Connecting Self-Reported Social Distancing to Real-World Behavior at the Individual and U.S. State Level

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Abstract

Social distancing is currently the single most effective method to reduce the spread of COVID-19. As such, researchers across varying fields are rushing to identify variables that predict social distancing and which interventions can heighten social distancing. Yet, much of this research relies on self-report measures (in part because of social distancing guidelines themselves). In two studies we examine whether self-reported social distancing overlaps with real-world behavior. In Study 1, individuals' self-reported social distancing predicted decreased movement as quantified by participants' average daily step-counts (assessed via smartphone pedometers). For every increase of one in self-reported social distancing (z-scored), individuals' daily steps decreased by approximately 21% (Exp(B) ~ .79). In Study 2, the degree of self-reported social distancing in different U.S. States predicted the degree to which people in those States reduced their overall movement and travel to non-essential retail as assessed by ~17 million smart-phone GPS coordinates (.34 < rs < .57). Collectively, our results indicate that self-report measures of social distancing track actual behavior both at the individual and at the group level.

Keywords: social distancing, COVID-19, self-report, behavior, physical distancing.

Connecting Self-Reported Social Distancing to Real-World Behavior at the Individual and U.S. State Level

The coronavirus (COVID-19) pandemic presents a public health crisis of massive proportions. In an effort to curb rapid infection rates (1), public health officials have strongly encouraged people to engage in social distancing—physically distancing oneself from others and limiting in-person interactions (2). Indeed, sustained social distancing measures have helped contain the spread of COVID-19 (3-5), and are essential for preventing critical care capacities from being overwhelmed (6).

Despite its importance, individual and community variability in social distancing exists. For instance, in mid-March 2020, when New Yorkers were following shelter-in-place orders, spring break revelers in Florida enjoyed packed beaches (7), and people in Chicago attended St. Patrick’s Day celebrations (8). Indeed, 30% of U.S. adults still report going to public places and congregating in small gatherings (as of March 20-22nd, 2020; Gallup poll) (9). Researchers have thus scrambled to elucidate the individual and group-level variables underlying social distancing behaviors as well as which interventions (e.g., type of messaging) can heighten such behavior. For instance, they have assessed whether women engage in more social distancing than men (10), how boredom proneness and self-control may impair social distancing (11), and whether analytical thinking promotes social distancing (12), among numerous other potential predictors. Studies have also examined the effectiveness of various messaging in encouraging people to adopt social distancing norms, including emphasizing one’s duty (13), drawing attention to the prosocial benefits of social distancing (14), and eliciting feelings of empathy (15) in addition to other emotions (16). These specific articles are merely a small portion of this research, however; 823 articles were found when we searched for “self-reported social distancing” on Google Scholar on

May 2nd, 2020 and selected 2020 as the publication criteria. And, when reviewing these articles, we observed at least 30 articles that utilized self-reported social distancing measures (see here for a list of these articles).[1] All these research efforts should ideally help inform policy makers' understanding of how to motivate people (and *whom* to motivate) to engage in social distancing measures during viral pandemics (17).

However, due to the urgency of this line of work and the inability to perform in-person behavioral studies (in part because of social distancing guidelines themselves), much of this research relies heavily on self-report measures. This may be a problem for several reasons. For instance, individuals may be inclined to over-report their social distancing behavior due to social desirability bias (18, 19), maintaining a positive self-impression (20), and evaluating themselves more favorably than the average person (i.e., the "better-than-average" effect) (21). Additionally, individuals may not remember their failures to appropriately social distance (22, 23). These mechanisms have been implicated in the over-reporting of various other normative behaviors, such as exercise and voting (24-26). Furthermore, extensive research has documented the gaps between self-reported judgments and actual behavior, including the intention-behavior gap (27), the attitude-behavior gap (28), and the knowledge-behavior gap (29). Overall, researchers in these domains acknowledge that self-reported intentions, attitudes, and knowledge leave a substantial amount of variance in behavior unexplained (30).

We conducted two studies to provide insight into the degree to which people's self-reported social distancing aligns with their actual behavior. In doing so, we can determine whether the self-reported social distancing measures already utilized in dozens of studies examining COVID-19 actually link to real-world behavior. In Study 1, we assessed whether individuals' self-reported

[1] We stopped after observing 30 such articles.

social distancing is linked to real-world behavior in terms of overall movement as quantified by participants' average daily step-counts (which are tracked by their smartphone pedometers). Because a core component of social distancing involves staying home (e.g., "shelter in place"), people who are social distancing should exhibit less movement than those who are not. Notably, smartphone pedometers and step-counts have been utilized as indirect behavioral measures in prior research, for instance, in research seeking to link self-reported and actual health behaviors (31).

Importantly, Study 1 provides a very conservative test of whether self-reported social distancing is linked to actual behavior – though researchers have validated smartphone step-counters (32), step-count data is noisy in that it can underestimate movement (e.g., people do not take their phones everywhere they go) but also overestimate it (e.g., if stride length is systematically overestimated) (33). Furthermore, several variables other than social distancing will undoubtedly predict variance in individuals' step-count, including exercise, long walks, and an active life-style (we made sure to control for these variables in our study).

In Study 2, we extended the results of Study 1 to the group level. We did so because social distancing varies considerably at the community level. For instance, U.S. States have embraced social distancing to strikingly different degrees. And, these differences seem only destined to continue as illustrated by the current patchwork approach to re-opening businesses (34). Thus, in Study 2, we tested whether the degree of self-reported social distancing in different U.S. States predicts the degree to which people in those States reduced their overall movement and travel to non-essential retail as assessed by the smartphone GPS coordinates of ~17 million people per day across the United States. Notably, there are an abundance of studies utilizing such cellphone GPS data as a measure of actual social distancing behavior at the U.S. State- and county-levels (35-38). And, data scientists, epidemiologists, demographers and representatives of mobile network operators have specifically encouraged the use of such data by government and health authorities when assessing the effectiveness of social distancing and shaping public policy regarding COVID-19 (39). As such, our study kills two birds with one stone; linking self-reported social distancing to behavior (as tracked by GPS coordinates) should help inform the use of self-reported social distancing measures while, at the same time, informing the use of GPS data as a measure of true social distancing behavior.

