Predicting Physical Distancing Over Time During COVID-19: Testing an Integrated Model

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Abstract

Objective: We applied an integrated social cognition model to predict physical distancing behavior, a key COVID-19 preventive behavior, over a four-month period. ***Design:*** A three-wave longitudinal survey design. ***Methods:*** Australian and US residents (*N*=601) completed self-report measures of social cognition constructs (attitude, subjective norm, moral norm, perceived behavioral control [PBC]), intention, habit, and physical distancing behavior on an initial occasion (T1) and on two further occasions one week (T2) and four months (T3) later. ***Results:*** A structural equation model revealed that subjective norm, moral norm, and PBC, were consistent predictors of physical distancing intention on all three occasions. Intention and habit at T1 and T2 predicted physical distancing behavior at T2 and T3, respectively. Intention at T2 mediated effects of subjective norm, moral norm, and PBC at T2 on physical distancing behavior at T3, and habit at T1 and T2 mediated effects of behavior at T1 and T2 on follow-up behavior at T2 and T3, respectively. ***Conclusion:*** Normative (subjective and moral norms) and capacity (PBC) constructs were consistent predictors of physical distancing intention, and intention and habit were consistent predictors of physical distancing behavior. Interventions promoting physical distancing should target change in normative and personal capacity beliefs, and habit.

Keywords: Social cognition theory; Habit; Integrated models; Social distancing; Behavior change.

Predicting Physical Distancing Over Time During COVID-19: Testing an Integrated Model

The COVID-19 pandemic is a global public health crisis that has made a substantive contribution to increases in excess deaths worldwide, and has emerged as one of the leading contributors to excess global deaths in 2020, and set to do so again in 2021 (Giattino et al., 2021). With COVID-19 cases soaring in many regions of the world, the roll-out of COVID-19 vaccines is likely to be the cornerstone in reversing infection rates. However, given that sufficient widespread immunity against the virus resulting from mass inoculation is unlikely for some time, continued promotion of engagement in behaviors known to be effective in curbing the spread of infections, particularly physical or ‘social’ distancing, still remains the pre-eminent means to prevent infection and save lives (Hodgson et al., 2020; Moghadas et al., 2020). Identifying potentially modifiable psychological determinants of physical distancing that show evidence of consistency over time is central to informing current and future campaigns and interventions aimed at stemming infections (West et al., 2020). Researchers have applied social cognition and motivational models from the behavioral sciences to identify these determinants in the context of the COVID-19 pandemic (Beeckman et al., 2020; Bogg & Milad, 2020; Clark et al., 2020; Gibson Miller et al., 2020; Hagger, Smith, et al., 2020; Hamilton, Smith, et al., 2020; Lin et al., 2020; Moussaoui et al., 2020), which has provided useful information that can be brought to bear on communicating public health advice aimed at promoting physical distancing. However, much of this research has focused on cross-sectional or relatively short-term prediction of physical distancing behaviors, with little control for previous experience or stability in the determinants over time. The present research aimed to fill this gap by identifying potentially modifiable determinants of physical distancing behavior over an extended period, and by adopting an integrated social cognition model that accounts for stability in the determinants and behavior over time.

Integrated Models

Integrated social cognition models, which draw their constructs and hypotheses from multiple theories and models (for reviews see Fishbein et al., 2001; Hagger & Hamilton, 2020; Montaño & Kasprzyk, 2015), have demonstrable utility in predicting health behaviors (e.g., Bogg, 2008; Hagger et al., 2017; Hamilton et al., 2017; Hamilton, van Dongen, et al., 2020; Jacobs et al., 2011; Kasprzyk et al., 1998). The practical utility of such models lies in their identification of constructs that are paramount to individuals' decision making and behavioral enactment, which can then be targeted in behavior change interventions through application of relevant behavior change techniques known to be efficacious in affecting change in the constructs (Hagger, Cameron, et al., 2020; Sheeran et al., 2017). Consistent with many models of social cognition (e.g., Ajzen, 1985; Ajzen & Fishbein, 1980; Rogers, 1975), integrated models (e.g., Fishbein & Ajzen, 2010; Fishbein et al., 2001; Schwarzer, 2008; Triandis, 1977; Witte, 1992) assume that individuals form an intention to perform a given behavior based on reasoned evaluation of the expected outcomes of performing the behavior in future, the conditions within the individual that may facilitate or inhibit the behavior, and the social and physical context in which the behavior will be performed. These include individuals' evaluations of the utility of the behavior in producing desired outcomes (often referred to as attitude), their capability of producing the outcomes (self-efficacy or perceived behavioral control (PBC)), and the normative influences arising from significant others (subjective norm) and social mores (moral norm). Intention is often conceptualized as the most proximal determinant of behavior and is assumed to mediate effects of individuals' behavioral evaluations on behavior (Ajzen, 1991). Prospective application of integrated social cognition models have demonstrated that they account for substantive variance in health behaviors (for reviews see Hagger & Chatzisarantis, 2009; Hamilton, van Dongen, et al., 2020; McEachan et al., 2016; Protogerou & Hagger, 2017; Zhang et al., 2019), including physical distancing behavior to prevent COVID-19 infection (Beeckman et al., 2020; Hagger, Smith, et al., 2020; Hamilton, Smith, et al., 2020; Lin et al., 2020; Lithopoulos et al., 2021; Norman et al., 2020).

