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#### **Abstract**

**Background** Social distancing is a key behavior to minimize COVID-19 infections. Identification of potentially modifiable determinants of social distancing behavior may provide essential evidence to inform social distancing behavioral interventions.

**Purpose** The current study applied an integrated social cognition model to identify the determinants

of social distancing behavior, and the processes involved, in the context of the COVID-19 pandemic. *Methods* In a prospective correlational survey study, samples of Australian (N = 365) and US (N = 440) residents completed online self-report measures of social cognition constructs (attitude, subjective norm, moral norm, anticipated regret, perceived behavioral control), intention, action planning, habit, and past behavior with respect to social distancing behavior at an initial occasion. Follow up measures of habit and social distancing behavior were taken one week later. *Results* Structural equation models indicated that subjective norm, moral norm, and perceived

behavioral control were consistent predictors of intention in both samples. Intention, action planning, and habit at follow-up were consistent predictors of social distancing behavior in both samples.

Action planning did not have consistent effects mediating or moderating the intention-behavior relationship. Inclusion of past behavior in the model attenuated effects among constructs, although effects of the determinants of intention and behavior remained.

Conclusions Current findings highlight the importance of subjective norm, moral obligation, and perceived behavioral control as determinants of social distancing intention, and intention and habit as behavioral determinants. Future research on long-range predictors of social distancing behavior and reciprocal effects in the integrated model is warranted.

*Keywords:* Social cognition theory; Health behavior; Dual-phase models; Dual-process models; Habit; Action planning.

## Introduction

The novel coronavirus disease 2019 (COVID-19) pandemic has emerged as a truly global public health crisis [1]. While symptoms of COVID-19 are relatively mild without serious consequences in the majority of cases [2], modeling data suggests that approximately 4% of the global population is at risk of severe COVID-19 if infected and would require hospital admission for treatment [3]. Furthermore, SARS-CoV-2, the virus that causes COVID-19, is highly contagious, spreading mainly through person-to-person contact. Government-mandated measures to reduce transmission include advocacy of behaviors like wearing face masks and social distancing, and issuing 'shelter-in-place' orders and bans on public gatherings [4].

Social distancing, defined as maintaining a distance of at least 3-6 feet (1-2m) from other people not from the same household, is considered particularly effective in minimizing SARS-CoV-2 transmission [5, 6]. 'Shelter-in-place' orders (also referred to as 'stay-at-home' or 'lockdown' orders) represent means to mandate social distancing by minimizing incidences of person-to-person contact outside individuals' immediate household. Similarly, bans on public gatherings seek to limit the frequency and number of people with whom they come into close contact. However, such actions do not eliminate all potential contact because individuals under such orders still need to break from shelter to fetch provisions and, for members of essential professions, to go to work. It is therefore imperative that individuals comply with public health guidelines advocating the practice of social distancing when they may come into contact with others. Compliance with guidelines is also highly important in regions that have not issued formal 'shelter-in-place' orders, but have instead provided 'safer-at-home' guidelines, and in areas that have begun to lift 'shelter-in-place' orders.

Public health organizations have been tasked with developing behavioral interventions that are efficacious in promoting social distancing behaviors among the general population [6]. Given that social distancing in a relatively novel behavior in many countries, identification of the determinants of social distancing behavior has become critical. Moreover, identifying determinants that are

potentially modifiable through intervention, that is, can be targeted in messages or campaigns of behavioral interventions aimed at promoting social distance, is a recognized priority [7]. There have, therefore, been calls for research informed by behavioral science that identifies key determinants of preventive behaviors in the context of the current pandemic, particularly social distancing [7, 8]. However, there is relatively little research on the determinants of social distancing, particularly in the context of communicable disease prevention (e.g., influenza) in a global pandemic [9]. Previous research, for example, has tended to focus on the social cognition determinants of other preventive behaviors such as facemask wearing [10], or focused on hypothetical scenarios [11], in the context of influenza prevention. To date, there are few studies informed by behavioral science on the individual determinants of social distancing in the context of the COVID-19 pandemic.

To fill this evidence gap, the current study aimed to identify the determinants of social distancing behavior among individuals subject to social distancing regulations during the COVID-19 pandemic. The research adopted an integrated theoretical approach based on social cognition theories to identify constructs that predict social distancing behavior and the processes involved. The research is expected to provide evidence of potentially modifiable targets for behavior change interventions aimed at promoting social distancing. Such interventions may contribute to reduced infection rates during the current pandemic, and may assist in preventing a 'second wave' of infections as 'shelter-in-place' orders are lifted [5].

# Social Distancing Determinants: An Integrated Social Cognition Approach

Research examining health behavior determinants has a long tradition of applying social cognition theories [12], which assume health behavior enactment is a reasoned process determined by beliefs such as risk perception, attitude, social norm, and perceptions of control or self-efficacy. A prototypical social cognition approach is offered by the theory of planned behavior [13]. In the theory, individuals' intention to perform the target behavior is proposed as the most proximal determinant of performance of a future target behavior. Intention is a function of three constructs

which summarize sets of beliefs regarding the future behavior: attitude (beliefs that the behavior will have advantageous or disadvantageous consequences), subjective norm (beliefs that significant others express support for performing the behavior), and perceived behavioral control (PBC; beliefs in capacity to perform the behavior and to overcome barriers to the behavior). Intention is proposed to mediate effects of attitude, subjective norm, and PBC on behavior. PBC is also proposed to predict behavior directly when it approximates actual control. Theory predictions have been supported in correlational and prospective research across multiple behaviors, contexts, and populations [14].

While the elegant parsimony of the theory of planned behavior is appealing, it is not without limitations. Research applying the theory has indicated that substantive variance in health behavior remains unexplained [14]. In addition, the size of the effect of intention on health behavior is often modest suggesting a 'shortfall' in those who report an intention to perform the behavior and those who act on their intention [15]. Researchers have therefore proposed modifications to the theory to resolve these limitations, such as integrating additional constructs and predictions from other theories in the theory to predict behavior more effectively and address the intention-behavior 'gap' [16].

Introducing additional constructs to the theory is one approach to increasing explained variance in health behavior. For example, researchers have examined relations between moral norms, an additional form of normative influence, and health behavior. Moral norms are considered particularly relevant when there is a moral imperative for acting (e.g., vaccination, blood donation) [17]. In the context of COVID-19, messaging from public health authorities on COVID-19 preventive behaviors has focused on protecting the vulnerable (e.g., immunosuppressed individuals, those with underlying health conditions, the elderly) [3]. On this basis, we reasoned that moral norm would constitute a highly relevant determinant of social distancing intention and behavior in the context of the pandemic. In addition, anticipated regret has been shown to predict behaviors perceived likely to have adverse consequences or result in significant losses if not performed [17]. Failure to perform social distancing behaviors may be perceived as having highly undesirable consequences such as becoming

infected or infecting vulnerable others. We therefore included moral norm and anticipated regret as additional predictors of intention to perform social distancing behavior in our integrated model.

Researchers have applied 'dual-phase' models as means to resolve the limitation of the intention-behavior 'gap'. Models like the model of action phases [18] and the health action process approach (HAPA) [19] propose that individuals need to augment their intentions with action plans in order to enact them. Action plans reflect the extent to which individuals have specified when, where, and how they will perform the intended behavior. The model of action phases [18] suggests that individuals will more likely enact their intentions if they form an action plan, so action plans are proposed to moderate the intention-behavior relationship. By contrast, the HAPA suggests that planning is part of the process of intention enactment such that action plans mediate the intention-behavior relationship [19]. Meta-analyses of studies in health behavior have supported both processes [20, 21], and we aimed to test both in our proposed integrated model of social distancing behavior.

While social cognition theories like the theory of planned behavior assume participation in health behavior to be a reasoned process, research applying such theories has shown that past behavior remains a pervasive determinant of behavior alongside the theory constructs [22, 23]. The inclusion of past behavior as an independent behavioral predictor in a social cognition theory is important because it provides a test of its sufficiency in accounting for unique variance in behavior. However, residual effects of past behavior on behavior is also assumed to model effects of other unmeasured constructs on behavior [23]. One candidate construct is habit, which reflects the 'non-conscious' or 'automatic' enactment of a behavior developed through its repeated performance in stable contexts [24, 25]. Research examining effects of habit in the context of social cognition theories has examined how self-reports of experiencing of the behavior as 'automatic' and 'unthinking' predict health behavior independent of intentions [26]. The introduction of habit in our augmented model, therefore, may provide important information on the extent to which social distancing behavior is determined by reasoned or non-conscious processes [27].

# **The Present Study**

The present study aimed to identify the determinants of participation in social distancing behavior among individuals in the context of COVID-19 using an integrated social cognition model that incorporated constructs from the theory of planned behavior with moral norm, anticipated regret, action planning, and self-reported habit. We tested predictions of the proposed model in a prospective correlational study in two separate samples of adults from Australia and the US, respectively. These countries provide an opportunity to examine the determinants of social distancing because they experienced rapid increases in COVID-19 cases relatively early in the pandemic and introduced public health advice and 'lockdown' measures to minimize transmission via social distancing. In our proposed model (Model 1, Figure 1), attitude, subjective norm, PBC, moral norm, and anticipated regret were specified as predictors of intention, and intention, PBC, and habit as predictors of social distancing behavior. Intention was proposed to mediate effects of the social cognition constructs on behavior. The role of action planning as a mediator and moderator of the intention-behavior relationship was also specified. We also specified a second model (Model 2, Figure 1) in which past social distancing behavior was included as a direct predictor of all constructs in the model, providing a test of its sufficiency. Although research demonstrating that social distancing behavior clusters with other health behaviors indicates that application of social cognition theories is viable for this behavior [28], research is needed to verify this contention and the current study contributes to this goal. The research may assist in identifying potentially modifiable constructs that relate to social distancing behavior. Such information may provide useful information to inform social distancing interventions focused on reducing the spread of COVID-19 and, more broadly, other communicable diseases.

#### Method

# **Participants and Recruitment**

Samples of Australian (N = 495, 50.1% female) and US (N = 701, 48.9% female) residents were recruited via an online research panel company. To be eligible for inclusion, participants needed to be

aged 18 years or older and not subject to formal quarantine for COVID-19. Participants were also screened for age, gender, and geographical region and quotas 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 May 6, 2020. All participants in the Australia sample were subject to a national 'shelter-in-place' order issued by the federal government. However, issuance of orders in the US was devolved to state governments resulting in some variations. The vast majority of participants in the US sample (n = 610, 87.0%) were subject to 'shelter-in-place' orders for the duration of the study. However, some states did not impose 'shelter-in-place' orders at all (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 follow-up data collection. However, among US states that did not have 'shelter-in-place' orders, or lifted their orders during the study, all issued social distancing guidelines and encouraged the population to follow those guidelines. Baseline sample characteristics are presented in Table 1.

# **Design and Procedure**

The study adopted a prospective correlational design with self-report measures of social cognition constructs from the proposed integrated model, intention, and past social distancing behavior administered at an initial data collection occasion in a survey administered using the Qualtrics<sup>TM</sup> online survey tool. Social cognition measures included theory of planned behavior (attitude, subjective norm, and PBC), moral norm, anticipated regret, action planning, and habit constructs. Participants were informed that they were participating in a survey on their social distancing behavior and provided with information outlining study requirements. They were required to provide informed consent before proceeding with the survey. Participants were also provided with instructions on how to complete study measures and a definition of the target 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 meter (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 1-2 m (3-6ft) distance from other people)". One-week later participants were contacted by the panel company and asked to self-report their habit and social distancing behavior over the previous week using the same measures used at the initial data collection occasion. Participants received a fixed sum of money for their participation based on expected completion time consistent with the panel company's published rates. Approval for study procedures was granted prior to data collection from the Griffith University Human Research Ethics Committee.

## Measures

Study measures were multi-item self-report measures of constructs based on published guidelines and measures used in previous studies [13, 29, 30]. Participants provided their responses on scales with seven-point response options. Complete study measures are provided in Appendix A (supplemental materials).

Social cognition constructs. Multi-item measures of attitude, subjective norm, PBC, moral norm, anticipated regret, and action planning were developed according to published guidelines [13, 29]. Each measure made explicit reference to the target behavior of social distancing, and participants were reminded of the definition of social distancing before completing the measures.

**Intention.** Participants' intention to participate in social distancing behavior over the next week was measured using a scale developed according to published guidelines [31].

**Habit.** Habit was measured at both time points using the behavioral automaticity items of Verplanken and Orbell's self-report habit index [25]. The measure measures individuals' reflections on the extent to which the behavior is experienced as automatic and enacted without thought.

Past behavior and behavior. Participants self-reported their participation in social distancing behavior to minimize transmission of the SARS-CoV-2 virus that causes COVID-19. The measure comprised two-items prompting participants to report their frequency of social distancing behavior in the previous week. This is based on previously-used self-report behavioral measures which have demonstrated concurrent validity with non-self-report measures in other behavioral contexts [32].

Demographic variables. Participants self-reported their age in years, gender, 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 ethnicity (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 ethnicity (Caucasian/White vs. non-White) variables were computed for use in subsequent analyses.