Study 1

Method

Participants. A sensitivity power-analysis indicated that with 258 participants we would have 90% power to find a correlation of r = .20 or greater in the general population (see pre-registration here).[2] We pre-registered to recruit 300 participants on MTurk (to account for participant exclusion). A total of 302 participants were recruited (126 Female; M_{age} = 35.26, SD_{age} = 10.83).[3] 21 participants were excluded for failing an attention check (see below). Importantly, because we wished to collect participants' step-counts, we only recruited iPhone users (the Health app on iPhones tracks people's steps).

Self-reported social distancing. We included four different measures of self-reported social distancing behavior. These measures assessed participants' social distancing (*personal* social distancing; e.g., "I have almost zero in-person social interactions with people I am not living with") as well as participants' judgments of their community's social distancing (*community* social distancing; e.g., "People in my community are social distancing"). The measures included both

[2] Some of the pre-registered analyses are not reported in the main text for brevity's sake. See Supplements for these analyses.

[3] Slight variations between intended and actual recruitment number are not uncommon on MTurk (e.g., someone failed to return the hit despite completing it).

more general items (e.g., “I am social distancing”), and items specifically asking participants about whether they were avoiding certain activities (e.g., small gatherings; see Methods below).

The first measure, an abbreviated version of a measure developed in political science (51), provided a definition of social distancing and included 3 items: “I am practicing social distancing,” “My friends and family are practicing social distancing”, and “People in my community are practicing social distancing.” Likert-scale: 1 = *Strongly disagree*, 2 = Somewhat *disagree*, 3 = *Neither agree nor disagree*, 4 = *Somewhat agree*, 5 = *Strongly agree*. The second measure, adapted from research out of psychology (14), asked participants the degree to which they are avoiding various activities (e.g., going to the grocery store, going to small gatherings, and 6 other items; see Appendix) on a 100-point scale (0 = *I make no effort to avoid this activity*, 50 = *I make some effort to avoid this activity*, 100 = *I completely avoid this activity*). As in Jordan et al. (preprint), we also asked participants whether they would engage in these activities if the coronavirus were not a concern, in order to control for participants’ typical activities. Third, we included a 6-item scale out of our own research group (e.g., ‘I have almost zero in-person social interactions with people I am not living with’; 1 = *Not at all true* to 9 = *Very true*). Fourth, we included 2 face-valid items. Participants were asked, “How would you rate your personal attempts at social distancing, specifically, in terms of reducing travel and staying home as much as possible?” and “How would you rate the average person’s attempts at social distancing in the state in which you live (i.e., in <participant’s region here>), specifically, in terms of reducing travel and staying home as much as possible?” (1 = *terrible* to 7 = *excellent*). Participants responded to these question sets in randomized order (see Appendix or Verbatim Material Files for full measures and all items). For more details see Supplements.

Step-Count. Participants reported their average daily step-count in the week prior to participation (April 3rd-April 9th, 2020) as indicated by their iPhone Health App (see Duncan, Wunderlich, Zhao, & Faulkner, 2018 for a validation of using iPhone Health to collect step-count data) (32). We also collected step-count in February 2020 and between April 3rd and April 9th, 2019 to control for steps taken before COVID-19. We also collected step-count in March, 2020 and again, as a pre-COVID control, steps in March 2019. Extensive instructions were provided to participants on how to locate the step counter on their phone and report the correct values (see Verbatim Materials). Given that we used the iPhone Health App, we recruited only iPhone users (approximately 45% of smartphone users have an iPhone in the United States) (46).

Additional measures. For validation purposes, we also assessed: participant's perceived control over the spread of coronavirus ("How much do you think you can control the spread of the coronavirus with your own behavior?" Likert-scale: 1 = *Not at all*, 7 = *Completely*), whether participants reported still traveling to go to work, and if so, if they qualify as an essential worker in their state of residence, and whether participants qualify as someone considered at risk for developing severe symptoms from COVID-19 (e.g., if they have diabetes, asthma, heart disease, or are immunocompromised). We also developed a quiz testing individuals' knowledge of COVID-19 (e.g., "The virus stays on plastic surfaces for a longer time than cardboard surfaces"; 1 = *True*, 2 = *False*).[4] For more details, see Supplements.

Procedure. Participants were first filtered by whether they had an iPhone. Participants then completed the self-reported social distancing measures (randomized, clustered together, including the COVID-19 knowledge quiz) and the step-count items (clustered together) in random order.

[4] We also assessed participants self-reported reason for social distancing (1 = *Entirely to reduce my own risk of catching COVID-19*, 7 = *Entirely to reduce the risk that people around me catch COVID-19*). This measure was included for exploratory reasons and did not relate to any pertinent variables.

Participants then completed the additional measures, the attention check item (see Supplements), and demographics.

Results

A principal component analysis revealed that the personal social distancing items and the community social distancing items loaded onto different factors (*eigenvalues* = 2.96 and 1.22), though, they were moderately correlated (r = .34). Importantly, in our analyses, we predominantly focused on personal social distancing (self-directed) since our research question centers around whether people's judgments of their own (rather than others') social distancing align with their actual behavior.

Providing validity for our self-reported personal social distancing measures, participants who reported still traveling for work reported lower personal social distancing, $F(1, 279) = 15.64$, $p < .001$, $\eta^2 = .053$.[5] Greater self-reported social distancing, on the other hand, was linked to reporting that one can control COVID-19 via one's own behavior, $r(279) = .33$, $p < .001$, and greater self-reported hygiene practices, $r(279) = .61$, $p < .001$.

In line with COVID-19 leading to an overall reduction in people's movement, average step-count reduced from pre-COVID-19, April 3^{rd} to April 3^{rd} 2019, $M = 4631.42$, $SD = 3435.78$, to during COVID-19, April 3^{rd} to April 9^{th}, 2020, $M = 4065.55$, $SD = 4298.21$, $t(244) = 2.29$, $p = .023$. And, further supporting the validity of our step-count measure, generalized linear models (GLMs; step-count exhibited a negative binomial distribution)[6] indicated that participants who reported still traveling for work had higher step-counts between April 3^{rd} and April 9^{th}, 2020, χ^2

[5] Although being at risk for experiencing severe symptoms in response to COVID-19 did not predict greater self-reported social distancing, $p = .885$, participants' age did, $r(278) = .21$, $p < .001$.