However, applications of social cognition models in general have numerous limitations, prominent among them is a non-trivial amount of variance in intention and behavior remaining unexplained by model constructs. Researchers have therefore sought to augment such models to include additional constructs with appropriate theoretical basis and account for substantive additional variance in intention and behavior. A prominent modification is the inclusion of constructs reflecting habit (Hagger et al., 2017; Hamilton, Gibbs, et al., 2020; Hamilton et al., 2017). These modifications are based on the premise that engagement in a particular behavior like physical distancing is not always based on reasoned evaluation, but rather a function of well-learned responses to contextual cues developed through repeated experience of the behavior in the stable presence of the cues (Wood & Rünger, 2016). Such behaviors are experienced as habitual or 'automatic' with little effort and cognitive deliberation, which can be captured through self-reports of the experience of the behavior as automatic and 'non-thinking' (Verplanken & Orbell, 2003). Such measures have been shown to be associated with habitual responding and explain effects of past behavior frequency, often used as a proxy for habit, on behavior (Brown et al., 2020; Orbell & Verplanken, 2010; van Bree et al., 2015).

In addition, a limitation of existing tests of integrated social cognition models applied to the prediction of health behavior, including COVID-19 preventive behaviors, is a lack of control for the stability of model constructs over time and a focus on cross-sectional or short-term behavioral prediction (Beeckman et al., 2020; Bogg & Milad, 2020; Hagger, Smith, et al., 2020; Hamilton, Smith, et al., 2020; Lin et al., 2020; Moussaoui et al., 2020). Few studies have adopted true longitudinal designs, in which all study constructs and outcomes are measured at each time point. These designs allow for the modeling change in model constructs and behavior over time, that is, their stability, and even fewer have adopted such designs using long-term follow-up of constructs and behavior beyond a few weeks (Hagger et al., 2001; Jacobs et al., 2011). The advantage of using extended longitudinal designs is twofold: (a) they enable control for change in model constructs and previous behavior over time, in recognition that individuals' beliefs are likely to be a function of previously held beliefs as well as their evaluation of current outcomes, capabilities, and social contexts, and (b) they enable tests of the sufficiency of a model in accounting for long-term behavior change, given that sustained change is required for ongoing prevention of negative health consequences, such as prevention of widespread COVID-19 infections. Taken together, such designs offer researchers and interventionists more comprehensive information on the determinants of sustained behavior change and simultaneously account for naturalistic change in constructs over time.

The Present Study

The aim of the present study was to apply an integrated social cognition model to predict physical distancing intention and behavior over an extended period. The study included a measure of habit as an additional determinant to account for behaviors that are performed through automatic, non-reasoned processes, and adopted a longitudinal design with measures of model constructs and behavior over three occasions; baseline (T1), one week later (T2), and four months later (T3). We hypothesized that: (a) model constructs representing reasoned action (attitude, subjective norm, PBC, and moral norm) would predict physical distancing intention on each occasion, and physical distancing behavior measured on the subsequent occasion; (b) habit measured on each occasion would predict physical distancing behavior measured on the subsequent occasion, but would not predict intention measured on the same occasion; (c) effects of social cognition constructs measured on each occasion on behavior measured on the subsequent occasion would be mediated by intention on the same occasion; (d) behavior measured on each occasion would predict social cognition constructs and intention measured on the same occasion, although model effects at each occasion would hold supporting model sufficiency; and (e) effects of behavior measured at each occasion on behavior measured on the subsequent occasion would be partially mediated by habit measured at the same occasion.

Method

Participants and Design

The present study adopted a three-wave prospective correlational design with data collected at an initial occasion (T1) and two subsequent data collection occasions one week (T2) and four months (T3) later[1]. Participants were Australian and US residents (*N* = 1,196, 48.9% female) recruited from an online research panel. Inclusion criteria were aged 18 years or older and not subject to formal quarantine for COVID-19. Participants were also screened for age, sex, and geographical region, and quotas were imposed during recruitment to ensure that the final samples closely matched the national distributions for these characteristics in each country. Data were collected between April 1 and September 10, 2020. Participants in the Australia sample (*N* = 495, 50.1% female) were subject to a national 'shelter-in-place' order issued by the federal government from recruitment until May 15, 2020 when a gradual easing of restrictions was introduced across Australia. However, participants living in the state of Victoria had 'shelter-in-place' orders reinstated on June 20, 2020, with restrictions still in place when data collection was completed. Shelter-in-place orders for the US sample varied by state. Of participants in the US sample (*N* = 701, 48.9% female), a large majority (*n* = 610, 87.0%) were subject to 'shelter-in-place' orders for the first wave. However, some states did not impose 'shelter-in-place' orders (Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, Wyoming), so a minority of participants in the US sample (*n* = 37, 5.3%) were never subject to an order. Furthermore, in some cases in the US sample (*n* = 47, 6.7%), 'shelter-in-place' orders had been lifted prior to the second follow-up data collection period. However, some states did not lift state-wide 'shelter-in-place' restrictions throughout the study (California and Oregon), yet some counties within these states started easing restrictions in phases between T2 and T3. US states that did not have 'shelter-in-place' orders, or lifted their orders during the study, all issued physical distancing

[1]Data from the present study is part of a larger study on the determinants of physical distancing behavior. The present study reports data from the four month follow-up. Preliminary findings based on prediction of T2 physical distancing behavior from T1 social cognition constructs has been published previously(Hagger, Smith, et al., 2020; Hamilton, Smith, et al., 2020). The previously published work did not report data from any of the measures taken at T2, other than the measure of physical distancing behavior, and any of the measures taken at T3.

guidelines and encouraged the population to follow those guidelines. Baseline sample characteristics are presented in Table 1.