# **Data Analysis**

Hypothesized relations among the integrated model constructs were tested in the Australia and US samples separately using variance-based structural equation modeling implemented in the WARP 7.0 analysis package [33]. Model parameters and standard errors were computed using the 'Stable3' estimation method, which has been shown to provide the most precise parameter estimates in complex structural models in smaller samples and outperforms bootstrapping methods in simulation studies [33]. Simulation studies have also shown this method to provide more consistent and precise estimates in data containing outliers, which may inflate standard errors and lead to abnormally high *p*-values [33]. Two models were estimated in each sample: a model testing predictions of the proposed

integrated model with the binary demographic variables also included as covariates (Model 1, Figure 1, upper panel), and a model that included effects of past social distancing behavior (Model 2, Figure 1, lower panel). All constructs were latent variables indicated by single or multiple items. There were no missing data for the social cognition and self-reported behavioral variables. There were a few instances of missing data for the demographic variables ranging from 0.5% to 8.8% in the Australia sample, and 0.9% to 6.4% in the US sample. Missing data are reported in Appendix B (supplemental materials). Missing data were imputed using stochastic hierarchical regression [33].

The analysis afforded a number of analyses to evaluate the adequacy of measures used to indicate the latent variables in the model. Construct validity of the latent factors for the social cognition, intention, and behavioral variables was established using the normalized factor pattern loadings after oblique rotation and Kaiser normalization [33] and the average variance extracted (AVE) which should approach or exceed .700 and .500, respectively. Internal consistency of the factors was estimated using omega reliability coefficients (ω) and composite reliability coefficients (ρ), which should exceed .700 and ideally approach .900. We also conducted tests of the discriminant validity of the constructs in the model. Discriminant validity was supported when the square-root of the AVE for each latent variable exceeded its correlation with other latent variables.

Adequacy of the proposed model in describing the data was established using the goodness-of-fit (GoF) index with values of .100, .250, and .360 corresponding to small, medium, and large effect sizes. Further information on model quality was provided by the average path coefficient (APC) and average R<sup>2</sup> (AR<sup>2</sup>) coefficient. These indices summarize the average parameter estimates of relations in the model and the amount of variance explained in each dependent variable, respectively, and should be statistically significant for a good-quality model. 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. These indices indicate the extent to which latent variables in the model

overlap and contribute to model multicollinearity. They therefore provide an indication as to the uniqueness of the existing latent variables in the model. Four further indices were also used to evaluate model quality: the Simpson's paradox ratio (SPR), R<sup>2</sup> contribution ratio (R<sup>2</sup>CR), the statistical suppression ratio (SSR), and the nonlinear bivariate causality direction ratio (NLBCDR). The SPR indicates whether the model is free from incidences of Simpson's paradox (i.e., when the path coefficient and the correlation associated with a latent variable have opposite signs), indicating a causality problem. The SPR should exceed .700 and ideally approach. 1.000. The R<sup>2</sup>CR and SSR provide indication of the extent to which models are free from instances of negative R<sup>2</sup> contributions and statistical suppression. The R<sup>2</sup>CR and SSR should exceed 0.900 and 0.700, respectively. The NLBCDR provides an estimate of the extent to which the proposed 'causal' associations in the proposed model are more tenable than those in the opposite direction and provide an initial indicator of support for the hypothesized directions of the causal links in the proposed model compared to if the proposed direction were reversed. The NLBCDR should exceed .700 for high quality models. Kock [33] provides further technical details on model fit and quality indices.

Model effects were estimated using standardized path coefficients with confidence intervals and test statistics. Effect sizes were estimated using a variant of Cohen's *f*-square coefficient and represents the individual contribution of the predictor variable to the R<sup>2</sup> coefficients of the criterion latent variable. Values of .02, .15, and .35 represent small, medium, and large effect sizes, respectively. Differences in the path coefficients in the models across the samples were tested using multiple group analysis using the Satterthwaite method with two-tailed significance tests.

We also tested whether inclusion of participants that were never under a 'shelter-in-place' order, or had the 'shelter-in-place' order lifted during the study, affected predicted relations in the models. The small numbers of participants that were, at some point, not subjected to 'shelter-in' place' orders meant we could not conduct a formal moderator analysis, so we conducted a sensitivity analyses testing whether effects in the models differed if data from these participants were excluded.

Models excluding and including past behavior were estimated in samples excluding participants who were never subject to a 'shelter-in place' order, and in the sample that were never subject to an order, or who had the order lifted at some stage during the study. Formal comparisons of parameter estimates in these models with those from the full sample were made using the Satterthwaite method. Data files, analysis scripts, and output files for all analyses are available online: <a href="https://osf.io/x9tms/">https://osf.io/x9tms/</a>.

## Results

# **Participants**

Attrition across the two data collection occasions resulted in final sample sizes of 365 (M age = 49.78, SD = 16.89; 50.1% female; retention rate 73.73%) and 440 (M age = 51.77, SD = 16.26; 46.6%female; retention rate = 62.77%) participants in the Australia and US samples, respectively. Sample characteristics at follow-up are presented in Table 1. Attrition analyses in the Australia sample revealed that participants lost to attrition were younger and were more likely to be non-White. However, there were no differences in proportion of gender, income, and education level. A MANOVA with the social cognition constructs and past behavior as dependent variables and attrition status (lost to attrition vs. included at follow-up) revealed no differences (Wilks' Lambda = 0.969, F(1,9) = 1.70, p = .077, partial  $\eta^2 = .031$ ). Attrition analyses in the US sample also indicated that participants lost to attrition were younger, and more likely to be male, non-White, and lower educated, and have low income, than those remaining in the study at follow-up. The MANOVA testing for differences on social cognition constructs and past behavior among participants lost to attrition and those included at follow-up revealed statistically significant differences (Wilks' Lambda = 0.969, F(1,9) = 2.40, p = .010, partial  $\eta^2 = .031$ ). Follow-up tests revealed that mean values for past behavior, attitude, subjective norm, intention, moral norm, and habit with respect to social distancing were significantly lower among participants lost to attrition compared to those retained at follow-up. However, effect sizes for these differences were small (ds < .25). Details of attrition analyses are presented in Appendix B (supplemental materials).

# **Preliminary Analyses**

Factor loadings and AVE values exceeded recommended 0.700 and 0.500 cut-off values in all cases. Omega reliability coefficients, inter-item correlations (for two-item scales), and composite reliabilities indicated good internal consistency of scales used. Latent variable correlations among social cognition constructs were all statistically significant. Correlations among the majority of constructs in the Australia sample were small-to-medium in size (r range = .161 to .564), with some smaller correlations involving the subjective and moral norms constructs and habit (r range = .094 to .118). Correlations were small-to-medium in size in the US sample (r range = .266 to .620). Square-roots of the AVE for each latent variable exceeded the correlation of that variable with all other latent variables supporting discriminant validity. Skewness and kurtosis estimates indicated many of the variables were not normally distributed, justifying use of the variance-based structural equation modeling which is a 'distribution free' analytic method. Factor loadings, reliability coefficients, and distribution statistics are presented in Appendix C (supplemental materials), and latent variable correlations for model variables in both are presented in Appendix D (supplemental materials).

# **Structural Equation Models**

Single sample analyses. Goodness-of-fit and quality indices of the structural equation models are presented in Table 2. The models that excluded (Model 1) and included (Model 2) past behavior exhibited adequate fit and quality indices in both the Australia and US samples. Standardized parameter estimates for the proposed direct effects for each model in the Australia and US samples are presented in Figure 1. Full parameter estimates for models in both samples are presented in Appendix E (supplemental materials). Parameter estimates, confidence intervals, and effect sizes for the indirect effects of the models in both samples are summarized in Table 3.

Focusing on the model excluding past behavior (Model 1), intention, action planning, and habit at follow-up were statistically significant predictors of social distancing behavior, with effect size for intention and habit generally larger in the US sample. PBC directly predicted behavior in the

Australia sample only, also with a small effect size. Intention predicted action planning in both samples with large effect sizes. Subjective norm, moral norm, and PBC predicted intention in both samples, with small-to-medium effect sizes, but effects of attitude were not significant. There was a small effect of anticipated regret on intention in the US sample only. Habit at baseline predicted habit at follow up in both samples, with large effect sizes. There was also a small-sized effect of habit at baseline on intention in the US sample only. Overall, the model accounted for significant variance in social distancing behavior (Australia sample,  $R^2 = .198$ ; US sample,  $R^2 = .361$ ), intentions (Australia sample,  $R^2 = .571$ ; US sample,  $R^2 = .623$ ), and habit at follow-up (Australia sample,  $R^2 = .416$ ; US sample,  $R^2 = .486$ ). Intentions (Australia sample,  $R^2 = .066$ ; US sample,  $R^2 = .148$ ), action planning (Australia sample,  $R^2 = .029$ ; US sample,  $R^2 = .044$ ), and habit at follow-up (Australia sample  $R^2 = .044$ ) .041; US sample,  $R^2 = .129$ ) each accounted for substantive variance in behavior. Action planning significantly moderated the intention-behavior relationship in the Australia sample only. While the effect was not in the predicted direction, probing the interaction revealed that the intention-behavior relationship increased as the level of planning increased, consistent with theory. However, the intention-behavior relationship is more likely to be smaller at lower levels of planning, and it seems that planning makes less of a difference when the intention-behavior relationship is large. A plot of the interaction effect is presented in Appendix F (supplemental materials).

Turning to the indirect effects, there were significant indirect effects of subjective norm, moral norm, and PBC on social distancing behavior mediated by intention in the US sample. By contrast, only the indirect effect of moral norm on behavior through intention was significant in the Australia sample. The smaller indirect effects in the Australia sample is principally due to the significantly smaller effect size for the intention-behavior relationship in this sample compared to the US sample. Habit at baseline predicted behavior through habit at follow-up in both samples. Effect sizes in all cases were small. There were significant total effects of intention, PBC, and habit at baseline on behavior, with effect sizes larger in the US sample than in the Australia sample.

For the model including past behavior, significant effects of past behavior on all model constructs were observed in both samples with effect sizes ranging from small to large. Effects of past behavior on social distancing behavior were particularly large. Inclusion of past behavior led to an attenuation of model effects in both samples. Specifically, effects of intention and habit at follow-up on behavior were reduced, but remained statistically significant in both samples with small effect sizes. In addition, effects of subjective norm, moral norm, and PBC on intention, and the effect of intention on action planning, remained statistically significant in both samples, with small-to-medium effect sizes. The effect of habit at baseline on habit at follow-up was statistically significant in both samples, with large effect sizes. Variance explained in social distancing behavior increased substantially with the inclusion of past behavior, with only modest changes in explained variance in intentions (Australia sample  $R^2 = .598$ ; US sample,  $R^2 = .702$ ) and habit at follow-up (Australia sample,  $R^2 = .029$ ; US sample,  $R^2 = .065$ ), past behavior (Australia sample,  $R^2 = .216$ ; US sample,  $R^2 = .029$ ; US sample,  $R^2 = .065$ ), past behavior (Australia sample,  $R^2 = .216$ ; US sample,  $R^2 = .311$ ), and habit at follow-up (Australia sample  $R^2 = .031$ ; US sample,  $R^2 = .101$ ) each accounted for substantive variance in behavior.

Turning to indirect effects, we found significant indirect effects of habit at baseline on behavior mediated by habit at follow-up in both samples with small effect sizes. There were also significant total effects of intention and habit at baseline on behavior in both samples, and of PBC on behavior for the US sample, with small effect sizes. There were significant total indirect and total effects of past behavior on behavior in both samples, with large effect sizes. There was a small sized indirect effect of past behavior on behavior mediated by habit at both time points in the US sample, but the effect was not significant in the Australia sample.

Multisample analyses. Multisample analyses permitted for tests of difference in parameter estimates for each model across the Australia and US samples. For the model excluding past behavior (Model 1), only effects of intention on habit at baseline, habit at follow-up on social distancing

behavior, and intention on action planning differed across samples. These effects were significantly larger in the US sample. Some effects with observed differences across samples, such as the effect of habit at baseline on intention or the moderator effect of planning on the intention-behavior relationship, did not differ significantly across samples. For the model including effects of past behavior (Model 2), multisample analysis revealed no differences in effect size across samples, indicating that the attenuating effect of past behavior on model effects also had the effect of eliminating the few differences in model effects across samples. Full details of the multiple group analysis are presented in Appendix G (supplemental materials).

**Sensitivity Analyses**. We re-estimated both models in samples excluding participants who were never subject to a 'shelter-in place' order, and in the sample that were never subject to an order, or who had the order lifted at some stage during the study. Comparisons of parameter estimates in these models with those from the models estimated in the full sample, revealed no significant differences in any of the model parameters. Results are reported in Appendices H and I (supplemental materials).

### Discussion

The present study aimed to identify the determinants of social distancing behavior in the context of COVID-19, through the application of an integrated social cognition model. The integrated model was based on the theory of planned behavior [13] augmented to include additional predictors relating to normative (moral norm), anticipated affect (anticipated regret), volitional (action planning), and non-conscious (habit) determinants of health behavior. The model was tested in data from a correlational prospective survey study in two samples of Australian and US residents subject to national or local 'shelter-in-place' orders. Results indicated that intention and habit were significant predictors of social distancing behavior in both samples. Subjective norm, moral norm, and PBC were significant predictors of social distancing intention. In addition, intention mediated effects of these social cognition constructs on social distancing behavior in the US sample, but did so only for moral norm in the Australia sample. Action planning did not mediate effects of intention on behavior in

either samples, but moderated the intention behavior relationship in the Australia sample. Inclusion of past behavior attenuated effects of social cognition constructs in the models in both samples, although habit and intention remained significant determinants of social distancing behavior in both samples. Excluding participants in the US sample not subject to formal 'shelter-in-place' orders, or had the orders lifted during the study, did not affect the pattern or size of the effects in the model, providing evidence that formal orders did not have a substantive bearing on the determinants of social distancing behavior in this sample.