[6] We had pre-registered that we would conduct correlations rather than generalized linear models. However, generalized linear models are more appropriate for step-count data. None of the results changed substantially when conducting Pearson's correlations.

(1, N = 249) = 6.34, p = .012, Exp(B) = 1.46, as did participants who reported going on jogs/hikes/ long walks, χ^2 (1, N = 249) = 12.17, p < .001, Exp(B) = 1.16.

We next tested whether participants' self-reported personal social distancing is linked to reduced step-count. As hypothesized, self-reported social distancing predicted lower daily average step-count, M = 4,202, SD = 4,546, between April 3rd and April 9th, 2020 χ^2 (1, N = 249) = 5.48, p = .019, Exp(B) = .842.[7,8] Importantly, this link strengthened when controlling for participants' steps pre-COVID 19, between April 3rd and April 9th the previous year (in 2019), χ^2 (1, N = 239) = 10.39, p = .001, Exp(B) = .791, and when additionally controlling for the number of times a participant reported going jogging, hiking, or on long walks either alone or with their quarantine partner between April 3rd and 9th, 2020, χ^2 (1, N = 239) = 10.20, p = .001, Exp(B) = .791.[9] Furthermore, the link remained consistent when controlling for participants' step-count in February, 2020, and March, 2019, on top of April 2019, χ^2 (1, N = 232) = 14.08, p < .001, Exp(B) = .757, and when additionally applying more stringent filters to the step-count variable, χ^2 (1, N = 170) = 8.95, p = .003, Exp(B) = .765 (see Supplements). Averaging across these analyses, for every increase of one in self-reported social distancing (z-scored), individuals' daily steps decreased by approximately 21.1% (Exp(B) ~ .789). For links between the individual social distancing measures and step-count, see Supplements. We observed similar results when relating participants' self-

[7] Participants who admitted to reporting inaccurate step-counts were excluded (n = 20), as were 2 participants whose responses were obviously false (e.g., 1267543.00 steps), 5 participants whose responses qualified as extreme outliers [+2 SD, e.g., 45,000 steps], 2 participants who reported 0 steps, and 1 participant who reported an implausible non-integer number of steps (.51 average steps). These exclusion criteria differed slightly depending on the specific step-count dates in question (see Supplements for details).

[8] Whether participants first completed the step-count measures or the self-reported social distancing measures did not impact the results, p = .568.

[9] We indicated in our pre-registration that we would control for traveling for work and being at risk for COVID-19. However, we later realized that, conceptually, these two variables are mechanisms rather than confounds. For instance, someone still traveling for work would self-report low social distancing and indeed would have a high step count due to traveling for work. Thus, their self-reported social distancing is an accurate representation of their actual social distancing, which is poor. Nonetheless, the observed link reduced but did not disappear when additionally controlling for these two variables χ^2 (1, N = 239) = 6.36, p = .012, Exp(B) = .822.

reported social distancing in March, 2020 to their March, 2020 step-count, though these findings were less conclusive (as noted in our pre-registration this may be due to individuals beginning to social distance at varying times during March, 2020; see Supplements).

Providing further validity for these findings, participants' self-reported social distancing did not predict their step-count before COVID-19, whether it be between April 3rd and April 9th, 2019 (the same week one year earlier), $p = .854$, or in February, 2020, $p = .763$, or in March, 2019, $p = .417$. And, unlike personal social distancing, participants' self-reported community social distancing (the extent to which participants judged others in their community as social distancing rather than themselves) did not consistently predict their own step-count in any of the above analyses, $.046 < ps < .760$. Further, adding personal social distancing into these models completely removed any predictive power of community social distancing, $.418 < ps < .822$ (notably, self-reported personal social distancing remained significant in these models, $.001 < ps < .006$).

We next examined participants' self-reported hygiene maintenance and general adherence to COVID-19 preventative guidelines. These analyses indicated that though our findings are largely specific to social distancing, they may also extend to other areas of COVID-19 prevention. Self-reported hygiene practices (e.g., washing hands, disinfecting surfaces) predicted reduced step-count in between April 3rd and 9th, 2020 when controlling for step-count prior to Covid-19 (in the same week in April 2019, in March, 2019, and in February, 2020), χ^2 (1, N = 232) = 11.22, p = .001, Exp(B) = .789, but not when failing to control for these previous step-counts, $p = .215$, or when applying more stringent filters, $p = .134$. Similarly, self-reported general adherence to COVID-19 guidelines (e.g., "I make sure to follow norms that help to stop COVID-19") predicted reduced step-count when controlling for previous step-counts (in the same week in April 2019, in March, 2019, and in February, 2020), χ^2 (1, N = 232) = 11.54, p = .001, Exp(B) = .797, but not when failing to control for these previous step-counts, $p = .203$, or when applying more stringent filters, $p = .060$.

Finally, we examined whether self-reported social distancing is linked to performance on the COVID-19 knowledge quiz that we developed for the purposes of this study, $\omega_t = .71$. Notably, this quiz is not a self-report measure and thus can be used to further validate the included self-report social distancing measures. In line with the observed step-count results, self-reported social distancing predicted greater performance on the COVID-19 quiz, $r(261) = .32$, $p < .001$.[10]

Discussion

The results of Study 1 indicate that self-reported social distancing aligns with actual behavior indicative of social distancing. We found that participants' self-reported social distancing predicts reduced average daily step-count as tracked by their smartphone pedometers. Despite these encouraging results, we note a number of caveats. First, though self-reported social distancing predicted reduced step-count, this does not mean that participants self-reported social distancing is free of reporting bias. Indeed, participants' personal social distancing was consistently higher than their community social distancing; participants rated themselves as better social distancers than the average person in their community (in their U.S. State), $t(278) = 12.93$, $p < .001$, $d = .97$.[11] As noted in research on the better-than-average effect (21), it is objectively impossible for most people to be better-than-average at something. Second, our results do not mean that step-count should be de facto adopted as a one-to-one behavioral measure of individuals' social distancing behavior. In other words, while our results indicate that step-count may be an adequate measure for behavior that is indicative of social distancing, it is not the *same* as social

[10] We excluded participants who admitted having looked up answers to the quiz questions online.
[11] Classical Cohen's d applied, not Cohen's d_z or d_{rm}.

distancing. Indeed, examples in which individuals have very high step-counts but are still social distancing (e.g., hiking alone in remote locations) and have very low step-counts but are not social distancing (e.g., interacting closely with neighbors) easily come to mind.