At T1, participants completed self-report measures of social cognition constructs from the proposed integrated social cognition model (attitude, subjective norm, PBC, moral norm, habit, and intention), physical distancing behavior over the past week, and socio-demographic variables (age, sex, marital status, ethnicity/race, education, income) using the Qualtrics™ online survey tool. Participants were informed that they were participating in a survey on physical distancing behavior, provided with information outlining study requirements, and provided opt-in consent to participate prior to completing the survey. Participants were initially presented with a definition of the physical distancing behavior: “The following survey will ask about your beliefs and attitudes about ‘social distancing’. What do we mean by social distancing? Social distancing (also known as ‘physical distancing’) is deliberately increasing the physical space between people to avoid spreading illness. The World Health Organization and other world leading health authorities suggest that you should maintain at least a 1-2 meters (3-6 feet) distance from other people to lessen the chances of getting infected with COVID-19. When answering the questions in this survey, think about your social distancing behavior (i.e., maintaining at least a 1-2m (3-6ft) distance from other people)”. Participants were invited to participate in the follow-up surveys comprising identical measures to the T1 survey at T2 and T3, one-week and four-months later, respectively. Participants received a fixed sum of money for their participation in accordance with the panel company’s rates. Approval for study procedures was granted prior to data collection from the Griffith University Human Research Ethics Committee (reference #2020/199).

Measures

Measures of constructs from the proposed integrated social cognition model were developed according to published guidelines (e.g., Abraham & Sheeran, 2003; Ajzen, 1991; Verplanken &

Orbell, 2003). Participants provided responses on 7-point response scales. Complete study measures are provided in Appendix A (supplemental materials).

Social cognition constructs. Multi-item measures of attitude, subjective norm, PBC, and moral norm were developed according to published guidelines (Abraham & Sheeran, 2003; Ajzen, 1991). Each measure made reference to physical distancing as the target behavior, and participants were reminded of the definition of physical distancing prior to completing the measures. Measures were identical at each data collection occasion.

Intention. Participants' intention to perform physical distancing behavior over the next week was measured using a scale developed according to published guidelines (Ajzen, 2002).

Habit. Habit was measured using the behavioral automaticity items from Verplanken and Orbell's (2003) self-report habit index. The scale measures individuals' reflections on the extent to which physical distancing is experienced as an automatic behavior and one that is enacted without thought.

Physical distancing behavior. Participants self-reported their participation in physical distancing behavior to reduce the spread of COVID-19 infections. The measure comprised two-items prompting participants to report their frequency of physical distancing behavior in the previous week. This is based on previously-used self-report measures of behavior, which have demonstrated concurrent validity with non-self-report measures (Kalajas-Tilga et al., 2021).

Socio-demographic variables. Participants self-reported their age in years, sex, employment status (currently unemployed/full time caregiver, currently full-time employed, part-time employed, on leave without pay/furloughed), marital status (married, widowed, separated/divorced, never married, in a de factor relationship), annual household income stratified by eleven income levels based on Australia and US national averages, highest level of formal education (completed junior/lower/primary school, completed senior/high/secondary school, post-school vocational qualification/diploma, further education diploma, undergraduate university degree, postgraduate university degree), and race (Black, Caucasian/White, Asian, Middle-eastern). Binary income (low income vs. middle/high income), highest education level (completed school education only vs. completed post-school education), and race (Caucasian/White vs. non-White) variables were computed for use in subsequent analyses.

Data Analysis

Preliminary analyses of the data involved generating descriptive statistics for sample socio-demographic variables and model constructs, and computing latent and non-latent variable correlations among the constructs, and between the socio-demographic variables and model constructs. Descriptive statistics and correlations were used in describing the sample, attrition analyses, and to establish relations between sample characteristics and model constructs.

Hypothesized relations among the integrated social cognition model constructs were tested using variance-based structural equation modeling implemented in the WARP 7.0 analysis package using the ‘Stable3’ estimation method (Kock, 2020). The model was tested in the pooled data from both samples. All constructs were latent variables indicated by single or multiple items. Missing data were imputed using linear multiple regression imputation method (Kock, 2020).

Measurement aspects of the latent variables provided means to establish validity and internal consistency of the model constructs. Construct validity was evaluated by inspection of the normalized factor pattern loadings of each variable on its respective factor after oblique rotation and Kaiser normalization (Kock, 2020) and the average variance extracted (AVE), which should approach or exceed .700 and .500, respectively. Internal consistency of the factors was estimated using the composite reliability coefficients (ρ), which should approach or exceed .900. Discriminant validity was evaluated using the square-root of the AVE for each latent variable, which should exceed its correlation with other latent variables.

Overall, adequacy of proposed relations among the integrated social cognition model constructs was established using multiple goodness-of-fit and model quality indices. An overall goodness-of-fit

(GoF) index was computed with values of .100, .250, and .360 corresponding to small, medium, and large effect sizes (Tenenhaus et al., 2005). In addition, an overall goodness-of-fit index is provided by the average block variance inflation factor for model parameters (AVIF) and the average full collinearity variance inflation factor (AFVIF), which should be equal to or lower than 3.3 for well-fitting models. Further information on the quality of the model was provided by the average path coefficient (APC) and average R^2 (AR^2) coefficients, both of which should be statistically significant. Four further indices were used to evaluate model quality: the Simpson's paradox ratio (SPR), R^2 contribution ratio (R^2CR), the statistical suppression ratio (SSR), and the nonlinear bivariate causality direction ratio (NLBCDR). The SPR should exceed .700 and ideally approach 1.000, the R2CR and SSR should exceed 0.900 and 0.700, respectively, and the NLBCDR should exceed .700 for high quality models. Technical details on model fit and quality indices are provided by Kock's (2020) lucid treatment of partial least squares structural equation modeling. Model effects were estimated using standardized path coefficients with confidence intervals and test statistics. Effect sizes were estimated using Cohen's *f*-square coefficient, which represents R^2 the contribution of each predictor variable to its respective dependent variable. Values of .02, .15, and .35 represent small, medium, and large effect sizes, respectively[2].