Current findings provide qualified support for some, but not all, predictions of the integrated social cognition model for social distancing behavior. A key assumption of the model, derived from the social cognition theories on which it is based, is that social distancing behavior is reasoned action and, therefore, determined predominantly by intention and the belief-based constructs that underpin them. Effects of intention on social distancing behavior and its mediation of constructs reflecting social reasons for acting, particularly beliefs relating to significant others and moral obligations to perform the behavior, and PBC is consistent with this assumption. This is unsurprising in this context, considering the widely publicized details of the relatively mild effects of the virus in the majority of the population. It is likely that the majority of individuals do not view themselves as at serious risk from COVID-19, but have internalized the view that significant others want them to engage in social distancing, and feel a moral obligation to perform the behavior to protect the health of those most at risk. Such a finding is consistent with research on similar health behaviors such as blood donation where behavioral performance is likely to promote the health of others rather than the self [34]. Similarly, the impact of PBC indicates the importance of perceived personal agency in maintaining social distancing behavior, consistent with previous research on health behaviors [14]. Individuals that see fewer barriers to maintaining social distancing and have the confidence to do so are more likely to intend to perform these behaviors.

The effects of subjective and moral norms and perceived behavioral control suggests that these should be viable targets for behavioral interventions aimed at promoting social distancing behavior based on the model. For example, messages promoting moral obligation (e.g., highlighting social responsibility for preventing transmission of the virus to vulnerable others through social distancing), and perceived control (e.g., demonstrating how to easily and successfully maintain appropriate social distance) may facilitate greater intention to socially distance. However, the intention-behavior relationship in the present study was relatively modest in size, particularly in the Australia sample, indicative of a substantive intention-behavior 'gap' [15]. This suggests that interventions targeting change in intention determinants such as moral norms and perceived behavioral control may have only small effects on social distancing behavior. It may be of value to explore how properties of intention may affect intention-behavior relations in the context of social distancing behavior [35]. Such properties may signal potential intervention strategies that may strengthen intention-behavior relations in conjunction with messaging targeting moral norms and perceived behavioral control.

Current findings also indicated consistent effects of self-reported habits on social distancing behavior. Importantly, effects of habit were direct and independent of intentions, consistent with theory that suggests effects of habits reflect non-conscious, automatic processes developed through consistent experience with the behavior in stable contexts over time. Habits also partially mediated effects of past behavior on social distancing behavior suggesting that past behavior effects, at least in part, reflect habits [27]. An implication of these findings is that facilitating habit development in behavioral interventions may be effective in promoting social distancing. Research suggests that strategies such as providing successful experiences of the desired behavior consistently over time and creating environment conditions that facilitate the behavior (e.g., consistent reminders, environmental restructuring) are effective in inducing habits [36], but the efficacy of such strategies in the context of social distancing behavior need to be verified empirically. Furthermore, legislation restricting or

mandating behavior change facilitates habit formation over time. This suggests that introduction of 'shelter-in-place' and other government-mandated restrictions may facilitate social distancing habits.

Inclusion of past behavior as a predictor of social distancing behavior at follow-up reduced effects of intention on behavior to a trivial size in both samples, and also attenuated effects of the social cognition constructs on intention. Such effects are consistent with previous research [22], and raise questions over the sufficiency of the model in identifying the determinants of social distancing behavior. However, such findings must be interpreted in light of the current study design, and how effects of past behavior can provide important information on the determinants of social distancing behavior. The one-week time lag means that past behavior was always likely to have a large effect because individuals' behavior tends to be relatively stable over short periods [22]. A more complete evaluation of model sufficiency would be afforded by testing its long range prediction, which has often been cited as a goal of social cognition theories [14], and should be considered a future research priority for research on social distancing behavior. However, past behavior effects can be informative on the determinants of social distancing behavior, as it may reflect effects of other unmeasured behavioral determinants. In particular, past behavior will likely reflect determinants that bypass the reasoned, intention-mediated processes that lead to behavior such as implicit attitudes and motives, personality traits, and variables reflecting the social and physical environment. Effects of such constructs are speculative and future tests of the integrated model that incorporate such factors alongside those from the current model may assist in resolving these effects.

Consistent with dual phase models [18, 19], we also tested the extent to which action planning was implicated in the process by which individuals act on their intention. Two patterns of effects were tested: mediation and moderation effects of action planning on the intention-behavior relationship.

The mediation effect was significant in the US sample, but not the Australia sample, while the moderation effect was significant in the Australia sample only. However, in both cases the effects were small in size. The small size of the mediation effects, suggests that action planning is a relatively

trivial component of the link between social distancing intention and behavior, particularly when past behavior was taken into account. The moderation of the intention-behavior relationship by action planning in the Australia sample was negative in sign, which is contrary to predictions [18]. However, probing this interaction indicated that individuals with stronger intention were more likely to follow through on their social distancing behavior at both high and low levels of action planning, but the rate of increase was much steeper for low planning, which supports the prediction. However, when the intention-behavior relationship was strongest, planning had little effect, so planning may only be effective for those with lower intentions. As with the mediation effect, the moderation effect was no longer present once past behavior was included in the model. Taken together, current results do not provide strong evidence for the role of action planning in mediating and moderating the intention-behavior relationship for social distancing.

# Limitations, and Avenues for Future Research

Current findings should be interpreted in light of some notable limitations. First, attrition rates in both samples were relatively high given the relatively brief time between the baseline survey and follow-up. High attrition could lead to selection bias with those who are more motivated or engaged overrepresented in the sample. While participants were reminded multiple times to complete follow-up measures, we acknowledge that more intensive recruitment and incentivization of non-responders may have minimized drop out. Attrition also affected the demographic profile of the sample, particularly among underrepresented groups. Although the effect sizes of these differences were small, they were not trivial. This is particularly pertinent in the current context given emerging data indicating that COVID-19 infection and mortality rates are significantly higher in underrepresented minority and socioeconomic groups [37]. A potential solution would be to oversample in underrepresented groups likely to have low retention rates, and is a recommendation for future research. It is also important to note that although our sampling strategy ensured that the distribution of participants in our samples matched those of the national population according to gender and state,

we did not stratify the sample by key demographic or socio-economic factors. The samples, therefore, should not be considered representative of the national populations of Australia or the US. Taken together, the bias linked to attrition rates and non-representativeness of the samples places limits on the extent to which current findings can be generalized to the broader population.

Second, the intention-behavior 'gap' in the current study resulted in small indirect effects of intention determinants such as subjective and moral norms and perceived behavioral control on social distancing behavior. This is a limitation of the current model and means that intervention strategies aimed at changing intention determinants may have relatively modest effects on behavior change. However, small effects may still translate to large numbers of people changing if interventions targeting change in these constructs are administered at the population level. Future intervention research is, nevertheless, needed to verify effects of targeting change in model constructs on behavior. Research should also adopt behavioral measures that can be converted to meaningful metrics that demonstrate practically significant changes in social distancing behavior (e.g., numbers of people complying with social distancing guidelines when venturing outside the home).

Third, the current study observed social distancing over a relatively brief time frame. Short-range prediction has value as it helps identify potential determinants of social distancing behavior. However, consistency in performing social distancing over time is important for effective prevention of virus transmission, so research on the determinants of social distancing in the long term is a priority. The relatively short time lag is also likely to be the reason why past behavior had such a pervasive effect in predicting behavior and other constructs in the model. The relevance of past behavior is likely to wane over time, so examining prediction over time may be more revealing as to the social cognition predictors of this behavior and the processes involved.

Fourth, the correlational design precludes the inference of causal effects among the constructs in the current model, so the proposed direction of effects are inferred from theory alone, not the data.

Causal sequencing among variables would necessitate experimental or controlled intervention

designs. Verification of such effects will highlight the value of the model in informing interventions to promote changes in social distancing behavior. In addition, the inclusion of past behavior in the current analysis modeled change in behavior over time. Past behavior also had the effect of modeling residual effects of unmeasured constructs on behavior, such as past measures of the model constructs. However, adoption of a cross-lagged panel design would better facilitate examination of how change in specific model constructs over time affects social distancing behavior and permit tests of reciprocal effects. It is also important that effects of past behavior do not provide definitive evidence that affecting change in model constructs, such as intentions or habit, through intervention will lead to concomitant change in social distancing behavior. This highlights the imperative of intervention research that tests the efficacy of manipulating constructs from the current model in promoting social distancing behavior and illustrate the extent to which model constructs can be modified.

Finally, the current research relies exclusively on self-report measures. While self-reported behavior has exhibited concurrent validity when evaluated against non-self-report measures, such as behavior measured using devices or direct observation, the potential for recall bias or inaccurate reporting likely introduces additional measurement error in the behavioral measure, which would affect model relations. Further, self-reported data are also at risk of self-presentation bias and socially desirable responding. Health behaviors, particularly social distancing behavior in the context of a pandemic, are likely to be considered desirable, which may have compelled respondents to provide positive responses, without even being aware of such biases. Although we stressed anonymity to participants to make it clear that they had license to report their behavior without prejudice, this is unlikely to have fully eliminated such biases. Current data should therefore be interpreted in light of these potential biases and their potential to contribute to error variance in observed effects. Future research may consider use of devices such as GPS tracking of cellular phones as alternative means to measure social distancing behavior that do not rely on self-report.

## Conclusion

The current research aimed to identify the determinants of social distancing behavior to prevent transmission of the SARS-CoV-2 virus in samples of Australian and US residents. The research applied an integrated theoretical model that included multiple social cognition determinants relevant to the behavioral context, and the processes involved, with the potential to be modifiable through intervention. Results provided qualified support for the proposed model, highlighting the importance of social and moral beliefs, and perceptions of control, in predicting intention, and habit and intention in predicting behavior, in both samples, although effects were relatively modest, particularly when past behavior was accounted for. Findings suggest that interventions aimed at promoting social distancing behavior should provide messages highlighting individuals' obligations to significant others and the moral imperative of protecting the most vulnerable as reasons for social distancing, provide environments (e.g., workplaces, grocery stores) that are barrier free and easy to socially distance, and provide consistent opportunities in regular, stable contexts to engage in social distancing to develop habits. Future research should seek to provide longer range prediction of social distancing behavior by the integrated model constructs and test the stability and reciprocal relations among its constructs using a cross-lagged panel design.

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Table 1
Sample Characteristics and Descriptive Statistics for Study Variables at Baseline and at One-Week
Follow-Up

Variable		lia sample	US sample			
	Baseline	Follow-up	Baseline	Follow-up		
Participants	495	365	701	440		
Age, $M$ years (SD)	47.09	49.78	45.55	51.77		
	(17.11)	(16.89)	(17.40)	(16.26)		
Gender, $n$ (%) <sup>a</sup>	, ,					
Female	252 (51.1)	182 (50.1)	352 (48.9)	205 (46.6)		
Male	241 (48.9)	181 (49.9)	341 (50.5)	231 (52.5)		
Not specified/prefer not to answer	0 (0.0)	0 (0.0)	4 (0.6)	4 (0.9)		
Employment status, $n$ (%) <sup>b</sup>	` ,	, ,				
currently unemployed/full-time caregiver	231 (46.7)	180 (49.3)	330 (47.3)	216 (49.5)		
part-time/casual employed	97 (19.6)	65 (17.8)	106 (15.2)	60 (13.8)		
currently employed full-time	140 (28.3)	104 (28.5)	233 (33.4)	147 (33.7)		
leave without pay/furloughed	27 (5.5)	16 (4.4)	28 (4.0)	13 (3.0)		
Marital status, $n \left( \frac{9}{9} \right)^{c}$	,	` ,	,	,		
Married	184 (37.2)	146 (40.0)	300 (43.0)	224 (51.4)		
Widowed	8 (1.6)	7 (1.9)	22 (3.2)	18 (4.1)		
Separated/divorced	53 (10.7)	39 (10.7)	69 (9.9)	47 (10.8)		
Never married	160 (32.3)	103 (28.2)	255 (36.6)	126(28.9)		
Married de facto	90 (18.2)	70 (19.2)	51 (7.3)	21 (4.8)		
Ethnicity, $n$ (%) <sup>d</sup>	,	,	,	( )		
Black	3 (0.6)	1 (0.3)	52 (7.5)	26 (6.0)		
Caucasian/White	392 (79.2)	304 (83.3)	566 (81.2)	376 (86.2)		
Asian (South-East Asia/South Asia)	71 (14.3)	43 (11.8)	39 (5.6)	24 (5.5)		
Middle-Eastern	6 (1.2)	3 (0.8)	1 (0.1)	0(0.0)		
Other	13 (2.6)	6 (1.6)	27 (3.9)	8 (1.8)		
Prefer not to answer	10 (2.0)	8 (2.2)	12 (1.7)	2 (0.5)		
Income, $n$ (%) <sup>e</sup>	,	,	,	,		
zero income	8 (1.7)	4 (1.2)	31 (4.4)	19 (4.4)		
\$1-\$199 (\$1-\$10,399)	9 (2.0)	6 (1.8)	40 (5.7)	24 (5.5)		
\$200-\$299 (\$10,400-\$15,599)	12 (2.6)	8 (2.4)	34 (4.9)	23 (5.3)		
\$300-\$399 (\$15,600-\$20,799)	19 (4.1)	12 (3.6)	38 (5.5)	23 (5.3)		
\$400-\$599 (\$20,800-\$31,199)	42 (9.2)	33 (9.9)	62 (8.9)	33 (7.6)		
\$600-\$799 (\$31,200-\$41,599)	57 (12.4)	42 (12.6)	61 (8.8)	39 (8.9)		
\$800-\$999 (\$41,600-\$51,999)	45 (9.8)	31 (9.3)	68 (9.8)	46 (10.6)		
\$1,000-\$1,249 (\$52,000-\$64,999)	39 (8.5)	32 (9.6)	48 (6.9)	38 (8.7)		
\$1,250-\$1,499 (\$65,000-\$77,999)	28 (6.1)	22 (6.6)	59 (8.5)	41 (9.4)		
\$1,500-\$1,999 (\$78,000-\$103,999)	72 (15.7)	50 (15.0)	72 (10.3)	48 (11.0)		
\$2,000 or more (\$104,000 or more)	81 (17.6)	62 (18.6)	108 (15.5)	74 (17.0)		
Prefer not to answer	47 (10.2)	32 (9.6)	76 (10.9)	28 (6.4)		
Education level, n (%)	· ()	- (>/	(-27)	- ()		
Completed junior/lower/primary school	18 (3.6)	17 (4.7)	6 (0.9)	0 (0.0)		
Completed senior/high/secondary school	133 (26.9)	98 (26.8)	265 (37.8)	132 (30.0)		
Post-school vocational qualification/diploma	147 (29.7)	111 (30.4)	138 (19.7)	94 (21.4)		
Undergraduate University degree	131 (26.5)	93 (25.5)	214 (30.5)	159 (36.1)		
Postgraduate University degree	66 (13.3)	46 (12.6)	78 (11.1)	55 (12.5)		