Finally, participants in Study 1 self-reported their step-counts. These values may have been reported in a biased manner. To address this substantial concern, we replicated the findings of Study 1 in Study S1 (N = 271) when having all participants upload screenshots of their reported step-counts so that we could verify these step-counts as accurate. In this study, we also verified that the link between self-reported social distancing and step-count replicates when assessing participants' step-count across the month of April, 2020 rather than in a specific week in April, 2020. And, we verified that the link between self-reported social distancing and step-count remains when controlling for numerous alternate predictors of step-count, including whether participants were going on remote walks, hikes, or jogs, exercising indoors in a way that would raise their step-count, spending time in a private backyard, walking around their house more so than usual, generally having their 'device' on them, and finally, whether participants rarely engaged in activities before COVID-19 that would raise their step-count (see Verbatim Materials of Study S1 for all items).

Study 2

The findings of Study 1 are limited to the individual level. Researchers have noted that communities and groups play an important role in motivating social distancing. For instance, which communities issued stay-at-home orders heavily influenced which areas practiced social distancing (35, 38), and much attention has focused on the stark divergence in responses to COVID-19 based on region. For instance, while New York remains in lock-down as of June 1st, 2020, numerous other states have begun to reopen business (e.g., Georgia, Florida) (40), resulting in a projected subsequent rise in fatalities (41).

In Study 2, we thus tested whether the observed link between self-reported social distancing and real-world behavior extends to the group-level (see pre-registration here). Specifically, we examined whether self-reported social distancing in U.S. States predicts reduced actual movement and travel to non-essential retail and services in those states. To quantify states' self-reported social distancing, we assessed the self-reported social distancing (both in terms of the past and intentions to social distance in the future) of 2,922 participants across the U.S and tracked their location. Our sample ultimately resulted in over 50 participants from 29 different U.S. States. We then examined whether the self-reported social distancing (past and future directed) of these 29 states (averaged across participants in each state) predicts real-world social distancing behavior as assessed by reduced general movement and visiting non-essential services (e.g., barbers, restaurants, clothing stores) in those states as compared to before Covid-19.[12] These two behavioral variables – general movement and visiting non-essential services – were calculated by Unacast (a software company that provides location and map services) using approximately 17 million smartphone GPS coordinates across the U.S per day and then shared with the authors (see Methods for more details).

Participants. As pre-registered, we aimed to recruit between 50 and 115 participants on MTurk per State for 35 U.S. States. A total of 2,922 participants were recruited (1,527 Female; M_{age} = 40.41, SD_{age} = 13.10); recruitment was ended 4 days after first posting the study. 71 participants were excluded for failing an attention check (see below), and 8 additional participants

[12] To explicate, we controlled for U.S. States' degree of general movement and visiting of non-essential retail before Covid-19.

for completing the study twice (identified via MTurk ID). The final sample included 2,843 participants. We ended with 50 participants or more for 29 of the 35 included U.S. States (for sample size per State see Appendix; $M_{Sample\ Size}$ ~ 88 per State). A sensitivity power-analysis revealed that with this sample size of 29 States we had 80% power to observe a large effect (*r* ~ .5) at the U.S. State level.

Self-reported social distancing. We slightly altered the four self-reported social distancing measures of Study 1. First, unlike Study 1 (in which we measured social distancing in general), we measured self-reported social distancing both in terms of the past (participants reported social distancing in the past week; "In the last week…"), and also in terms of the future (participants' intention to social distance in the next week; "In the next week, I intend…").[13] Second, we adapted the Jordan et al. (2020) items because social distancing practices became stricter in the U.S. as COVID-19 progressed. For instance, we changed the avoided activities from going to restaurants to getting take out from restaurants (see Supplements for all items) (14).

Social distancing behavior. Social distancing behavior was assessed in two ways: U.S. States' decrease in overall movement and U.S. States' decrease in traveling to non-essential retail and services as compared to pre-COVID-19 (before March 9th; individually controlled for in each

[13] All four measures were used to measure self-reported social distancing in the past week. Due to time constraints, only the Jordan et al. (2020) measure and the face-valid measure were included when measuring intentions. We included specifically the Jordan et al. measure when measuring intentions because this is how the measure was originally construed (14).

State).[14,15,16] We were able to quantify these variables through the aggregated movement of approximately 17 million participants across the U.S. per day between March 9th and April 21th (dataset was shared with the authors by Unacast). These data are anonymized in that they aggregate GPS coordinates by State.

Procedure. Participants completed the self-reported social distancing measures (randomized, clustered together). Participants then completed the attention check item, and demographics.

Results

A principal component analysis again revealed two factors underlying self-reported social distancing: *personal* social-distancing (e.g., "I was social distancing"; *eigenvalue* = 2.96) and *community* social-distancing (e.g., "People in my community were social distancing", *eigenvalue* = 1.26). However, because most of the following analyses were significant for both types of self-reported social distancing (unlike in Study 1), we first present the results collapsed across these types of social distancing.

Participants' self-reported social distancing in the past week (collapsed across personal and community social distancing) was calculated by averaging across all four social distancing

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[14] Non-essential retail and services is anything that falls within restaurants, department stores, clothing stores, footwear, discount stores, jewelry, computers & consumer electronics, gifts, seasonal, books, office supplies, hair, cosmetics and beauty supplies, Gyms + Fitness Facilities, Communications, New/Used Car Dealers, Hotels, Used Products, "Crafts, Toys, and Hobbies", Travel, "Spa, Massage, + Esthetics", Sports + Recreation, Weight Loss, Furnishings, Home + Housewares, Home Improvement +Building Supplies, "Printing, Copying + Publishing", Theatres, Music, Amusement, Furnishing Rentals, Shared Offices + Coworking, Car Wash, Cannabis Retail, Flowers, bars, pubs, cafes, nightclubs, cinemas, casinos.