To ensure we were justified in pooling data from each sample when estimating the model, we also conducted a multi-group analysis in which we compared model the path coefficients across the samples using the Satterthwaite method with two-tailed significance tests[3].

Results

Participants

Sample characteristics for the study sample at each data collection occasion are presented in Table 1. Attrition across the three data collection occasions resulted in a final sample size of 601 (*M*

[2]Data files and analysis output are available online: https://osf.io/f95zh/
[3]For completion we also estimated the model separately in both samples and data files and analysis output for these ancillary analyses are available online: https://osf.io/f95zh/

age = 54.51, SD = 15.42; 46.2% female; retention rate 50.25%). Full sample characteristics are presented in Appendix B (supplemental materials). Attrition analyses revealed that participants lost to attrition were younger (lost to attrition, M age = 37.79, SD = 14.84; retained sample, M age = 54.51, SD = 15.42), and more likely to be female (lost to attrition, n = 328 (27.7%); retained sample, n = 276 (23.3%)), non-White (lost to attrition, n = 153 (12.8%); retained sample, n = 81 (6.8%)), and less educated (lost to attrition, n = 233 (19.5%); retained sample, n = 189 (15.8%)) than those retained at follow-up. A MANOVA testing for differences on social cognition constructs and behavior among participants lost to attrition and those included at follow-up revealed statistically significant differences for measures taken at T1 (Wilks' Lambda = 0.981, $F(7,1188) = 3.315$, $p = .002$, partial $\eta^2 = .019$), but no differences for measures taken at T2 (Wilks' Lambda = 0.990, $F(7,797) = 1.093$, $p = .366$, partial $\eta^2 = .010$). Follow-up tests revealed that mean values for behavior, habit, attitude, subjective norm, moral norm, and intention with respect to physical distancing taken at T1 were significantly lower among participants lost to attrition compared to those retained at follow-up. However, effect sizes for these differences were relatively modest (ds < .25). Full details of attrition analyses are presented in Appendix C (supplemental materials).

Preliminary Analyses

Factor loadings and AVE values exceeded recommended 0.700 and 0.500 cut-off values in all cases, and composite reliability coefficients indicated acceptable internal consistency for each scale (see Appendix D, supplemental materials). Correlations among social cognition constructs were all statistically significant and small-to-medium in size (r range = .161 to .564). Correlations of social cognition and behavioral constructs with socio-demographic variables revealed few statistically significant associations. The most consistent relations were between social cognition constructs and age, although effect sizes were small in all cases. Square-roots of the AVE for each latent variable exceeded the correlation of that variable with all other latent variables providing support for discriminant validity (see Appendices E and F, supplemental materials).

Structural Equation Model

The proposed model exhibited adequate fit with the data according to the quality indices adopted (APC = .248, $p < .001$; $AR^2 = .453$, $p < .001$; AVIF = 1.494; AFVIF = 2.965; GoF = .603; SPR = .985; R2CR = 1.000; SSR = 1.000; NLBCDR = 1.000). Standardized parameter estimates for the proposed direct effects for the model are presented in Figure 1 and parameter estimates, confidence intervals, and effect sizes are summarized in Table 2.

Consistent with predictions, subjective norm, PBC, and moral norm were statistically significant predictors of physical distancing intention at all three time points, with small-to-medium effect sizes. However, the effect of attitude on intention was not statistically significant at any of the time points, contrary to predictions. Intention and habit measured at T1 and T2 were significant predictors of follow-up physical distancing behavior at T2 and T3, respectively, with small effect sizes. Behavior predicted all constructs in the model at each time point. There were significant indirect effects of subjective norm, PBC, and moral norm measured at T2 on behavior measured at T3 mediated by intention measured at T2. However, indirect effects of these constructs measured at T1 on behavior measured at T2 mediated by intention measured at T2 were not statistically significant, largely due to the small-sized effect between intention measured at T1 and behavior measured at T2. Habit measured at T1 mediated the effect of behavior measured at T1 on behavior measured at T2, but this was not the case for the indirect effect of behavior measured at T2 on behavior measured at T3 mediated by habit measured at T2. As expected, auto-regressions of the social cognition constructs and behavior variables on themselves over time were statistically significant with medium-to-large sized effects. The only exception was the intention constructs for which the auto-regressions were small in size. Overall, the model accounted for significant variance in physical distancing intention (T1, $R^2 = .635$; T2, $R^2 = .694$; T3, $R^2 = .790$) and behavior (T2, $R^2 = .339$; T3, $R^2 = .339$) at each time point.

Multisample analyses testing differences in parameter estimates in the proposed model across the Australia and US samples revealed models that fit the data well[4], with few differences in effects, particularly in effects of constructs on physical distancing intention and behavior. The subjective norm-intention relation was larger, and PBC-intention effect, smaller in the Australia sample relative to the US sample at T2, with the opposite pattern observed at T3. The only other differences of note were for effects of past behavior. Overall, the consistency in the pattern of effects across samples with relatively trivial differences justify pooling data across samples for analysis.