*Note*. <sup>a</sup>Two participants in the Australia sample did not report their gender, four participants in the US sample not report their gender; <sup>b</sup>Four participants in the US sample did not report their employment status; <sup>c</sup>Four participants in the US sample did not report their marital status; <sup>d</sup>Four participants in the US sample did not report their ethnicity; <sup>e</sup>Thirty-one participants in the Australia sample did not report their income and four participants in the US sample did not report their income.

Table 2
Model Quality and Goodness-of-Fit Statistics for the Structural Equation Models of the Integrated
Model in the Australian and US Samples and Multigroup Model

Sample	Model	APC	$AR^2$	AVIF	AFVIF	GoF	SPR	$R^2$ CR	SSR	NLBCDR
Australia	1	.104**	.177***	1.177	1.561	.391	.841	.977	.889	.873
	2	.116***	.338***	1.222	1.904	.543	.819	.991	.931	.785
US	1	$.098^{**}$	.192***	1.187	1.823	.410	.889	.995	.825	.754
	2	.116***	.338**	1.222	1.904	.543	.819	.991	.931	.785
MS	1	.100***	.182***	1.159	1.704	.398	.905	.995	.794	.817
	2	.113***	.300***	1.186	1.760	.511	.931	.997	.917	.840

Note. Model 1 = Model excluding past behavior; Model 2 = Model including past behavior; MS = Multiple sample analysis; APC = Average path coefficient;  $AR^2$  = Average  $R^2$ ; AVIF = Average block variance inflation factor; AFVIF = Average full collinearity variance inflation factor; GoF = Tenenhaus's goodness-of-fit index; SPR = Sympson's paradox ratio;  $R^2CR = R^2$  contribution ratio; SSR = Statistical suppression ratio; NLBCDR = Nonlinear bivariate causality direction ratio.

\*p < .05 \*\*p < .01 \*\*\*p < .001

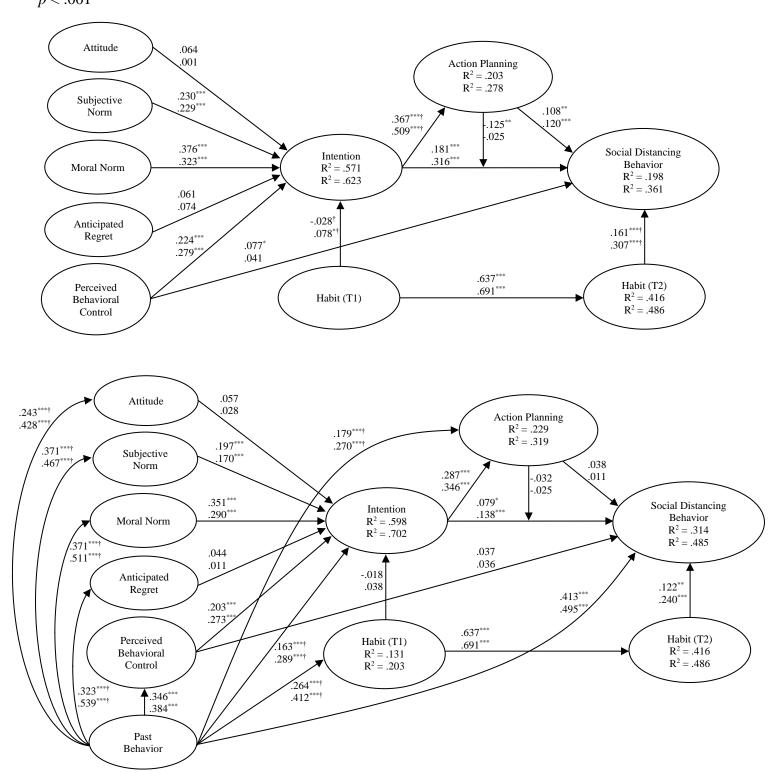
Table 3
Standardized Parameter Estimates for Indirect Effects for the Structural Equation Model of the Integrated Model in the Australian and US Samples

Effect		ior	Model including past behavior							
	β	p	95%	6 CI	ES	β	p	95%		ES
			LB	UB				LB	UB	
Australia sample										
Indirect effects										
$Att. \rightarrow Int. \rightarrow Beh.$	.011	.359	052	.074	.003	.004	.444	059	.067	.001
$SN \rightarrow Int. \rightarrow Beh.$	.042	.094	021	.105	.016	.016	.312	047	.079	.006
$MN \rightarrow Int. \rightarrow Beh.$	.068	.016	.005	.131	.024	.028	.192	035	.091	.010
$AR \rightarrow Int. \rightarrow Beh.$	.011	.356	052	.074	.003	.003	.457	060	.066	.001
$PBC \rightarrow Int. \rightarrow Beh.$	.040	.101	023	.103	.011	.016	.307	047	.079	.005
Int. $\rightarrow$ AP $\rightarrow$ Beh.	.040	.106	023	.103	.014	.011	.365	052	.074	.004
Hab. $(T1)$ . $\rightarrow$ Hab. $(T2)$ $\rightarrow$ Beh.	.102	<.001	.041	.163	.016	.078	.007	.017	.139	.013
PB→Hab.→Beh.	_	_	_	_	_	.021	.214	030	.072	.011
PB→Beh. <sup>a</sup>	_	_	_	_	_	.081	.034	007	.169	.042
Total effects <sup>b</sup>										
Int.→Beh.	.220	<.001	.134	.306	.081	.090	.022	.004	.176	.033
PBC→Beh.	.126	<.001	.040	.212	.036	.055	.110	033	.143	.016
Hab. $(T1)\rightarrow$ Beh.	.096	.016	.010	.182	.015	.076	.044	012	.164	.012
PB→Beh.	_	_	_	_	_	.494	<.001	.412	.576	.258
US sample										
Indirect effects										
$Att. \rightarrow Int. \rightarrow Beh.$	<.001	.495	052	.054	<.001	.004	.443	049	.057	.001
SN→Int.→Beh.	.072	.003	.019	.125	.029	.023	.190	030	.076	.009
$MN \rightarrow Int. \rightarrow Beh.$	.102	<.001	.051	.153	.044	.040	.067	013	.093	.017
$AR \rightarrow Int. \rightarrow Beh.$	.023	.192	030	.076	.011	.001	.478	052	.054	.001
$PBC \rightarrow Int. \rightarrow Beh.$	.088	<.001	.037	.139	.025	.038	.079	015	.091	.011
Int. $\rightarrow$ AP $\rightarrow$ Beh.	.061	.011	.008	.114	.029	.004	.441	049	.057	.002
Hab. $(T1)$ . $\rightarrow$ Hab. $(T2)$ $\rightarrow$ Beh.	.212	<.001	.161	.263	.075	.166	<.001	.115	.217	.059
PB→Hab.→Beh.	_	_	_	_	_	.068	<.001	.025	.111	.043
PB→Beh. <sup>a</sup>	_	_	_	_	_	.178	<.001	.105	.251	.112
Total effects <sup>b</sup>								.100	.201	
Int.→Beh.	.377	<.001	.306	.448	.177	.142	<.001	.069	.215	.066
PBC→Beh.	.146	<.001	.073	.219	.042	.074	.024	.001	.147	.021
Hab. (T1)→Beh.	.242	<.001	.169	.315	.086	.171	<.001	.098	.244	.061
PB→Beh.						.673	<.001			.423
rb→Ben.	_	_	052	.074	_	.673	<.001	.604	.742	.423

*Note.* <sup>a</sup>Sum of indirect effects of past behavior on behavior through all model constructs; <sup>a</sup>Total effect comprising sums of all indirect effects through model constructs plus the direct effect;  $\beta$  = 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. Int. = Intention; Beh. = Behavior; PBC = Perceived behavioral control; Hab. (T1) = Self-reported habit measured at baseline (T1); Hab. (T2) = Self-reported habit measured at follow-up (T2); AP = Action planning; PB = Past behavior; Att. = Attitude; SN = Subjective norm; MN = Moral norm; AR = Anticipated regret.

Figure 1. Standardized parameter estimates of the integrated model. Upper panel presents the model excluding past behavior (Model 1) and the lower panel presents the model including past behavior (Model 2). Coefficients printed on the upper line are for the Australia sample and coefficients printed on the lower line are for the US sample.

†Effect is significantly different across the Australia and US samples in multiple group analyses. \*p < .05 \*\*\*p < .01\*\*\*\*p < .001



# Appendix A

Items and Response Scales for Variables of the Integrated Model

Variable	Item(s)/measure	Scale
Attitude	My maintaining social distancing in the next week would be	1 = unpleasant, 7 = pleasant 1 = bad, 7 = good 1 = worthless, 7 = valuable
Subjective	In the next week, do you agree that	1 = strongly disagree, 7 =
norm	Those people who are important to me would want me to maintain social distancing	strongly agree
	Most people who are important to me would approve of me maintaining social distancing	
	Most people who are important to me think I should maintain social distancing	
Moral norm	In the next week, do you agree that	1 = strongly disagree, 7 =
	It is the right thing to do to maintain social distancing	strongly agree
	It is morally responsible to maintain social distancing	
	It is my moral obligation to maintain social distancing	
Anticipated	In the next week, do you agree that	1 = strongly disagree, 7 =
regret	If I did not maintain social distancing it would upset me	strongly agree
	If I did not maintain social distancing, I would feel regret	
	If I did not maintain social distancing, I would feel sorry for not	
	doing it	
Perceived	In the next week, do you agree that	1 = strongly disagree, 7 =
behavioral	It is mostly up to me whether I maintain social distancing	strongly agree
control	I have complete control over whether I maintain social distancing	
	It would be easy for me to maintain social distancing	
	I am confident that I could maintain social distancing	
Intention	In the next week	1 = strongly disagree, 7 =
	It is likely that I will maintain social distancing	strongly agree
	I intend to maintain social distancing	
	I plan to maintain social distancing	
Action	In the next week, I have made a plan	1 = strongly disagree, 7 =
planning	When to maintain social distancing	strongly agree
	Where to maintain social distancing	
	How often to maintain social distancing	
	How to maintain social distancing	
Habit	Maintaining social distancing is something	1 = strongly disagree, $7 =$
	I do automatically	strongly agree
	I do without having to consciously remember	
	I do without thinking	
	I start to do before I realise I'm doing it	
Past behavior/	In the past week, how often did you maintain social distancing?	1 = never, 7 = always;
behavior	In the past week, I maintained social	1 = false, 7 = true
	distancing	

Appendix B
Attrition Analyses Comparing Differences on Demographic Variables and Social Cognition Constructs for Participants Included at Follow-Up and Participants Lost to Attrition

