictor of future COVID-19 health outcomes (e.g., Allcott et al., 2020; Baker et al., 2020; Engle et al., 2020; Gollwitzer et al., 2020; Jia et al., 2020; Woody et al., 2020). Additionally, data scientists, epidemiologists, demographers, and representatives of mobile networks have specifically encouraged the use of mobile data to investigate COVID-19 (Oliver et al., 2020). Our findings help validate these conclusions by illustrating that GPS mobile data align with self-reported distancing measures (at least at the group level).

Limitations

First, Study 1 relied on participants honestly reporting their step count. Addressing this concern, we replicated our findings in Study S1 ($N = 271$) when verifying participants' step counts via uploaded screenshots. Additionally, in Study S1, we replicated our results when expanding the step count time period to April 2020, controlling for additional variables (e.g., exercising indoors, having one's smartphone on one's person), and also including Android users. Second, Study 2 entailed a small sample (29 states). Although not ideal, our study still had 80% power to detect an effect size of $r \sim .50$ or larger. Further, reliable measures can compensate for small samples (Horwitz & Horwitz, 2012); we included multiple self-reported distancing measures and objective distancing was calculated via the daily GPS coordinates of $\sim$15 million individuals. Third, regarding generalizability, our findings may not extend to alternate cultures, pandemics, and groups that are not based on geographic region.

Finally, it is unknown whether self-reported distancing, akin to objective distancing, predicts COVID-19 health outcomes (e.g., Gollwitzer et al., 2020; Johnson & Thompson, 2020). Indeed, in supplemental analyses, we found states' self-reported distancing to predict a time-lagged decrease in COVID-19 infection and fatality growth rates. These results, however, were not robust to corrections for temporal and geo-spatial autocorrelation (potentially due to the small sample). We thus deemed these results inconclusive and report them in the Supplements.

Caveats

Readers should not draw individual-level conclusions from Study 2, which was at the group level; that is, readers should not commit the ecological fallacy (Piantadosi et al., 1988). That being said, the ecological fallacy itself produces several fallacies (Schwartz, 1994). For instance, the fallacy implies that group-level results are less rigorous and that group-level variables play no role in psychological processes and health outcomes. However, group-level variables (e.g., group tightness) play a substantial role in disease and disease spread (Eubank et al., 2004; Klovdahl, 1985). Indeed, numerous COVID-19 group-level findings have been documented, for instance, that distancing interventions at the U.S. state level curbed infection rates (Courtemanche et al., 2020). As such, though Study 2 should not be interpreted at the individual level, the study still provides a valuable contribution to COVID-19 at the group level.

While our results provide support for step count and GPS-based mobility as indicators of objective distancing, these measures are not the *exact same* as objective distancing. For instance, regarding step count, someone hiking in a remote place is distancing despite having a high step count. Indicating that our step count measure did capture variance in objective distancing, however, our results were observed when controlling for such third variables (e.g., jogging remotely).

Conclusion

We demonstrated that self-reported social distancing is linked to objective distancing both at the individual level and the group level. By demonstrating these associations, our findings provide initial support for the use of self-report measures as a means of assessing social distancing behavior during pandemics. Additionally, the presented studies inform our understanding of social distancing at the individual and group level more generally and, finally, contribute to a rich tradition of determining the efficacy of self-reported information at tracking real-world behavior.

Data Availability

The data sets, analyses files, and verbatim method files of the presented studies are available open source here: https://osf.io/gtjur/?view_only=baafb4c672f54bd2ac38026d7a431831.

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Supplemental Material

The supplemental material is available in the online version of the article.

Notes

1. We found at least 30 articles utilizing self-reported social distancing measures (see https://docs.google.com/spreadsheets/d/1BAaLE9R6h_xyGuWGCOAoOAQLBzmayCik9HP5OWXuNcA/edit#gid=0). We stopped searching at 30.
2. These points were either brought to our attention during the review processes or due to the results of data analyses (e.g., examining the structure of the self-reported social distancing measures). As such, they were not points directly raised in our original preregistrations and should be considered exploratory. For a detailed description of how our analyses differed from our preregistrations, see Supplements.
3. See here: https://aspredicted.org/blind.php?x=2ny5rk. Please note: several of the presented analyses differ from the

preregistered analyses. See Supplements for a thorough discussion of these changes.

4. Slight variations between intended and actual recruitment numbers can happen on MTurk (e.g., someone failed to return the hit despite completing it).
5. We also collected participants' average daily step count in March 2020. Given that these step counts fell between before COVID-19 (early March 2020 in the United States) and during COVID-19 (mid- and late-March 2020 in the United States), these results are discussed in the Supplements.
6. One concern is that participants reported biased step count estimates. Arguing against this, the order in which participants completed the self-reported distancing and step count measures did not impact the results. Additionally, we replicated our results in Study S1, in which we verified participants' step counts via screenshots of said data. Furthermore, in Study S1, we found no systematic differences between participants' self-reported step count data and the step count data documented by the screenshots they submitted. Screenshot failures largely occurred due to user error (e.g., submitting the wrong time frame, wrong metric, or random content).
7. Consistent results with respect to our key analyses were also found when simply collapsing across all the social distancing measures/items (i.e., ignoring a personal vs. community distinction).
8. Validation analyses supported the validity of the included self-report and objective distancing measures (see Supplements).
9. Sixty-one participants were excluded from all analyses involving step count data for reporting inaccurate step counts, qualifying as extreme outliers, reporting zero steps, or for missing data (see Supplements).
10. The applied analyses differed from our preregistered analyses in specific ways (see Supplements).
11. Whether participants first completed the self-reported social distancing measures or the step count measures did not impact the results, $p = .888$.
12. Two models conceptually replicated these findings when replacing personal social distancing with self-reported hygiene practices (e.g., washing hands) and general adherence to COVID-19 guidelines (see Supplements).
13. See Online Supplemental Table S1 for links between the individual social distancing measures and step count.
14. Providing further support for these results, personal social distancing did *not* predict reduced step count before COVID-19; between April 3 and 9, 2019 (the same week 1 year earlier), $p = .786$, in February 2020, $p = .916$, or in March 2019, $p = .417$.
15. Consistent results were also observed when conducting a generalized linear mixed-effects model that included participant id as a random intercept. Interaction term between personal distancing and time: $F(3, 866) = 8.43$, $p < .001$ (see Analysis syntax on OSF [https://osf.io/gtjur/]).
16. We also included Fitbit users. Parallel results were not found for Fitbit users potentially because Fitbit users specifically use Fitbit to track exercise (Supplements: Study S1).
17. https://aspredicted.org/blind.php?x=k224pj
18. We also assessed intentions to distance in the week after participation ("In the next week, I intend . . . "). The results regarding intentions to social distance in the next week largely echoed those of self-reported distancing in the past week. As such, these results are presented in the Supplements.
19. For what exactly qualified as nonessential retail and services, see Supplements.
20. Before March 9 was chosen by Unacast (the software company that shared these data with the authors) as pre-COVID.
21. The significant interaction was for Model 3 (community distancing predicting movement), $p < .001$. Community distancing was slightly more predictive of movement in the middle of the 7 days as compared to at the end points (i.e., Day 1, Day 6, and Day 7; see results in R Markdown on OSF (https://osf.io/gtjur/?view_only=baafb4c672f54bd2ac38026d7a431831). As this result was not found for the other models, however, this interaction appears not to represent the general pattern of our data.
22. This error variance was not propagated to additional analyses (see Cone et al., 2020). See Supplements.

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Author Biographies

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