Discussion

The present study applied an integrated social cognition model to predict physical distancing intention and behavior of Australian and US residents using a three-wave longitudinal design over four months. A well-fitting structural equation model indicated that subjective norm, PBC, and moral norm, but not attitude, were consistent predictors of concurrently-measured physical distancing intention at each occasion, and intention and habit were consistent predictors of subsequent physical distancing behavior. Intention measured at T2 mediated effects of subjective norm, moral norm, and PBC on physical distancing behavior at T3, but these mediation effects were not found for social cognition constructs and intention at T1 on behavior at T2 due to a very small intention-behavior relationship across these occasions. Physical distancing behavior on each occasion predicted all concurrently-measured model constructs, and predicted behavior on subsequent occasions mediated by concurrently-measured habit. Model constructs exhibited high stability across each occasion, with the exception of intention which had modest stability effects.

A key finding of the current research is the prominence of three model constructs as consistent predictors of intention to perform physical distancing behavior on each occasion: subjective norm, PBC, and moral norm. These effects corroborate predictions of the integrated social cognition model and augment prior short-range research applying integrated models to predict COVID-19 preventive

[4]Goodness of fit and model quality indices for models estimated separately in each sample are presented in Appendix G (supplemental materials).

behaviors (e.g., Gibson Miller et al., 2020; Hagger, Smith, et al., 2020; Hamilton, Smith, et al., 2020; Lin et al., 2020; Lithopoulos et al., 2021; Norman et al., 2020) by demonstrating the temporal consistency of these effects. The small, non-significant effects of attitude were, however, contrary to predictions of the integrated model and other social cognition theories. Taken together, these finding suggest that individuals intend to physically distance themselves to prevent COVID-19 infections due to normative and personal capacity considerations, rather than their personal evaluation of potentially important outcomes. This is consistent with prior research in the context of infection prevention behaviors including studies on COVID-19 preventive behaviors, which demonstrate stronger effects for normative or capacity-related constructs on intention relative to attitude (e.g., Gibson Miller et al., 2020; Hagger, Smith, et al., 2020; Lin et al., 2020; Moussaoui et al., 2020; Zhang et al., 2020). The present research adds to these findings by demonstrating that the effects are sustained over a four-month period and hold when accounting for the stability of the constructs over time and past experience. The latter is important given that belief-based constructs tend to be based on previously held beliefs and experience, not just on the evaluation of current status of the behavior, context, and the individual in isolation (Bagozzi et al., 1992; Hagger et al., 2001). In other words, individuals lean on past experience and beliefs stored in memory when making decisions not just on situational considerations. That attitude did not predict intention suggests that personally-relevant outcomes are not so salient when it comes to forming an intention to physically distance. This finding suggests that although individuals rated physical distancing behavior as one that will lead to any personal advantages, as attitude scores were relatively high, it was not relevant to forming intentions to perform it in future. Instead, individuals formed their intentions based on normative considerations to prevent COVID-19 infections in others – a behavior that significant others want them to do and one they are morally obliged to do to protect others (Van Bavel et al., 2020). It is also important to note that we did not make the distinction between instrumental and affective attitudes in the current study, and there is evidence that different attitude components may predict intentions and behavior differently (e.g., Conner et al., 2015), including COVID-19 preventive behaviors (Norman et al., 2020). However, the measurement aspect of our model indicated that items from the different components of attitude were effective indicators of a latent attitude factor at all three time points, and indicated strong inter-item correlations, so there is no reason to expect that separate attitude components would have different patterns of effects on intentions in this study.

A further important finding is the indirect effects of subjective norm, moral norm, and PBC measured at T2 on behavior at T3 mediated by intention. These indirect effects support proposed mechanisms derived from the integrated social cognition model and models that have informed it such as the theories of reasoned action and planned behavior (Ajzen, 1985; Ajzen & Fishbein, 1980). Also important is the fact that these predictions remain when accounting for construct stability and previous experience, which has been seldom demonstrated in research applying these models to the prediction of health behavior in general (cf., Chan et al., 2020; Jacobs et al., 2011) and has not, to our knowledge, been demonstrated in the context of physical distancing behavior for the prevention of COVID-19 infections. Taken together, these findings provide potentially useful information for interventionists aimed at developing public health communications to promote uptake and maintenance of physical distancing behavior in the context of the pandemic. Such messages should highlight normative- and personal capacity-related beliefs, such as emphasizing obligations to significant others and those in society who may be vulnerable to infection, and outlining some simple rules of thumb to follow when in situations where individuals are likely to come into close contact with others (Miller & Prentice, 2016; Warner & French, 2020).

Habit was also a pervasive determinant of physical distancing behavior across all time points, and also accounted for a proportion of the effect of past behavior on subsequent behavior. These findings corroborate previous research applying social cognition models augmented to include self-reported habit to predict health behaviors (Arnautovska et al., 2017; Brown et al., 2020; Hagger et al., 2015; Hamilton et al., 2017; van Bree et al., 2015), including physical distancing (Hagger, Smith, et al., 2020), and extend them to demonstrate that habit effects are sustained over time. The finding also demonstrates that past behavior, to some extent, reflects habit, consistent with previous research (Brown et al., 2020; van Bree et al., 2015) and theoretical contentions that past behavioral frequency measures can reflect habits (Ouellette & Wood, 1998). Taken together, present findings suggest that physical distancing is a function of constructs that reflect both reasoned and automatic processes. It is unlikely that individuals' physical distancing behavior is determined by both processes simultaneously. Rather, it probably means that groups of individuals have performed the behavior with sufficient regularity and consistency for it to develop into a habit while, for others, the behavior is one that is determined by reasoned considerations on most occasions. However, given that habits are a consistent predictor of physical distancing, it seems prudent for interventions to include strategies that foster development of physical distancing habits. Such interventions would focus on encouraging repeated experience with the behavior in stable contexts, and to focus on concomitant positive evaluations which may develop positive implicit beliefs that may reinforce the behavior over time and help foster the habit (Gardner et al., 2020). For example, introducing signage and floor markings may provide useful cues for individuals to maintain the appropriate physical distance in public spaces, which may ultimately reinforce consistent repeated experiences and lead to adoption of similar distances in similar contexts even in the absence of markings.