Variable	s Lost to Attrition	Australia	n sample		US sample							
	Included	Lost to attrition	Difference test	Missing	Included	Lost to attrition	Difference test	Missing				
Age	49.78 (16.89)	39.58 (15.45)	t(493) = 6.05, p <	0 (0.0)	51.77 (16.26)	35.16 (13.95)	<i>t</i> (695) = 13.75, <i>p</i> <	4 (0.9)				
			.001, d = 0.54				.001, d = 0.73					
Gender, $n$ (%) <sup>a</sup>	182 (36.92)	70 (14.20)	$\chi^2(1) = 0.39, p =$	2 (0.5)	205 (29.58%)	147 (21.21%)	$\chi^2(1) = 6.30, p =$	4 (0.9)				
	181 (36.71)	60 (12.17)	.533, d = 0.06		231 (33.33%)	110 (15.87%)	.012, d = 0.19					
Income, $n$ (%) <sup>a</sup>	63 (14.06)	27 (603)	$\chi^2(1) = 0.84, p =$	32 (8.8)	122 (19.52%)	83 (13.28%)	$\chi^2(1) = 5.16, p =$	28 (6.4)				
	270 (60.27)	88 (19.64)	.359, d = 0.08		290 (46.40%)	130 (20.80%)	.023, d = 0.19					
Education, $n$ (%) <sup>a</sup>	115 (23.23)	36 (7.27)	$\chi^2(1) = 0.49, p =$	0(0.0)	132 (18.83%)	139 (19.83%)	$\chi^2(1) = 36.39, p <$	0(0.0)				
	250 (50.51)	94 (18.99)	.484, d = 0.06		308 (43.94%)	122 (17.40%)	.001, d = 0.47					
Ethnicity, $n$ (%) <sup>a</sup>	61 (12.32)	42 (8.48)	$\chi^2(1) = 13.22, p <$	0(0.0)	60 (8.61%)	71 (10.19%)	$\chi^2(1) = 18.46, p <$	4 (0.9)				
	304 (61.41)	88 (17.78)	.001, d = 0.33		376 (53.95%)	190 (27.26%)	.001, d = 0.33					
Past behavior, $M(SD)$	6.50 (0.70)	6.37 (0.75)	F(1,493) = 3.57, p	0(0.0)	6.46 (0.89)	6.22 (1.13)	F(1,699) = 9.28, p	0(0.0)				
			= .059, d = 0.17				= .002, d = 0.23					
Attitude, $M(SD)$	5.90 (1.11)	5.94 (1.19)	F(1,493) = 0.09, p	0(0.0)	5.87 (1.18)	5.54 (1.48)	F(1,699) = 10.61, p	0(0.0)				
			= .765, d = 0.03				= .001, d = 0.25					
SN, M(SD)	6.39 (0.79)	6.21 (1.10)	F(1,493) = 4.35, p	0(0.0)	6.29 (0.97)	6.13 (1.20)	F(1,699) = 3.97, p	0(0.0)				
			= .038, d = 0.19				= .047, d = 0.15					
Moral norm, $M(SD)$	6.58 (0.81)	6.57 (0.73)	F(1,493) = 0.04, p	0(0.0)	6.33 (0.99)	6.16 (1.12)	F(1,699) = 4.16, p	0(0.0)				
			= .850, d = 0.02				= .0.42, d = 0.15					
AR, M(SD)	5.51 (1.34)	5.54 (1.34)	F(1,493) = 0.04, p	0(0.0)	5.20 (1.59)	5.04 (1.62)	F(1,699) = 1.66, p	0(0.0)				
			= .837, d = 0.02				= .198, d = 0.10					
PBC, M(SD)	6.02 (0.95)	5.84 (1.07)	F(1,493) = 3.16, p	0(0.0)	5.98 (0.92)	5.84 (1.16)	F(1,699) = 3.13, p	0(0.0)				
			= .076, d = 0.16				= .077, d = 0.13					
Intention, $M(SD)$	6.54 (0.66)	6.40 (0.69)	F(1,493) = 4.04, p	0(0.0)	6.39 (0.85)	6.15 (1.19)	F(1,699) = 9.90, p	0(0.0)				
			= .045, d = 0.18				= .002, d = 0.24					
AP, M(SD)	5.83 (1.28)	5.90 (1.18)	F(1,493) = 0.30, p	0(0.0)	5.76 (1.43)	5.71 (1.42)	F(1,699) = 0.22, p	0(0.0)				
			= .582, d = 0.02				= .641, d = 0.04					
Habit, $M(SD)$	5.02 (1.47)	4.80 (1.52)	F(1,493) = 2.14, p	0(0.0)	5.19 (1.47)	4.83 (1.63)	F(1,699) = 8.88, p	0(0.0)				
			= .144, d = 0.13				= .002, d = 0.23					

*Note*. <sup>a</sup>Statistics presented on the upper line are for female, low income, lower education level, and non-white ethnicity and statistics presented on the lower line are for male, high income, higher education, and white ethnicity. Missing = Number and proportion of missing cases; SN = Subjective norm; PBC = Perceived behavioral control; AP = Action planning; AR = Anticipated regret.

Supplemental Materials: Appendix C

Appendix C

Factor Loadings, Reliability Estimates, Average Variances Extracted, and Descriptive Statistics for the Variables of the Integrated Model

Construct			, 11, 0, 0		alian sar		., 2 0	<u> </u>	· · · · · · · · · · · · · · · · · · ·	jor me	, 67, 767,		S sampl	•		
	FL	Rel.	CR	AVE	M	SD	Skew.	Kurt.	FL	Rel.	CR	AVE	$\overline{M}$	SD	Skew.	Kurt.
Past behavior <sup>a</sup>		.734	.883	.790	6.503	0.697	-2.325	8.372		.846	.928	.866	6.457	0.891	-2.379	6.739
Past behavior item 1	.953								.981							
Past behavior item 2	.969								.970							
Habit T1 <sup>b</sup>		.943	.948	.821	5.024	1.471	-0.604	-0.377		.939	.950	.828	5.186	1.468	-0.669	-0.399
Habit T1 item 1	.968								.987							
Habit T1 item 2	.993								.990							
Habit T1 item 3	.997								.997							
Habit T1 item 4	.966								.972							
Habit T2 <sup>b</sup>		.938	.914	.726	5.258	1.437	-0.731	0.102		.950	.888	.665	5.253	1.471	-0.720	0.242
Habit T2 item 1	.960								.976							
Habit T2 item 2	.988								.982							
Habit T2 item 3	.991								.976							
Habit T2 item 4	.960								.940							
Intention <sup>b</sup>		.933	.955	.876	6.540	0.660	-1.578	2.697		.944	.962	.895	6.391	0.848	-2.089	5.288
Intention item 1	.966								.984							
Intention item 1	.991								.992							
Intention item 1	.995								.994							
Attitude <sup>b</sup>		.823	.859	.671	5.901	1.110	-1.441	2.26		.828	.885	.719	5.875	1.185	-1.452	2.151
Attitude item 1	.921								.943							
Attitude item 2	.983								.990							
Attitude item 3	.905								.940							
Subjective norm <sup>b</sup>		.907	.940	.838	6.393	0.787	-2.120	6.759		.925	.952	.868	6.290	0.968	-2.081	5.483
Subjective norm item 1	.990								.973							
Subjective norm item 2	.994								.994							
Subjective norm item 3	.994								.979							
Moral norm <sup>b</sup>		.941	.961	.890	6.584	0.807	-3.111	13.986		.945	.963	.897	6.330	0.991	-1.969	4.517
Moral norm item 1	.988								.979							
Moral norm item 2	.995								.997							
Moral norm item 3	.996								.991							
Anticipated regret <sup>b</sup>		.926	.951	.866	5.508	1.342	-1.066	0.861		.942	.961	.892	5.202	1.592	-0.774	-0.238
Anticipated regret item 1	.985								.991							
Anticipated regret item 2	.998								.997							
Anticipated regret item 3	.989								.992							

PBC <sup>b</sup>		.841	.851	.594	6.015	0.951	-1.224	1.729		.872	.854	.596	5.978	0.921	-1.296	2.103
PBC Item 1	.807								.821							
PBC Item 2	.956								.896							
PBC Item 3	.971								.681							
PBC Item 4	.905								.642							
Action planning <sup>b</sup>		.806	.959	.853	5.829	1.282	-1.465	2.161		.966	.968	.882	5.761	1.429	-1.493	1.918
Action planning item 1	.993								.983							
Action planning item 2	.995								.993							
Action planning item 3	.996								.997							
Action planning item 4	.992								.985							
Behavior <sup>a</sup>		.750	.853	.744	6.096	0.671	-2.506	12.448		.877	.865	.762	6.397	0.971	-1.963	6.257
Behavior item 1	.983								.985							
Behavior item 2	.985								.986							

*Note*. <sup>a</sup>Reliability coefficient for this factor is Spearman Brown coefficient between items; <sup>b</sup>Reliability coefficient for this factor is Revelle's omega (ω) coefficient; Rel. = Reliability coefficient; CR = Composite reliability coefficient from partial least squares structural equation model; FL = Factor loading of each item on designated factor, coefficients are factor pattern loadings from partial least squares structural equation model with oblique rotation and Kaiser normalization; Rel. = Reliability coefficient; AVE= Average variance extracted for factor from partial least squares structural equation model; Skew. = Skewness estimate; Kurt. = Kurtosis estimate; PBC = Perceived behavioral control.

Appendix D
Latent Variable Correlations Among Integrated Model Variables Used in Structural Equation Models

Supplemental Materials: Appendix D

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Behavior	_	.355***	.405***	.462***	.377***	.397***	.434***	.458***	.270***	.357***	.064	$.078^{*}$	.062	$.080^{*}$	.043		280***
2. Habit T1	.161***	_	.687***	.427***	.468***	.338***	.331***	.425***	.432***	.381***	063	.146***	.048	.015	052	.420***	241***
3. Habit T2	.237***	.647***	_	.314***	.394***	.266***	.332***	.400***	.339***	.289***	025	.081*	.068	003	004	.346***	186***
4. Intention	.350***	.244***	.135**	_	.469***	.620***	.663***	.559***	.575***	.504***	.039	.121**	009	.141***	.053	.635***	621***
5. Attitude	.271***	.271***	.189***	.420***	_	.428***	.532***	.488***	.434***	.362***	.004	.110**	$.078^{*}$	.006	050	.434***	297***
6. SN	.396***	.187***	.118**	.564***	.368***	_	.598***	.491***	.436***	.439***	001	.137***	.038	.065	025	.482***	386***
7. MN	.360***	$.094^{*}$	$.095^{*}$	.522***	.390***	.593***	_	.667***	.399***	.572***	.046	$.089^{*}$	.004	.054	.005	.516***	455***
8. AR	.227***	.290***	.181***	.423***	.318***	.436***	.512***	_	.371***	.578***	$.087^{*}$	.055	.066	.036	.037	.535***	287***
9. PBC	.245***	.427***	.318***	.504***	.330***	.315***	.285***	.291***	_	.338***	.012	$.087^{*}$	.073	025	012	.350***	282***
10. AP	.253***	.217***	.187***	.390***	.256***	.361***	.403***	.442***	.270***	_	.109**	.020	.062	013	026	.481***	346***
11. Gender	.039	010	010	.139**	$.098^{*}$	.123**	.087	.147**	.085	.232***	_	273***	019	125	.021	.050	.040
12. Age	.135**	.187***	.160***	.171***	.175***	.247***	.130**	.086	.179***	.059	141**	_	210***	.236***	.002	.164***	092*
13. Ethnicity	049	011	029	061	008	117**	068	.070	051	.003	.003	373***	_	048	061	.020	.022
14.Education	014	055	048	.003	033	.016	.043	.079	035	.021	.001	072	.199***	_	.131***	.139***	071
15. Income	084	088*	024	030	012	026	050	102*	054	083	085	049	004	.034	_	026	.035
16. PB	.520***	.231***	.196***	.500***	.266***	.402***	.369***	.322***	.322***	.297***	.048	.130**	039	044	022	_	489***
17. AP*Int.	238***	020	051	452***	208***	247***	254***	195***	128**	098*	003	004	117**	.035	.070	341***	_

Note. Coefficients below the principal diagonal are for the Australia sample, coefficients above the principal diagonal are for the US sample. Habit T1 = Self-reported habit measured at baseline (T1); Habit T2 = Self-reported habit measured at follow-up (T2); SN = Subjective norms; MN = Moral norms; AR = Anticipated regret; PBC = Perceived behavioral control; AP = Action planning; PB = Past behavior; AP\*Int. = Action planning-Intention interaction term.

\*\*\*p < .001 \*\* p < .01 \* p < .05.