[15] We had pre-registered that we would also include unique social interactions as a measure of social distancing behavior, however, this data included numerous extreme outliers and only controlled for encounters pre-COVID at the national baseline level. Thus, we decided not to include this variable.

[16] Before March 9th was chosen by Unacast (the software company that shared this data with the authors) as pre-COVID.

measures (after *z*-scoring each measure), ω_t = .82.[17] The self-reported social distancing of the 29 included U.S. States was then calculated by averaging across the scores of participants in each of the States (see OSF repository; *n* per state ~ 88; see Fig. S3). Because participants completed the study on different days, the corresponding real-world social distancing was calculated by averaging across the reduction in general movement and visiting of non-essential retail in the U.S. State in the *specific week* before the participant completed the study (see Fig. S4).

As predicted, U.S. States' self-reported social distancing the week prior to participation predicted the degree of actual social distancing in that U.S. State in that week, both in terms of reduced overall movement, $r(27) = .57$, p =.001, 95% CI [.26, .77] and reduced travel to non-essential retail, $r(27) = .52$, p =.004, 95% CI [.19, .75]. Importantly, in these links, we adjusted for potential differences in states' general movement and visiting non-essential retail before COVID-19 began (we looked at the *reduction* in these practices from pre- to post-COVID-19, as provided by Unacast). These links were not moderated by the specific self-reported social distancing measure, *p*s > .160 (for correlations with the individual social distancing measures, see Supplements).

In addition, our data also explanatorily identifies which States under self-report (below the slope-line in Fig. 1) and over self-report (above the slope-line in Fig. 1) their social distancing versus their true social distancing behavior (as compared to other states; also see Fig. S5). For instance, comparatively, New York and Massachusetts exhibited higher degrees of actual social distancing relative to their self-reported social distancing, whereas Oregon and Tennessee appeared to be overestimating how well they are actually social distancing. Potentially,

[17] We had pre-registered that we would exploratorily include States in which we had between 45 and 50 participants. These analyses were not conducted given that no States had this number of participants.

communities that over-estimate their social distancing may experience an unexpected increase in COVID-19 cases in the future (which future research can test as time passes and new data becomes available).

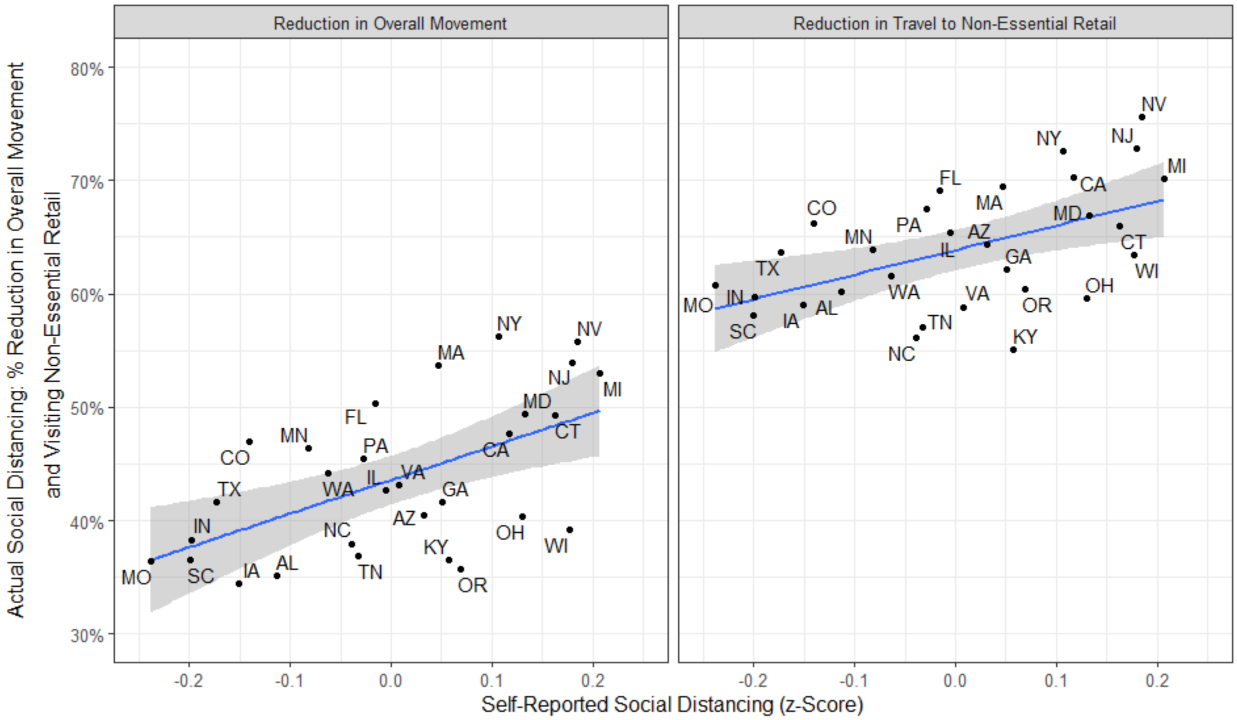

Figure 1. Study 2: Correlations between U.S. States' self-reported social distancing (*z*-scored) and actual behavior, as measured via states' percentage reduction in overall movement (left) and travel to non-essential retail (right). Error bands: +/- 1 *SE*.

Extending our findings to preventing COVID-19 more generally (as in Study 1), self-reported adherence to hygiene practices in the last week (e.g., "When I could, I washed my hands for at least 10 seconds or more") also predicted States' actual social distancing: reduction in overall movement, $r(27) = .49$, $p = .008$, 95% CI [.14, .72], and reduction in visiting non-essential retail, $r(27) = .45$, $p = .015$, 95% CI [.10, .70]. These results indicate that even self-reported preventative practices aside from social distancing may be indicative of actual social distancing behavior.

We next exploratorily examined, as in Study 1, whether our results differed for personal versus community social distancing items (e.g., "I am social distancing" versus "People in my community are social distancing"). Overall, models including community social distancing items were a better predictor of States' actual social distancing than models including personal social distancing items (for both general movement and visiting non-essential retail; see Figs. S1 and S2); community social distancing explained approximately 30% of the variance in States' actual social distancing as compared to approximately 10% for personal social distancing, χ^2s > 7.44, *p*s < .001.[18] These results indicate that people's intuitions of how well their community is social distancing is a surprisingly accurate account of their communities' actual degree of social distancing.