Strengths, Limitations, and Avenues for Future Research

The present study has a number of strengths including the application of an integrated social cognition model that specified potentially modifiable reasoned and automatic determinants of physical distancing intention and behavior, and the adoption of a three-wave longitudinal design that permitted modeling of the stability of social cognition constructs and behavior measures and examination of sustained effects over time. However, current findings should be interpreted in light of a number of salient limitations.

First, while recruitment of our sample aimed to match population distributions, the sample was not randomly selected or stratified on socio-demographic variables beyond age, sex, and geographic location within each country, so we cannot contend that the current findings will generalize to the wider population. Also important is the substantive sample attrition rate across the three time points, and attrition analyses demonstrated that those who dropped out were more likely to be younger, non-white, have low income, and have lower education levels. While participants were provided with multiple reminders to complete surveys at each data collection occasion, future research should attempt to replicate current findings in more representative samples. Such studies should apply even more intensive recruitment strategies including targeted incentivization of non-responders to minimize drop out. The substantive attrition also places limits on generalizability of findings because participants remaining in the study may have had higher general levels of motivation and self-efficacy, which may have been manifested in their beliefs and behavior.

Second, while the adoption of the longitudinal design enabled the modeling of change in model constructs and physical distancing behavior and the specification of a temporal order in model predictions, these data are still correlational and so preclude causal inference. Therefore, any causal effects are inferred from theory alone and not the data. To better infer causality, researchers are encouraged to use the current findings as a basis for developing intervention studies that adopt behavior change techniques that target change in the salient constructs from the current model. This would permit evaluation of the extent to which such techniques lead to change in the constructs themselves and, particularly, change in physical distancing behavior.

Third, effect sizes for the prediction of physical distancing behavior over time were relatively small. Effect sizes for relations between constructs and intentions were small-to-medium in size, and this was the case for within- and across-time relations, suggesting that the model is very effective in predicting intentions, which was mirrored in the substantive variance accounted for in intentions at all time points. However, effect size and variance accounted for in physical distancing behavior was much smaller by comparison. The model is less adept at explaining behavior itself, an observation that has been levelled as social cognition models elsewhere (Orbell, 2004; Orbell & Sheeran, 1998; Sheeran, 2002). Inclusion of measures of individuals' use of volitional strategies (e.g., planning) that facilitate intention enactment may yield important insight into the small intention-behavior effect size in integrated models such as these. However, it should also be noted that sizes of effects over time are likely to wane, and although models such as these are unlikely to be entropic, the increased likelihood of new information becoming available that lead individuals to modify their beliefs means that effect sizes will deteriorate over time. Solitions lie in increased frequency of measurement to account for frequent changes in beliefs using methods such as ecological momentary assessment may provide better insight as to the influences on preventive behaviors, including COVID-19 behaviors like social distancing, over time.

Finally, the current study relied exclusively on self-report measures of constructs and behaviors. Researchers have advocated for the adoption of non-self-report measures of behavior and constructs such as habit to allay potential recall bias and socially desirable responding (Kalajas-Tilga et al., 2021; Wood & Neal, 2009). Collecting data on physical distancing behavior using a non-self-report measure through, for example, covert observation, will likely present practical and ethical challenges. While we sought to minimize socially desirable responding by assuring anonymity, future research may consider validating self-report measures of physical distancing through controlled behavioral observation in a sub-sample to also minimize the impact of recall bias. Such research will not only provide corroboration of behavioral measures, but also serve to establish a protocol to validate self-report measures of physical distancing behaviors in future.

Conclusion

While the introduction of COVID-19 vaccines promises to accelerate bringing the COVID-19 virus pandemic under control in the long term, preventive behaviors to stem the spread of infection are still paramount to reduce numbers of severe cases and mortality rates. Public health messaging is, therefore, needed to communicate to the general public the imperative of maintaining these behaviors, with physical distancing pre-eminent among them. Such messaging should be informed by research identifying modifiable determinants that are linked to physical distancing behavior over time and can be targeted in the messages. While previous research has identified predictors of physical distancing (e.g., Beeckman et al., 2020; Bogg & Milad, 2020; Hagger, Smith, et al., 2020; Moussaoui et al., 2020), few have studied these determinants over time. The present study fills this knowledge gap by examining determinants of physical distancing behavior in the context of COVID-19 over time. Results reveal that normative, particularly subjective and moral norms, and personal capacity beliefs were consistent predictors of physical distancing intention, and, indirectly, predicted physical distancing behavior along with habits and past behavior while simultaneously controlling for construct stability. These findings can contribute to the body of evidence on which messages promoting physical distancing behavior should be based. Current findings should serve as a platform for future longitudinal studies and, in particular, intervention studies which examine long-term effects of changing the salient determinants of physical distancing. These results also highlight the importance of adopting integrated social cognition models that derive constructs and predictions from multiple theories and models, and provide the basis for future research on behaviors relevant to infection control for upper respiratory infections.

Disclosure statement

No potential conflict of interest was reported by the authors.