Appendix E
Table E1
Standardized Parameter Estimates for Direct and Indirect Effects for the Structural Equation Model of the Integrated Model in the Australian Sample

Effect Model		odel excl		st behav	rior	M	odel incl	uding pas	t behav	ior
	β	р		6 CI	ES	В	p	96%		ES
	,	1	UL	LL			1	UL	LL	
Direct effects										
Int.→Beh.	.181	<.001	.095	.267	.066	.079	.039	009	.167	.029
AP→Beh.	.108	.008	.022	.194	.029	.038	.197	050	.126	.010
PBC→Beh.	.077	.043	011	.165	.022	.037	.207	051	.125	.010
Hab. $(T2)\rightarrow$ Beh.	.161	<.001	.075	.247	.041	.122	.003	.036	.208	.031
AP*Int.→Beh.	125	.003	211	039	.030	032	.234	120	.056	.008
PB→Beh.	_	_	_	_	_	.413	<.001	.329	.497	.216
Gender→Beh.	046	.154	134	.042	.003	056	.105	144	.032	.003
Age→Beh.	.050	.133	038	.138	.007	.049	.138	039	.137	.007
Ethnicity→Beh.	023	.302	111	.065	.001	011	.403	099	.077	.001
Education→Beh.	.016	.360	072	.104	<.001	.026	.279	062	.114	<.001
Income→Beh.	063	.081	151	.025	.006	066	.074	154	.022	.006
Att. $\rightarrow$ Int.	.064	.078	024	.152	.027	.057	.102	031	.145	.024
$SN\rightarrow Int.$	.230	<.001	.144	.316	.139	.197	<.001	.111	.283	.120
$MN\rightarrow Int.$	.376	<.001	.292	.460	.256	.351	<.001	.267	.435	.239
$AR \rightarrow Int.$	.061	.087	027	.149	.029	.044	.164	044	.132	.021
PBC→Int.	.224	<.001	.138	.310	.120	.203	<.001	.117	.289	.109
Hab. $(T1)\rightarrow Int$ .	028	.267	116	.060	.009	018	.346	106	.070	.006
$PB \rightarrow Int.$	-	_	_	_	_	.163	<.001	.077	.249	.082
Gender→Int.	.034	.225	054	.122	.005	.038	.200	050	.126	.006
Age→Int.	.029	.261	059	.117	.005	.024	.293	064	.112	.005
Ethnicity→Int.	.017	.355	071	.105	.003	.014	.381	074	.102	.003
Education→Int.	.026	.279	062	.114	<.001	.032	.240	056	.120	<.001
Income→Int.	002	.484	090	.086	<.001	002	.485	090	.086	<.001
Int. $\rightarrow AP$	.367	<.001	.283	.451	.146	.287	<.001	.203	.371	.114
PB→AP	-	~.001 _	-	-	_	.179	<.001	.093	.265	.056
Gender→AP	.196	<.001	.110	.282	.048	.201	<.001	.115	.287	.049
Age→AP	.038	.197	050	.126	.003	.037	.202	051	.125	.003
Ethnicity→AP	.047	.146	041	.135	<.001	.043	.170	045	.131	<.001
Education→AP	.014	.374	074	.102	<.001	.043	.276	043	.115	.001
Income→AP	070	.059	158	.018	.001	065	.071	153	.023	.001
PB→Att.	070	.039	136	.016	-	.243	<.001	.157	.329	.066
Gender→Att.	.126	.002	.040	.212	.014	.108	.008	.022	.194	.012
Age→Att.	.216	<.001	.130	.302	.040	.100	<.001	.104	.276	.012
Ethnicity→Att.	.073	.051	015	.161	.001	.074	.049	014	.162	.001
Education→Att.	014	.376	102	.074	<.001	008	.429	014	.080	<.001
Income→Att.	.093	.018	.007	.179	.010	.089	.023	.003	.175	.010
PB→SN	.093		.007			.371	<.001	.287	.455	.150
Gender→SN	.200	<.001	.114	.286	.035	.189	<.001	.103	.433	.033
Age→SN	.263	<.001	.114	.349	.065	.207	<.001	.103	.273	.053
•	006	.446	094		.003	016		104	.072	
Ethnicity→SN Education→SN	.038	.198	050	.082 .126	.001	.051	.363 .127	104		.002 .001
									.139	
Income→SN	082	.034	170	.006	.008	.075	.045	013 .287	.163	.008
PB→MN Gandar MN	- 190	- < 001	- 004	- 266	- 021	.371	<.001		.455	.141
Gender→MN	.180	<.001	.094	.266	.031	.178	<.001	.092	.264	.031
Age→MN	.150	<.001	.064	.236	.021	.117	.004	.031	.203	.016
Ethnicity→MN	014	.381	102	.074	.001	017	.353	105	.071	.001

T1 1 101	0-0	0 = 4	0.4 <b>-</b>		000	00.5		000		004
Education→MN	.073	.051	015	.161	.003	.086	.027	.000	.172	.004
Income→MN	032	.235	120	.056	.002	027	.273	115	.061	.002
PB→AR	_	_	_		_	.323	<.001	.239	.407	.105
Gender→AR	.181	<.001	.095	.267	.033	.169	<.001	.083	.255	.031
Age→AR	.146	<.001	.060	.232	.018	.141	<.001	.055	.227	.018
Ethnicity→AR	.096	.015	.010	.182	.007	.103	.010	.017	.189	.007
Education→AR	.083	.032	003	.169	.007	.097	.015	.011	.183	.008
Income→AR	078	.041	166	.010	.008	073	.051	161	.015	.008
$PB \rightarrow PBC$	_	_	_	_	_	.346	<.001	.262	.430	.130
Gender→PBC	.130	.002	.044	.216	.014	.100	.013	.014	.186	.011
Age→PBC	.204	<.001	.118	.290	.037	.143	<.001	.057	.229	.026
Ethnicity→PBC	.037	.207	051	.125	.002	.030	.249	058	.118	.002
Education→PBC	024	.300	112	.064	.001	018	.343	106	.070	.001
Income→PBC	039	.192	127	.049	.003	041	.177	129	.047	.003
PB→Hab. (T1)	_	_	_	_	_	.264	<.001	.178	.350	.078
Gender→Hab. (T1)	.107	.008	.021	.193	.012	094	.018	180	008	.010
Age→Hab. (T1)	.219	<.001	.133	.305	.042	.172	<.001	.086	.258	.033
Ethnicity→Hab. (T1)	.086	.027	.000	.172	.001	.082	.034	006	.170	.001
Education→Hab. (T1)	061	.086	149	.027	.003	056	.107	144	.032	.003
Income→Hab. (T1)	080	.036	168	.008	.007	083	.031	169	.003	.008
Hab. $(T1)\rightarrow$ Hab. $(T2)$	.637	<.001	.555	.719	.413	.637	<.001	.555	.719	.413
Gender→Hab. (T2)	.042	.171	046	.130	.005	.042	.171	046	.130	.005
Age→Hab. (T2)	.044	.161	044	.132	.007	.044	.161	044	.132	.007
Ethnicity→Hab. (T2)	002	.482	090	.086	<.001	002	.482	090	.086	<.001
Education→Hab. (T2)	009	.418	097	.079	<.001	009	.418	097	.079	<.001
Income→Hab. (T2)	019	.336	107	.069	.001	019	.336	107	.069	.001
Indirect effects								.000	.000	
$Att. \rightarrow Int. \rightarrow Beh.$	.011	.359	052	.074	.003	.004	.444	059	.067	.001
SN→Int.→Beh.	.042	.094	021	.105	.016	.016	.312	047	.079	.006
$MN \rightarrow Int. \rightarrow Beh.$	.068	.016	.005	.131	.024	.028	.192	035	.091	.010
$AR \rightarrow Int. \rightarrow Beh.$	.011	.356	052	.074	.003	.003	.457	060	.066	.001
PBC→Int.→Beh.	.040	.101	023	.103	.011	.016	.307	047	.079	.005
Int. $\rightarrow$ AP $\rightarrow$ Beh.	.040	.106	023	.103	.014	.011	.365	052	.074	.004
Hab. (T1).→Hab.	.102	<.001	.041	.163	.016	.078	.007	.017	.139	.013
(T2)→Beh.										
PB→Hab.→Beh.	_	_	_	_	_	.021	.214	030	.072	.011
PB→Beh. <sup>a</sup>	_	_	_	_	_	.081	.034	007	.169	.042
Total effects <sup>b</sup>										
Int.→Beh.	.220	<.001	.134	.306	.081	.090	.022	.004	.176	.033
PBC→Beh.	.126	<.001	.040	.212	.036	.055	.110	033	.143	.016
Hab. (T1)→Beh.	.096	.016	.010	.182	.015	.076	.044	012	.164	.012
PB→Beh.	_	_	-	-	-	.494	<.001	.412	.576	.258
Marta aCross of indicate	CC .	C . 1 1	•		• .1		1 1		Takal af	

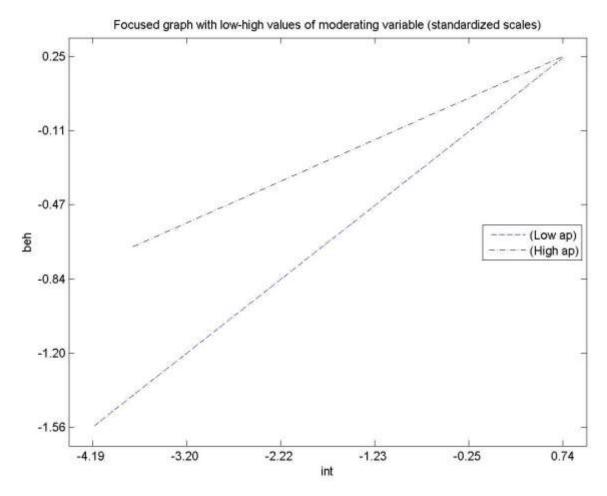
Table E2
Standardized Parameter Estimates for Direct and Indirect Effects for the Structural Equation Model of

the Integrated Model in the US Sample

Effect		odel excl	uding pa	st behav	rior	M	odel incl	uding pas	t behavi	ior
	β	р		6 CI	ES	В	р	96%		ES
	'	1	UL	LL			1	UL	LL	
Direct effects										
Int.→Beh.	.316	<.001	.243	.389	.148	.138	<.001	.065	.211	.065
AP→Beh.	.120	<.001	.047	.193	.044	.011	.381	063	.085	.004
PBC→Beh.	.041	.141	033	.115	.012	.036	.171	038	.110	.010
Hab. $(T2)\rightarrow Beh$ .	.307	<.001	.234	.380	.129	.240	<.001	.167	.313	.101
AP*Int.→Beh.	025	.255	099	.049	.007	.056	.067	018	.130	.016
PB→Beh.	_	_	_	_	_	.495	<.001	.424	.566	.311
Gender→Beh.	.073	.026	.000	.146	.005	.049	.097	025	.123	.004
Age→Beh.	.065	.042	009	.139	.006	018	.315	092	.056	.002
Ethnicity→Beh.	.065	.042	009	.139	.005	.047	.105	027	.121	.004
Education→Beh.	.034	.187	040	.108	.003	.002	.475	072	.076	<.001
Income→Beh.	.050	.090	024	.124	.003	.067	.037	007	.141	.004
Att. $\rightarrow$ Int.	.001	.489	073	.075	.001	.028	.232	046	.102	.013
$SN \rightarrow Int.$	.229	<.001	.156	.302	.146	.170	<.001	.097	.243	.108
$MN \rightarrow Int.$	.323	<.001	.250	.396	.217	.290	<.001	.217	.363	.194
$AR \rightarrow Int.$	.074	.025	.001	.147	.041	.011	.389	063	.085	.006
$PBC \rightarrow Int.$	.279	<.001	.206	.352	.161	.273	<.001	.200	.346	.157
Hab. $(T1)\rightarrow Int$ .	.078	.019	.005	.151	.033	.038	.155	036	.112	.016
PB→Int.	_	_	_	_	_	.289	<.001	.216	.362	.186
Gender→Int.	.074	.025	.001	.147	.007	.054	.074	020	.128	.005
Age→Int.	012	.371	086	.062	.002	.005	.451	069	.079	.001
Ethnicity→Int.	001	.492	075	.073	<.001	002	.484	076	.072	<.001
Education→Int.	.110	.002	.037	.183	.016	.077	.020	.004	.150	.011
Income→Int.	.045	.116	029	.119	.003	.050	.093	024	.124	.003
Int. $\rightarrow$ AP	.509	<.001	.438	.580	.258	.346	<.001	.275	.417	.175
$PB \rightarrow AP$	_	_	_	_	_	.270	<.001	.197	.343	.130
Gender→AP	.084	.013	.011	.157	.010	.070	.032	004	.144	.008
$Age \rightarrow AP$	.045	.118	029	.119	.002	038	.157	112	.036	.001
Ethnicity→AP	.063	.047	011	.137	.005	.054	.077	020	.128	.004
Education→AP	075	.022	148	002	.001	092	.007	165	019	.001
Income→AP	045	.117	119	.029	.001	023	.272	097	.051	.001
PB→Att.	_	_			_	.428	<.001	.357	.499	.187
Gender→Att.	.039	.151	035	.113	.001	.002	.474	072	.076	<.001
Age→Att.	.133	<.001	.060	.206	.015	.069	.032	005	.143	.008
Ethnicity→Att.	.112	.001	.039	.185	.009	.081	.015	.008	.154	.007
Education→Att.	017	.326	091	.057	<.001	063	.046	137	.011	<.001
Income→Att.	060	.056	134	.014	.004	045	.115	119	.029	.003
PB→SN	_	_	_	_	_	.467	<.001	.396	.538	.225
Gender→SN	.057	.065	017	.131	.004	023	.271	097	.051	<.001
$Age \rightarrow SN$	.147	<.001	.074	.220	.022	.077	.021	.004	.150	.011
Ethnicity→SN	.081	.015	.008	.154	.005	.048	.099	026	.122	.003
Education→SN	.053	.079	021	.127	.003	006	.432	080	.068	<.001
Income→SN	024	.259	098	.050	.001	023	.274	097	.051	.003
PB→MN	_	_	_	_	_	.511	<.001	.440	.582	.264
Gender→MN	.105	.003	.032	.178	.009	.042	.131	032	.116	.003
Age→MN	.095	.006	.022	.168	.008	.015	.345	059	.089	.001
Ethnicity→MN	.054	.074	020	.128	.002	021	.286	095	.053	.001
Education→MN	.047	.104	027	.121	.003	015	.342	089	.059	.001