Study 2 also considered participants' self-reported *intentions* to social distance (*N* = 2,843). Specifically, we measured not only participants' self-reported social distancing in the past week (as described above), but also participants' self-reported intentions to social distance in the upcoming week. A link between intentions to social distance and actual social distancing would provide initial support for the validity of intervention work utilizing self-reported social distancing intentions as a proxy for actual future social distancing (14-16).

Notably, self-reported intentions to social distance in the next week per State predicted the degree of actual social distancing in that State in that week, both in terms of reduced overall movement, albeit marginally, $r(27) = .34$, $p = .067$, 95% CI [-.03, .63] and in terms of reduced travel to non-essential retail, $r(27) = .43$, $p = .021$, 95% CI [.07, .69]. Furthermore, we again observed variance among states in terms of their overestimation (below the slope-line; Fig. 2) and underestimation (above the slope-line; Fig. 2) of their degree of actual social distancing versus self-reported intentions to social distance (as compared to the average state; see also Figs. S6 through S8).

[18] Personal judgments also significantly predicted actual social distancing on their own.

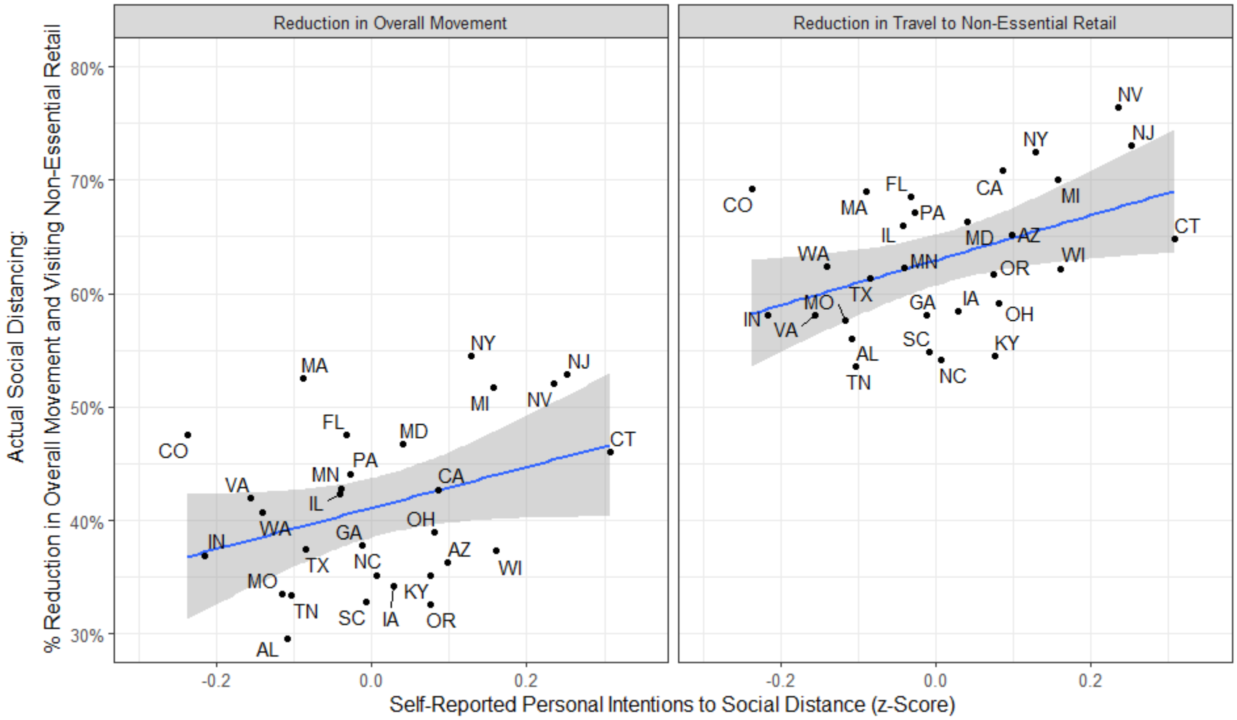

Figure 2. Study 2: Correlations between U.S. States' self-reported *intentions* to social distance (z-scored) and actual behavior in following week, as measured via percentage reduction in overall movement (left) and travel to non-essential retail (right). Error bands: +/- 1 *SE*.

We next examined whether participants' self-reported social distancing predicts actual state social distancing depending on time. For instance, potentially, the intention to social distance predicts actual social distancing initially, but weakens with time. Intentions to social distance in the next week, however, did not interact with Time to predict actual social distancing, (this was true for self-reported social distancing in the past week as well), $ps > .197$ (see Figs. 3 and 4). These results indicate that the links between States' self-reported social distancing and their actual behavior is relatively stable across time (though, of course, this may change when major policy is passed, for instance States' official re-opening).