Data Availability

Data files and analysis output are available online: https://osf.io/f95zh/

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Table 1
Sample Characteristics and Descriptive Statistics for Study Variables at Baseline (T1) and at the One-Week (T2) and Four-month (T3) Follow-Up Occasions

Variable	T1	T2	T3
Participants	1196	805	601
Age, *M* years (SD)	46.19 (17.29)	50.86 (16.57)	54.51 (15.42)
Sex, *n* (%)[a]			
Female	604 (48.9)	412 (51.6)	276 (46.2)
Male	582 (50.8)	387 (48.4)	321 (53.8)
Not specified/prefer not to answer	4 (0.3)	0 (0.0)	0 (0.0)
Employment status, *n* (%)[b]			
currently unemployed/full-time caregiver	561 (47.1)	396 (49.4)	317 (52.9)
part-time/casual employed	203 (17.0)	125 (15.6)	88 (14.7)
currently employed full-time	373 (31.3)	251 (31.3)	176 (29.4)
leave without pay/furloughed	55 (4.6)	29 (3.6)	18 (3.0)
Marital status, *n* (%)[c]			
Married	484 (40.6)	370 (46.2)	290 (48.4)
Widowed	30 (2.5)	25 (3.1)	24 (4.0)
Separated/divorced	122 (10.2)	86 (10.7)	67 (11.2)
Never married	415 (34.8)	229 (28.6)	145 (24.2)
Married de facto	141 (11.8)	91 (11.4)	73 (12.2)
Ethnicity, *n* (%)[d]			
Black	55 (4.6)	27 (3.4)	15 (2.5)
Caucasian/White	958 (80.1)	680 (84.9)	518 (86.5)
Asian (South-East Asia/South Asia)	110 (9.2)	67 (8.4)	49 (8.2)
Middle-Eastern	7 (0.6)	3 (0.4)	2 (0.3)
Other	40 (3.3)	14 (1.7)	9 (1.5)
Prefer not to answer	22 (1.8)	10 (1.2)	6 (1.0)
Income, *n* (%)[e]			
zero income	39 (3.4)	23 (3.0)	15 (2.6)
$1-$199 ($1-$10,399)	49 (4.2)	30 (3.9)	20 (3.5)
$200-$299 ($10,400-$15,599)	46 (4.0)	31 (4.0)	24 (4.1)
$300-$399 ($15,600-$20,799)	57 (4.9)	35 (4.5)	28 (4.8)
$400-$599 ($20,800-$31,199)	104 (9.0)	66 (8.6)	56(9.7)
$600-$799 ($31,200-$41,599)	118 (10.2)	81 (10.5)	61 (10.5)
$800-$999 ($41,600-$51,999)	113 (9.8)	77 (10.0)	55 (9.5)
$1,000-$1,249 ($52,000-$64,999)	87 (7.5)	70 (9.1)	53 (92)
$1,250-$1,499 ($65,000-$77,999)	87 (7.5)	63 (8.2)	43 (7.4)
$1,500-$1,999 ($78,000-$103,999)	144 (12.5)	98 (12.7)	75 (13.0)
$2,000 or more ($104,000 or more)	189 (15.8)	136 (17.7)	108 (18.7)
Prefer not to answer	123 (10.6)	60 (7.8)	41 (7.1)
Education level, *n* (%)			
Completed junior/lower/primary school	24 (2.0)	17 (2.1)	14 (2.3)
Completed senior/high/secondary school	398 (33.3)	230 (28.6)	175 (29.1)
Post-school vocational qualification/diploma	285 (23.8)	205 (25.5)	148 (24.6)
Undergraduate University degree	345 (28.8)	252 (31.3)	191 (31.8)
Postgraduate University degree	144 (12.0)	101 (12.5)	73 (12.1)

Note. T1 = First data collection occasion; T2 = Second data collection occasion; T3 = Third data collection occasion; [a]Six participants did not report their sex at T1; [b]Four participants did not report their employment status at T1; [c]Four participants did not report their marital status at T1; [d]Four participants did not report their ethnicity at T1; [e]Forty participants did not report their income at T1.

Table 2
Standardized Parameter Estimates for Indirect Effects for the Structural Equation Model of the Integrated Social Cognition Model