I	010	201	004	064	. 001	002	400	076	072	. 001
Income→MN	010	.391	084	.064	<.001	002	.480	076	.072	<.001
PB→AR	125	- 001	- 052	- 100	- 011	.539	<.001	.468	.610	.294
Gender→AR	.125	<.001	.052	.198	.011	.056	.066	018	.130	.005
$Age \rightarrow AR$	.099	.004	.026	.172	.006	.018	.318	056	.092	.001
Ethnicity→AR	.113	.001	.040	.186	.010	.068	.036	006	.142	.006
Education→AR	.028	.225	046	.102	.001	034	.181	108	.040	.001
Income→AR	.047	.106	027	.121	.003	.053	.080	021	.127	.003
PB→PBC	-	- 170	-	- 110	-	.384	<.001	.313	.455	.148
Gender→PBC	.036	.172	038	.110	.002	.013	.365	061	.087	.001
Age→PBC	.119	<.001	.046	.192	.011	.063	.047	011	.137	.006
Ethnicity→PBC	.103	.003	.030	.176	.009	.077	.020	.004	.150	.007
Education→PBC	050	.092	124	.024	.001	090	.008	163	017	.002
Income→PBC	037	.164	111	.037	.002	.051	.089	023	.125	.002
$PB \rightarrow Hab. (T1)$	-	-	-	_	-	.412	<.001	.341	.483	.175
Gender→Hab. (T1)	053	.079	127	.021	.005	066	.040	140	.008	.006
Age→Hab. (T1)	.157	<.001	.084	.230	.024	.103	.003	.030	.176	.016
Ethnicity→Hab. (T1)	.100	.004	.027	.173	.009	.069	.034	005	.143	.006
Education→Hab. (T1)	019	.308	093	.055	<.001	064	.045	138	.010	.001
Income→Hab. (T1)	049	.098	123	.025	.003	027	.235	101	.047	.002
Hab. $(T1)\rightarrow$ Hab. $(T2)$	.691	<.001	.622	.760	.479	.691	<.001	.622	.760	.479
Gender→Hab. (T2)	.002	.477	072	.076	.000	.002	.477	072	.076	<.001
Age→Hab. (T2)	.004	.458	070	.078	<.001	.004	.458	070	.078	<.001
Ethnicity→Hab. (T2)	.099	.004	.026	.172	.011	.099	.004	.026	.172	.011
Education $\rightarrow$ Hab. (T2)	014	.357	088	.060	<.001	014	.357	088	.060	<.001
Income $\rightarrow$ Hab. (T2)	.060	.055	014	.134	.004	.060	.235	014	.134	.004
Indirect effects										
$Att. \rightarrow Int. \rightarrow Beh.$	<.001	.495	052	.054	<.001	.004	.443	049	.057	.001
$SN \rightarrow Int. \rightarrow Beh.$	.072	.003	.019	.125	.029	.023	.190	030	.076	.009
$MN \rightarrow Int. \rightarrow Beh.$	.102	<.001	.051	.153	.044	.040	.067	013	.093	.017
$AR \rightarrow Int. \rightarrow Beh.$	.023	.192	030	.076	.011	.001	.478	052	.054	.001
$PBC \rightarrow Int. \rightarrow Beh.$	.088	<.001	.037	.139	.025	.038	.079	015	.091	.011
Int. $\rightarrow$ AP $\rightarrow$ Beh.	.061	.011	.008	.114	.029	.004	.441	049	.057	.002
Hab. $(T1)$ . $\rightarrow$ Hab.	212	< 001			.075	166	< 001			050
(T2)→Beh.	.212	<.001	.161	.263	.075	.166	<.001	.115	.217	.059
PB→Hab.→Beh.	_	_	_	_	_	.068	<.001	.025	.111	.043
PB→Beh. <sup>a</sup>	_	_	_	_	_	.178	<.001	.105	.251	.112
Total effects <sup>b</sup>										
Int.→Beh.	.377	<.001	.306	.448	.177	.142	<.001	.069	.215	.066
PBC→Beh.	.146	<.001	.073	.219	.042	.074	.024	.001	.147	.021
Hab. $(T1)\rightarrow$ Beh.	.242	<.001	.169	.315	.086	.171	<.001	.098	.244	.061
PB→Beh.	_	_	_	_	_	.673	<.001	.604	.742	.423
M 4 ac C: 1: 4	22							0.		

Appendix F
Plot of Moderation Relationship of Action Planning (ap) on the Effect of Intention (int) on Behavior (beh) at High and Low Levels of Action Planning



Appendix G
Differences in Parameter Estimates Across Australia and US Samples from Multisample Structural
Equation Modeling Analysis with Difference Tests and 95% Confidence Intervals Using Satterthwaite
Method

Effect	Mode	l excludi	ng past bel	navior	Mod	Model including past behavior Diff. p 95% CI				
	Diff.	p	95%	6 CI	Diff.	p	95%	CI		
			LL	UL			LL	UL		
Int.→Beh.	.069	.113	043	.181	.002	.485	112	.116		
AP→Beh.	.017	.383	096	.130	.010	.431	104	.124		
PBC→Beh.	.015	.399	100	.030	.011	.423	104	.126		
Hab. $(T2)\rightarrow$ Beh.	.111	.026	001	.224	.095	.050	018	.208		
AP*Int.→Beh.	.072	.107	042	.186	.062	.145	053	.177		
PB→Beh.	_	_	_	_	.075	.089	034	.185		
Att.→Int.	.060	.153	055	.174	.026	.327	088	141		
SN→Int.	.006	.459	106	.118	.033	.282	079	.146		
$MN \rightarrow Int.$	.058	.154	053	.168	.067	.119	044	.178		
$AR \rightarrow Int.$	.020	.366	094	.134	.025	.336	090	.139		
PBC→Int.	.054	.172	100	.130	.068	.117	044	.180		
Hab. $(T1)\rightarrow Int$ .	.102	.040	012	.217	.052	.186	063	.167		
PB→Int.	_	_	_	_	.124	.015	.012	.237		
Int.→AP	.140	.006	.031	.250	.057	.158	054	.168		
$PB \rightarrow AP$	_	_	_	_	.095	.048	017	.208		
PB→Att.	_	_	_	_	.182	<.001	.071	.294		
PB→SN	_	_	_	_	.119	.017	.009	.229		
$PB \rightarrow MN$	_	_	_	_	.148	.004	.038	.258		
$PB \rightarrow AR$	_	_	_	_	.219	<.001	.109	.328		
$PB \rightarrow PBC$	_	_	_	_	.040	.240	071	.150		
PB→Hab. (T1)	_	_	_	_	.151	.044	.040	.262		
Hab. $(T1)\rightarrow$ Hab. $(T2)$	.102	.054	019	.194	.087	.054	019	.194		

*Note*. Diff. = Absolute difference in standardized parameter estimate; SE = Standard error of the standardized parameter estimate; 95% CI = 95% confidence intervals of ansolute difference in parameter estimate; LL = Lower limit of 95% CI; UL = Upper limit of 95% CI; Int. = Intention; Beh. = Behavior; PBC = Perceived behavioral control; Hab. (T1) = Self-reported habit measured at baseline (T1); Hab. (T2) = Self-reported habit measured at follow-up (T2); AP = Action planning; PB = Past behavior; Att. = Attitude; SN = Subjective norm; MN = Moral norm; AR = Anticipated regret.

Appendix H
Table H1
Standardized Parameter Estimates for Direct and Indirect Effects for the Structural Equation Model of the Integrated Model in the US Sample Excluding Participants Never Subject to a 'Shelter-in-Place'

Oraer										
Effect	M	odel excl	uding pa	st behav	ior	M	lodel incl	uding pas	st behav	ior
	β	p		6 CI	ES	В	p	96%		ES
			UL	LL				UL	LL	
Direct effects						<u> </u>			·	<u> </u>
Int.→Beh.	.296	<.001	.222	.370	.138	.098	.006	.022	.174	.046
AP→Beh.	.169	<.001	.095	.243	.063	.075	.026	001	.151	.028
PBC→Beh.	007	.427	083	.069	.002	026	.253	102	.050	.008
Hab. $(T2)\rightarrow$ Beh.	.287	<.001	.213	.361	.116	.217	<.001	.143	.291	.088
AP*Int.→Beh.	013	.369	089	.063	.004	.003	.474	073	.079	.001
PB→Beh.	_	_	-	_	_	.450	<.001	.377	.523	.281
Gender→Beh.	.069	.037	007	.145	.007	.034	.191	042	.110	.003
Age→Beh.	.039	.156	037	.115	.004	.007	.431	069	.083	.001
Ethnicity→Beh.	.041	.146	035	.117	.002	.026	.254	050	.102	.001
Education→Beh.	.068	.039	008	.144	.008	.036	.178	040	.112	.004
Income→Beh.	.030	.222	046	.106	.002	.038	.164	038	.114	.002
Att.→Int.	.013	.367	063	.089	.006	.033	.200	043	.109	.015
$SN\rightarrow Int.$	.206	<.001	.132	.280	.126	.157	<.001	.083	.231	.096
$MN\rightarrow Int.$	.318	<.001	.244	.392	.208	.292	<.001	.218	.366	.192
$AR \rightarrow Int.$	.090	.010	.014	.166	.050	.031	.215	045	.107	.017
PBC→Int.	.309	<.001	.235	.383	.179	.301	<.001	.227	.375	.174
Hab. $(T1)\rightarrow Int$ .	.069	.038	007	.145	.028	.028	.236	048	.104	.011
$PB \rightarrow Int.$	_	_	_	_	_	.266	<.001	.192	.340	.162
Gender→Int.	.074	.028	002	.150	.007	.061	.057	015	.137	.006
Age→Int.	009	.411	085	.067	.001	.006	.435	070	.082	.001
Ethnicity→Int.	052	.090	128	.024	.001	048	.109	124	.028	.001
Education→Int.	.108	.003	.032	.184	.016	.076	.025	.000	.152	.011
Income→Int.	.034	.188	042	.110	.003	.039	.156	037	.115	.003
Int.→AP	.485	<.001	.412	.558	.232	.349	<.001	.275	.423	.167
PB→AP	-	-	-	-	-	.244	<.001	.170	.318	.108
Gender→AP	.083	.016	.007	.159	.009	.065	.047	011	.141	.007
Age→AP	.059	.064	017	.135	.003	045	.121	121	.031	.007
Ethnicity—AP	.067	.041	009	.143	.003	.057	.070	019	.133	.002
Education→AP	086	.013	162	010	.004	099	.005	019	023	.003
Income→AP	086 046	.119	102	.030	.001	034	.191	173	.042	.001
PB→Att.	040					.408	<.001	.335	.481	.169
	.034	.188	042	110	.001	007	.433	083		<.001
Gender→Att.			042	.110					.069	
Age→Att.	.155	<.001	.081	.229	.020 .007	.099	.005	.023 .004	.175	.013
Ethnicity→Att.	.102	.004	.026	.178		.080	.019		.156	.006
Education→Att.	015	.354	091	.061	<.001	064	.049	140	.012	.001
Income→Att.	053	.087	129	.023	.003	039	.156	115	.037	.002
PB→SN	_ 05.4	- 001	022	- 120	- 002	.434	<.001	.361	.507	.196
Gender→SN	.054	.081	022	.130	.003	023	.281	099	.053	.001
Age→SN	.150	<.001	.076	.224	.023	.089	.011	.013	.165	.014
Ethnicity→SN	.058	.068	018	.134	.001	.037	.168	039	.113	.001
Education→SN	.055	.078	021	.131	.004	003	.471	079	.073	<.001
Income→SN	060	.062	136	.016	.004	048	.110	124	.028	.004
PB→MN	_	_	_	_	_	.471	<.001	.398	.544	.225
Gender→MN	.098	.006	.022	.174	.008	.038	.167	038	.114	.003
Age→MN	.100	.005	.024	.176	.010	.025	.261	051	.101	.002