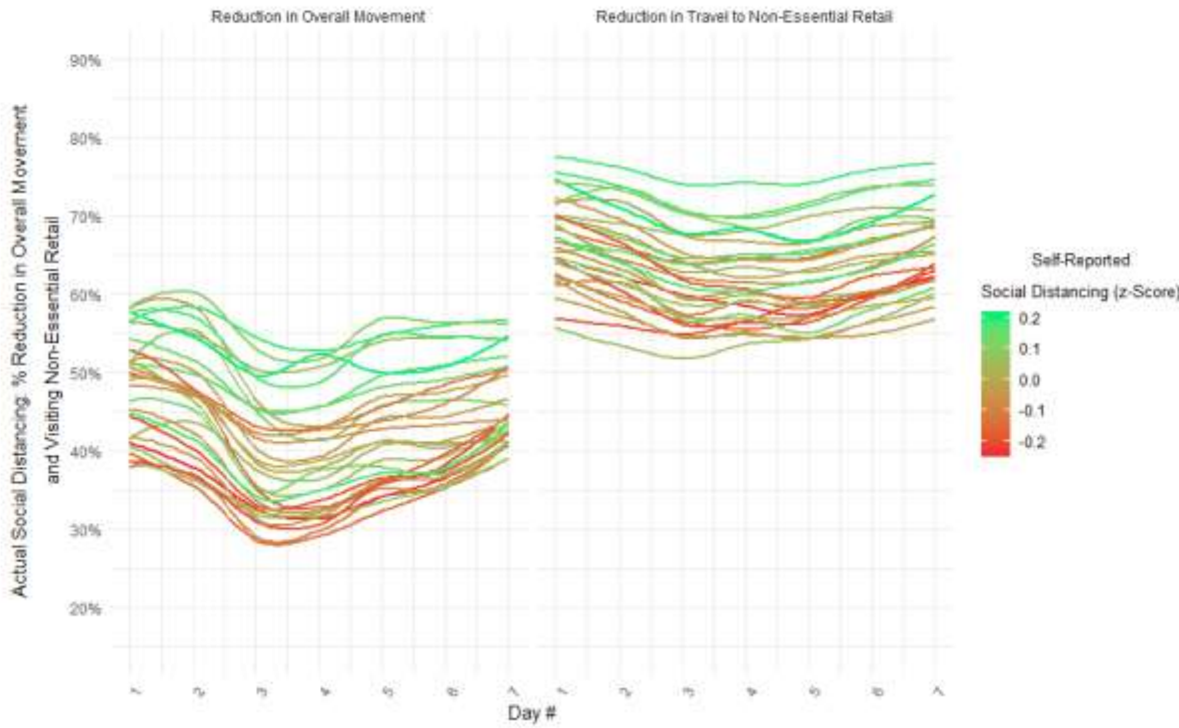

Figure 3. Study 2: Actual social distancing of each U.S. State as a function of Time (Day 7 on the x-axis indicates the day before participants completed the study; Day 1 indicates 7 days before the participant completed the study) and self-reported social distancing (*z*-scored).

Figure 4. Study 2: Actual social distancing of each U.S. State as a function of Time (Day 7 on the x-axis indicates 7 days after participants completed the study; Day 1 indicates 1 day after the participant completed the study) and self-reported intentions to social distance (*z*-scored).

Discussion

Across two studies, we demonstrated a consistent link between self-reported social distancing and measures of actual social distancing behavior at both the individual and group level. In Study 1, participants' self-reported personal social distancing (e.g., "If I have to leave the house, I make sure to stay at least 6 feet away from other people") predicted approximately a 20% reduction in daily step-count between April 3rd and April 9th, 2020, as assessed via their smartphone pedometers. And, this link strengthened when controlling for participants' step-counts prior to the COVID-19 pandemic (including the identical week in April in 2019) and for alternate step-count predictors (e.g., jogging, hiking, or going on long walks alone or with a quarantine partner). Further substantiating these findings, self-reported social distancing did not relate to participants' step-count at any time before COVID-19, whether it be April 2019, March 2019, or February 2020, and participants' self-reported community social distancing (judgments of how well their communities are social distancing) did not predict their own step-count. Finally, self-reported personal social distancing also predicted higher scores on a performance-based measure of COVID-19 prevention (a quiz assessing knowledge about COVID-19; e.g., "Which of the following is *not* a symptom of COVID-19?" *Fatigue*, *High Fever*, *Shortness of Breath*, *Cough*, or *Sneezing*)

Study 2 examined social distancing at the group-level. Groups and communities have played a major role in how people approach COVID-19 and social distancing more specifically. For instance, stay-at-home-orders, enacted on the State-level, have had a major impact on the spread of COVID-19 (35), as may have states' political partisanship (38), and countries' initial responses (3, 4). In line with these group-level differences, self-reported social distancing of individuals living in U.S. States predicted actual social distancing behavior in those states as assessed by the aggregated cellphone GPS data of approximately 17 million people per day. Specifically, states' self-reported social distancing predicted a greater reduction in U.S. States' overall movement and travel to non-essential retail locations. Furthermore, we found that self-reported intentions to social distance in the next week at the U.S. State level predicted the degree of actual social distancing in States in the next week as well. And finally, the degree to which participants rated their community as social distancing was a better predictor of states' actual social distancing behavior than the degree to which participants rated themselves as social distancing.

Our results have several meaningful implications. For one, our studies collectively show that self-reported social distancing tracks multiple measurements of real-world social distancing behavior. These findings indicate that self-reported social distancing measures do not suffer from self-report biases (30) to the extent that they no longer predict actual behavior. Practically, these findings provide initial support for self-reported social distancing as a valid indication of true social distancing behaviors, and thus, tentatively suggest that self-report may be appropriate when in-person behavioral designs are infeasible due to COVID-19 restrictions (we identified at least 50 articles either published or in preprint format that include self-report but not behavioral measures of social distancing).[19] Nonetheless, we believe that behavioral measures should be used when possible; indeed, our article raises two potential methods to measure such behavior (step-count and GPS coordinates).

Our U.S State-level findings also contribute to research on social distancing. For one, our results help validate group-level research on social distancing (42) by demonstrating that self-reported social distancing in communities predicts the actual social distancing of those communities. And further, we documented that certain regions may over-report versus under-report their social distancing (as compared to other regions). Future research could examine whether such over-estimation vs. under-estimation predicts future health consequences (e.g., rate of new COVID-19 cases; difficulty containing a potential second outbreak in Fall, 2020).

Additionally, the results of Study 2 support the validity of using GPS data as a behavioral measure of social distancing. A multitude of recent studies have utilized similar cellphone GPS data as indicative of actual social distancing behavior at the group-level (35-38), including using such data as the basis for modeling future COVID-19 cases (43). Further, numerous news outlets have recently concluded from such GPS data that the recent re-opening of U.S. States (at the end of April and beginning of May, 2020) has already led to decreased social distancing (44). Our

[19] We stopped tracking these articles after identifying the first 50. Links to the identified articles can be found in the OSF project associated with this article (see here).

study helps validate this work and these conclusions by illustrating that such GPS data aligns with self-reported social distancing behavior at the group-level.