Effect	β	95% CI LB	95% CI UB	ES	Effect	β	95% CI LB	95% CI UB	ES
Direct effects					Beh (T3)→Hab (T3)	.360***	.305	.415	.188
Hab (T1)→MN (T1)	.098***	.041	.155	.024	Beh (T3)→MN (T3)	.371***	.316	.426	.238
Hab (T1)→Att (T1)	.298***	.243	.353	.119	Beh (T3)→Att (T3)	.368***	.313	.423	.212
Hab (T1)→SN (T1)	.164***	.107	.221	.051	Beh (T3)→Att (T3)	.326***	.271	.381	.191
Hab (T1)→PBC (T1)	.353***	.298	.408	.157	Beh (T3)→PBC (T3)	.229***	.174	.284	.114
Hab (T1)→Int (T1)	.009	-.048	.066	.003	Beh (T3)→Int (T3)	.259***	.204	.314	.191
Hab (T1)→Beh (T2)	.087**	.030	.144	.027	MN (T3)→Int (T3)	.317***	.262	.372	.257
Beh (T1)→Hab (T1)	.366***	.311	.421	.134	Att (T3)→Int (T3)	.023	-.034	.080	.105
Beh (T1)→MN (T1)	.448***	.393	.503	.216	SN (T3)→Int (T3)	.156***	.099	.213	.117
Beh (T1)→Att (T1)	.277***	.222	.332	.107	PBC (T3)→Int (T3)	.164***	.107	.221	.104
Beh (T1)→SN (T1)	.413***	.358	.468	.195	Autoregressions				
Beh (T1)→PBC (T1)	.249***	.194	.304	.095	Hab (T1)→Hab (T2)	.650***	.597	.703	.459
Beh (T1)→Int (T1)	.285***	.230	.340	.174	Beh (T1)→Beh (T2)	.480***	.425	.535	.272
MN (T1)→Int (T1)	.291***	.236	.346	.192	MN (T1)→MN (T2)	.683***	.630	.736	.522
Att (T1)→Int (T1)	.020	-.037	.077	.009	Att (T1)→Att (T2)	.495***	.440	.550	.297
SN (T1)→Int (T1)	.190***	.135	.245	.119	SN (T1)→SN (T2)	.507***	.452	.562	.328
PBC (T1)→Int (T1)	.248***	.193	.303	.138	PBC (T1)→PBC (T2)	.486***	.431	.541	.293
PBC (T1)→Beh (T2)	.048*	-.009	.105	.014	Int (T1)→Int (T2)	.155***	.098	.212	.091
Int (T1)→Beh (T2)	.065*	.008	.122	.026	Hab (T2)→Hab (T3)	.507***	.452	.562	.316
Hab (T2)→MN (T2)	.058*	.001	.115	.017	Beh (T2)→Beh (T3)	.361***	.306	.416	.192
Hab (T2)→Att (T2)	.156***	.099	.213	.059	MN (T2)→MN (T3)	.536***	.481	.591	.387
Hab (T2)→SN (T2)	.077**	.020	.134	.024	Att (T2)→Att (T3)	.375***	.320	.430	.208
Hab (T2)→PBC (T2)	.159***	.102	.216	.066	SN (T2)→SN (T3)	.455***	.400	.510	.287
Hab (T2)→Int (T2)	.021	-.036	.078	.007	PBC (T2)→PBC (T3)	.390***	.335	.445	.217
Hab (T2)→Beh (T3)	.098***	.041	.155	.031	Int (T2)→Int (T3)	.164***	.107	.221	.103
Beh (T2)→Hab (T2)	.181***	.124	.238	.069	Indirect effects				
Beh (T2)→MN (T2)	.175***	.118	.232	.080	MN (T1)→Int (T1)→Beh (T2)	.019	-.020	.058	.007
Beh (T2)→Att (T2)	.169***	.112	.226	.065	Att (T1)→Int (T1)→Beh (T2)	.001	-.038	.040	.000
Beh (T2)→SN (T2)	.302***	.247	.357	.160	SN (T1)→Int (T1)→Beh (T2)	.012	-.027	.051	.005
Beh (T2)→PBC (T2)	.179***	.122	.236	.068	PBC (T1)→Int (T1)→Beh (T2)	.016	-.023	.055	.005
Beh (T2)→Int (T2)	.188***	.133	.243	.108	Beh (T1)→Hab (T1)→Beh (T2)	.043*	.004	.082	.024
MN (T2)→Int (T2)	.243***	.188	.298	.167	MN (T2)→Int (T2)→Beh (T3)	.052**	.013	.091	.023
Att (T2)→Int (T2)	.000	-.057	.057	.000	Att (T2)→Int (T2)→Beh (T3)	.000	-.039	.039	.000
SN (T2)→Int (T2)	.316***	.261	.371	.173	SN (T2)→Int (T2)→Beh (T3)	.051**	.012	.090	.022
PBC (T2)→Int (T2)	.256***	.201	.311	.150	PBC (T2)→Int (T2)→Beh (T3)	.055**	.016	.094	.018
PBC (T2)→Beh (T3)	.048***	-.009	.105	.016	Beh (T2)→Hab (T2)→Beh (T3)	.026	-.013	.065	.014
Int (T2)→Beh (T3)	.213***	.158	.268	.101	Sum of indirect effects[a]				
Hab (T3)→MN (T3)	.079**	.022	.136	.035	Hab (T1)→Beh (T2)	.027	-.030	.084	.008
Hab (T3)→Att (T3)	.157***	.100	.214	.075	Hab (T2)→Beh (T3)	.028	-.029	.085	.009
Hab (T3)→SN (T3)	.127***	.070	.184	.054	Total effects[b]				
Hab (T3)→PBC (T3)	.243***	.188	.298	.123	Hab (T1)→Beh (T2)	.114***	.057	.171	.035
Hab (T3)→Int (T3)	.005	-.052	.062	.003	Hab (T2)→Beh (T3)	.126***	.069	.183	.040

Note. [a]Sum of indirect effects of through all model constructs; [b]Total effect comprising sums of all indirect effects through model constructs plus the direct effect; β = Standardized parameter estimate; 95% CI = 95% confidence interval of standardized parameter estimate; LB = Lower bound of 95% CI; UB = Upper bound of 95% CI; ES = Effect size of the standardized parameter estimate. T1 = First data collection occasion; T2 = Second data collection occasion; T3 = Third data collection occasion; Hab = Self-reported habit; MN = Moral norm; Att = Attitude; SN = Subjective norm; PBC = Perceived behavioral control; Int = Intention; Beh = Physical distancing behavior.
*** $p < .001$ ** $p < .01$ * $p < .05$

Figure 1. Standardized parameter estimates from the structural equation model of the proposed integrated social cognition model.
Note. T1 = First data collection occasion; T2 = Second data collection occasion; T3 = Third data collection occasion. Hab = Self-reported habit; MN = Moral norm; Att = Attitude; SN = Subjective norm; PBC = Perceived behavioral control; Int = Intention; Beh = Physical distancing behavior. *** $p < .001$ ** $p < .01$ * $p < .05$