Importantly, our results at the State-level extended to intentions to social distance. In Study 2, the intentions of individuals in U.S. States to social distance in the next week predicted those U.S. States' actual social distancing behavior. This observed link provides the first-step for validating intervention attempts that solely measure self-reported social distancing (14-16). That is, if we had not observed this link, it would be highly unlikely that interventions heightening individuals' intentions to social distance have an actual effect on social distancing behavior. Nonetheless, we believe that a large amount of future validation work is necessary for such intervention studies to be considered reliable. Indeed, though intentions to social distance were linked to behavior in Study 2, experimentally manipulated intentions may function differently, especially in terms of individuals' instead of groups' intentions. Nonetheless, we note that even though the current results only weakly inform the efficacy of such interventions, the present results do directly inform studies using self-reported social distancing to identify the predictors of social distancing at the individual and group level.

The observed link between intentions and States' actual future behavior also suggests that public officials and data scientists may be able to estimate the future social distancing of communities by assessing their constituents' intentions. Notably, this approach may be particularly useful as States begin to re-open businesses (34) and public officials try to identify the degree of social distancing required to keep the R0 value of COVID-19 under one (45). For instance, after enacting a policy shift (e.g., opening bars) public officials could assess the intentions to social distance of a sample of constituents and in turn potentially predict the degree of change in actual social distancing that that policy shift induces. Again, however, we consider this point tentative given that intentions altered by public policy may differ from the intentions we assessed.

Finally, our results also indicate that public officials and researchers polling self-reported social distancing should consider the difference between self-reported *personal* social distancing (e.g., "I am social distancing") and self-reported *community* social distancing (e.g., "People in my community are social distancing"). Providing unique predictive validity to our findings, in Study 1, participants' self-reported personal social distancing predicted their reduced step-count, whereas their judgments of their communities' social distancing did not. And, in Study 2, when looking at the group-level, community social distancing was a better predictor of actual social distancing at the State-level as compared to personal social distancing. For one, these results support the validity of our findings. For another, they indicate that people's intuitions about how well those around them are social distancing are surprisingly accurate despite the fact that they may be staying home themselves. And furthermore, future research attempting to accurately estimate communities' actual social distancing behavior should assess individuals' self-reported community rather than personal social distancing.

Our current work has several limitations. First, Study 1 relied on participants honestly reporting their step-count, as recorded by their smartphone. Addressing this concern, we replicated the findings of Study 1 in Study S1 (N = 271; see Supplements) while having all participants upload screenshots of their step-counts so that we could verify these numbers. And, we replicated our results when additionally controlling for alternate factors predicting step-count irrespective of social distancing, including whether participants were going on remote walks, hikes, or jogs, exercising indoors in a way that would raise their step-count, spending time in a private backyard, walking around their house more so than usual, generally having their 'device' on them, and finally, whether participants rarely engaged in activities before COVID-19 that would raise their step-count (see Verbatim Materials of Study S1 for all items).

Study 1 was also limited in that it included only iPhone users. Although approximately 45% of smartphone users use an iPhone in the United States (46), a substantial percentage of Americans do not own an iPhone. Study S1 (see Supplements) also attempted to address this limitation by including users of Fitbit devices and Android devices (that have step-count apps on them).[20] Nonetheless, these studies still omitted individuals who do not use electronic devices, and thus our participant selection may skew along lines such as wealth. In the same vein, our studies relied on convenience samples from MTurk. MTurk populations tend to be disproportionately White and Democratic (47, 48), and thus our sample may not be representative of the population at large. Future research should examine whether our results are generalizable to more representative populations.

Study 2 is limited in terms of the small sample size (29 U.S. States). Given this sample size, we had at least 80% power to detect a true correlation of $r \sim .50$ or larger. Though not ideal, our study still had high enough power to detect a large effect if that effect exists in the population. Further, low power in terms of sample size can be compensated for by the use of reliable measures (49). We believe the measures of Study 2 were reliable given that (1) we included multiple social distancing measures (which exhibited high inter-measure reliability) per individual participant and over at least 50 participants per State to estimate the self-reported social distancing of States, and (2) the actual social distancing estimates of States was calculated via the GPS coordinates of

[20] Notably, in Study S1, the link between social distancing and step-count was moderated by device. The observed link between social distancing and step-count was driven by iPhone and Android users rather than Fitbit users. Further analyses revealed that Fitbit users may be specifically using Fitbit for exercise and as such, Fitbit may not reliably track participants' general movement outside of exercise (see Supplements for details). We recommend that future studies assessing step-count as a potential proxy for social distancing not collect Fitbit data.

approximately 17 million individuals. While these considerations give us confidence in the integrity of our results, it is possible that the observed correlation effect-sizes in Study 2 are inflated (see the Winner's Curse) (50).

We advise readers to approach the observed results cautiously. First, our results do not mean that step-count or general movement (as assessed by GPS coordinates) should be de facto adopted as direct measures of individuals' and groups' social distancing behavior. While our results provide support for these measures as behavioral assessments indicative of social distancing, they are not the *exact same* as social distancing. Indeed, someone hiking in a remote place, for instance, is still engaging in social distancing despite having a high step-count. Second, we do not know how the observed link between self-reported intentions and behavior in Study 2 may change in the context of experimental manipulations or policy changes. And finally, the current results should not be used as an excuse to abandon attempts to behaviorally measure social distancing when possible. Indeed, our article suggests two possible methods via which researchers' can begin to get at measuring social distancing behavior (step-counts and GPS data).

In conclusion, we demonstrated that self-reported social distancing is linked to real-world behavior as assessed individually via step-count and collectively via aggregated cellphone GPS data. By demonstrating these associations, our findings provide initial support for the use of self-report measures as a means of assessing true social distancing behavior during the COVID-19 pandemic. Additionally, the presented studies inform our understanding of social distancing at the individual and the 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 datasets, analyses files, and verbatim method files of the presented studies are available here.

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Author Contributions

A. Gollwitzer developed the study concept and study design. Study creation, testing, and data collection were performed by A. Gollwitzer, J. Marshall, and J.M. Höhs. A. Gollwitzer completed the data analysis and interpretation. A. Gollwitzer, C. Martel, and J. Marshall drafted the manuscript, and J.A. Bargh provided critical revisions. All authors approved the final version of the manuscript for submission.

Competing Interests

The authors declare no competing interests.