Ethnicity→MN	.020	.301	056	.096	<.001	007	.432	083	.069	<.001
Education→MN	.054	.083	022	.130	.004	007	.424	083	.069	<.001
Income→MN	014	.356	090	.062	.001	.012	.375	064	.088	<.001
$PB \rightarrow AR$	_	_	_	_	_	.520	<.001	.447	.593	.272
Gender→AR	.125	<.001	.051	.199	.012	.058	.068	018	.134	.005
Age→AR	.095	.007	.019	.171	.006	.010	.398	066	.086	.001
Ethnicity→AR	.084	.015	.008	.160	.005	.052	.092	024	.128	.003
Education→AR	.040	.151	036	.116	.002	026	.252	102	.050	.001
Income→AR	.053	.086	023	.129	.004	.065	.046	011	.141	.004
$PB \rightarrow PBC$	_	_	_	_	_	.363	<.001	.289	.437	.132
Gender→PBC	.027	.241	049	.103	.000	.001	.494	075	.077	<.001
$Age \rightarrow PBC$	.131	<.001	.057	.205	.012	.078	.023	.002	.154	.007
Ethnicity→PBC	.097	.006	.021	.173	.007	.077	.023	.001	.153	.006
Education→PBC	051	.096	127	.025	.001	091	.009	167	015	.002
Income→PBC	.016	.339	060	.092	<.001	.016	.345	060	.092	<.001
PB→Hab. (T1)	_	_	_	_	_	.407	<.001	.334	.480	.168
Gender→Hab. (T1)	064	.050	140	.012	.006	074	.028	150	.002	.007
Age→Hab. (T1)	.164	<.001	.090	.238	.025	.111	.002	.035	.187	.017
Ethnicity→Hab. (T1)	.076	.025	.000	.152	.004	.055	.077	021	.131	.003
Education→Hab. (T1)	037	.171	113	.039	<.001	083	.016	159	007	.001
Income→Hab. (T1)	039	.157	115	.037	.002	026	.253	102	.050	.002
Hab. $(T1)\rightarrow$ Hab. $(T2)$	.692	<.001	.621	.763	.480	.692	<.001	.621	.763	.480
Gender→Hab. (T2)	017	.335	093	.059	.001	017	.335	093	.059	.001
Age→Hab. (T2)	004	.463	080	.072	<.001	004	.463	080	.072	<.001
Ethnicity→Hab. (T2)	.032	.202	044	.108	.002	.032	.202	044	.108	.002
Education→Hab. (T2)	034	.194	110	.042	.001	034	.194	110	.042	.001
Income→Hab. (T2)	026	.252	102	.050	<.001	026	.252	102	.050	<.001
Indirect effects										
$Att. \rightarrow Int. \rightarrow Beh.$	.004	.444	051	.059	.001	.003	.454	052	.058	.001
$SN \rightarrow Int. \rightarrow Beh.$	.061	.013	.008	.114	.023	.015	.288	040	.070	.006
$MN \rightarrow Int. \rightarrow Beh.$	.094	.000	.041	.147	.038	.029	.149	026	.084	.011
$AR \rightarrow Int. \rightarrow Beh.$	.027	.166	028	.082	.012	.003	.457	052	.058	.001
$PBC \rightarrow Int. \rightarrow Beh.$	.092	.000	.039	.145	.028	.029	.142	026	.084	.009
Int. $\rightarrow$ AP $\rightarrow$ Beh.	.082	.001	.029	.135	.038	.026	.170	029	.081	.012
Hab. $(T1)$ . $\rightarrow$ Hab.										
(T2)→Beh.	.198	<.001	.145	.251	.066	.150	<.001	.097	.203	.050
$PB \rightarrow Hab. \rightarrow Beh.$	_	_	_	_	_	.061	.003	.018	.104	.038
PB→Beh. <sup>a</sup>	_	_	_	_	_	.147	<.001	.073	.221	.092
Total effects <sup>b</sup>										
Int.→Beh.	.378	<.001	.305	.451	.176	.124	<.001	.048	.200	.058
PBC→Beh.	.110	.002	.034	.186	.034	.011	.384	065	.087	.004
Hab. $(T1)\rightarrow$ Beh.	.224	<.001	.150	.298	.075	.153	<.001	.079	.227	.051
PB→Beh.				_	_	.597	<.001	.524	.670	.373

Table H2
Standardized Parameter Estimates for Direct and Indirect Effects for the Structural Equation Model of the Integrated Model in the US Sample Excluding Participants Never Subject to 'Shelter-in-Place'
Order or Had an Order Lifted During the Study

Effect Model excluding past behavior Model including past behavior β p 96% CI ES B p 96% CI	
$\beta$ $p$ 96% CI ES B $p$ 96% CI .	ES
UL LL UL LL	
Direct effects	
Int.→Beh247 <.001 .171 .323 .108 .061 .065017 .139	.027
AP→Beh190 <.001 .112 .268 .072 .090 .013 .012 .168	.034
PBC→Beh002 .482080 .076 .001019 .320097 .059	.006
Hab. (T2)→Beh325 <.001 .249 .401 .141 .254 <.001 .178 .330	.110
AP*Int.→Beh013 .371065 .091 .004030 .226108 .048	.009
PB→Beh. – – – .465 <.001 .391 .539	.291
Gender→Beh059 .073019 .137 .004 .028 .242050 .106	.002
Age→Beh041 .155119 .037 .003 .001 .489077 .079	<.001
Ethnicity → Beh052 .097026 .130 .005 .017 .333061 .095	.002
Education → Beh105 .005 .027 .183 .014 .063 .058015 .141	.008
Income→Beh065 .052013 .143 .006 .081 .022 .003 .159	.008
Att.→Int021 .305057 .099 .009 .042 .148036 .120	.019
SN→Int188 <.001 .110 .266 .113 .149 <.001 .071 .227	.090
MN→Int330 <.001 .254 .406 .216 .306 <.001 .230 .382	.200
AR→Int077 .027001 .155 .042 .029 .234049 .107	.016
PBC→Int321 <.001 .245 .397 .189 .313 <.001 .237 .389	.185
Hab. (T1)→Int074 .033004 .152 .030 .038 .171040 .116	.016
PB→Int. – – .239 <.001 .163 .315	.140
Gender→Int085 .018 .007 .163 .009 .071 .039007 .149	.008
Age→Int009 .410087 .069 .001 .001 .490077 .079	<.001
Ethnicity→Int029 .233107 .049 .004019 .319097 .059	.003
Education → Int113 .002 .035 .191 .016 .081 .022 .003 .159	.011
Income→Int067 .049011 .145 .006 .069 .043009 .147	.006
Int.→AP .485 <.001 .411 .559 .235 .356 <.001 .280 .432	.173
PB→AP243 <.001 .167 .319	.107
Gender→AP .077 .029001 .155 .009 .059 .072019 .137	.007
Age→AP .046 .125032 .124 .002035 .191113 .043	.001
Ethnicity AP055 .084133 .023 .006 .035 .191043 .113	.004
Education AP090 .013168012 .001104 .005182026	.001
Income→AP064 .057142 .014 .003069 .043147 .009	.004
PB→Att. – – .409 <.001 .333 .485	.170
Gender→Att034 .203044 .112 .002 .007 .431071 .085	<.001
Age→Att120 .001 .042 .198 .013 .074 .034004 .152	.008
Ethnicity→Att120 .001198042 .015085 .017163007	.011
Education → Att028 .244106 .050 <.001080 .024158002	.001
Income→Att056 .081134 .022 .004050 .107128 .028	.004
PB→SN404 <.001 .328 .480	.173
Gender→SN .039 .164039 .117 .003013 .377091 .065	.001
Age→SN .135 <.001 .057 .213 .019 .089 .013 .011 .167	.013
Ethnicity→SN145 <.001223067 .023091 .012169013	.014
Education → SN .037 .177041 .115 .002016 .348094 .062	.001
Income→SN047 .120125 .031 .002031 .221109 .047	.001
PB→MN453 <.001 .377 .529	.210
Gender→MN .082 .020 .004 .160 .007 .027 .253051 .105	.002
Age→MN .074 .034004 .152 .007 .022 .294056 .100	.002
Ethnicity→MN122 .001200044 .018068 .046146 .010	.010

Education→MN	.030	.225	048	.108	.002	028	.245	106	.050	.002
Income→MN	066	.050	144	.012	.005	.092	.011	.014	.170	.007
$PB \rightarrow AR$	_	_		_	_	.496	<.001	.422	.570	.249
Gender→AR	.120	.001	.042	.198	.012	.055	.086	023	.133	.005
Age→AR	.079	.025	.001	.157	.004	025	.267	103	.053	.001
Ethnicity→AR	154	<.001	232	076	.024	092	.011	170	014	.014
Education→AR	.002	.482	076	.080	<.001	064	.057	142	.014	.002
Income→AR	.071	.038	007	.149	.006	.105	.005	.027	.183	.009
PB→PBC	_	_		_	_	.362	<.001	.286	.438	.130
Gender→PBC	.047	.123	031	.125	.001	.001	.491	077	.079	<.001
Age→PBC	.101	.006	.023	.179	.008	.049	.114	029	.127	.004
Ethnicity→PBC	102	.005	180	024	.011	092	.011	170	014	.009
Education→PBC	039	.167	117	.039	.001	085	.017	163	007	.002
Income→PBC	019	.316	097	.059	<.001	.010	.403	068	.088	<.001
$PB \rightarrow Hab. (T1)$	_	_		_	_	.391	<.001	.315	.467	.155
Gender→Hab. (T1)	063	.058	141	.015	.006	072	.037	150	.006	.007
Age→Hab. (T1)	.151	<.001	.073	.229	.022	.110	.003	.032	.188	.016
Ethnicity→Hab. (T1)	069	.043	147	.009	.006	021	.297	099	.057	.002
Education→Hab. (T1)	052	.098	130	.026	.001	099	.007	177	021	.001
Income→Hab. (T1)	045	.130	123	.033	.002	035	.192	113	.043	.001
Hab. $(T1)\rightarrow$ Hab. $(T2)$	.695	<.001	.621	.769	.486	.695	<.001	.621	.769	.486
Gender→Hab. (T2)	004	.465	082	.074	<.001	004	.465	082	.074	<.001
Age→Hab. (T2)	.015	.355	063	.093	.001	.015	.355	063	.093	.001
Ethnicity→Hab. (T2)	.025	.266	053	.103	.001	.025	.266	053	.103	.001
Education→Hab. (T2)	042	.148	120	.036	.002	042	.148	120	.036	.002
Income→Hab. (T2)	001	.494	079	.077	<.001	001	.494	079	.077	<.001
Indirect effects										
$Att. \rightarrow Int. \rightarrow Beh.$	.005	.429	052	.062	.002	.003	.464	054	.060	.001
$SN \rightarrow Int. \rightarrow Beh.$	.046	.052	009	.101	.018	.009	.376	048	.066	.004
$MN \rightarrow Int. \rightarrow Beh.$	.082	.002	.027	.137	.030	.019	.257	038	.076	.007
$AR \rightarrow Int. \rightarrow Beh.$	.019	.252	038	.076	.008	.002	.475	055	.059	.001
$PBC \rightarrow Int. \rightarrow Beh.$	.079	.003	.022	.136	.024	.019	.252	038	.076	.006
Int. $\rightarrow$ AP $\rightarrow$ Beh.	.092	<.001	.037	.147	.040	.032	.131	025	.089	.014
Hab. $(T1)$ . $\rightarrow$ Hab.										
(T2)→Beh.	.226	<.001	.171	.281	.076	.176	<.001	.121	.231	.059
$PB \rightarrow Hab. \rightarrow Beh.$	_	_		_	_	.069	.002	.024	.114	.043
PB→Beh. <sup>a</sup>	_	_		_	_	.140	<.001	.062	.218	.087
Total effects <sup>b</sup>										
Int.→Beh.	.339	<.001	.263	.415	.148	.094	.010	.016	.172	.041
PBC→Beh.	.107	.004	.029	.185	.032	.010	.400	068	.088	.003
Hab. $(T1)\rightarrow$ Beh.	.251	<.001	.175	.327	.084	.180	<.001	.102	.258	.060
PB→Beh.	_	_		_	_	.605	<.001	.531	.679	.378

Appendix I
Table I1
Differences in Parameter Estimates in Models Estimated in the Full US Sample and in the US Sample
Excluding Participants Never Subject to a Shelter-in-Place Order

Effect	Model e	xcluding pas	t behavior	Model in	ncluding past	behavior
	Diff.	t	p	Diff.	t	р
Int.→Beh.	.020	0.377	.706	.040	0.745	.456
AP→Beh.	049	-0.924	.355	064	-1.176	.240
PBC→Beh.	.048	0.882	.378	.062	1.139	.255
Hab. (T2)→Beh.	.020	0.377	.706	.023	0.434	.664
AP*Int.→Beh.	012	-0.220	.826	.053	0.974	.330
PB→Beh.	_	_	_	.045	0.872	.383
Att.→Int.	012	-0.220	.826	005	-0.092	.927
$SN\rightarrow Int.$	.023	0.434	.664	.013	0.245	.806
$MN \rightarrow Int.$	.005	0.094	.925	002	-0.038	.970
$AR \rightarrow Int.$	016	-0.298	.766	020	-0.367	.713
PBC→Int.	030	-0.566	.572	028	1.139	.597
Hab. $(T1)\rightarrow Int$ .	.009	0.168	.867	.010	0.184	.854
PB→Int.	_	_	_	.023	0.434	.664
Int.→AP	.024	0.465	.642	003	-0.057	.954
$PB \rightarrow AP$	_	_	_	.026	0.490	.624
PB→Att.	_	_	_	.020	0.388	.698
PB→SN	_	_	_	.033	0.640	.523
$PB \rightarrow MN$	_	_	_	.040	0.775	.438
$PB \rightarrow AR$	_	_	_	.019	0.368	.713
$PB \rightarrow PBC$	_	_	_	.021	0.402	.688
PB→Hab. (T1)	_	_	_	.005	0.097	.923
Hab. (T1)→Hab. (T2)	001	-0.020	.984	001	-0.020	.984

*Note*. Diff. = Absolute difference in standardized parameter estimate; t = t-value from test of mean difference in parameter estimates using the Satterthwaite method; Int. = Intention; Beh. = Behavior; PBC = Perceived behavioral control; Hab. (T1) = Self-reported habit measured at baseline (T1); Hab. (T2) = Self-reported habit measured at follow-up (T2); AP = Action planning; PB = Past behavior; Att. = Attitude; SN = Subjective norm; MN = Moral norm; AR = Anticipated regret.

Table I2
Differences in Parameter Estimates in Models Estimated in the Full US Sample and in the US Sample
Excluding Participants Never Subject to a 'Shelter-in-Place' Order or Had an Order Lifted During the
Study

Effect	Model e	Model excluding past behavior			Model including past behavior		
	Diff.	t	p	Diff.	t	р	
Int.→Beh.	.069	1.283	.200	.077	1.415	.157	
AP→Beh.	070	-1.286	.199	079	-1.431	.153	
PBC→Beh.	.043	0.779	.436	.055	0.996	.319	
Hab. (T2)→Beh.	018	-0.335	.738	014	-0.260	.795	
AP*Int.→Beh.	038	-0.688	.491	.086	1.558	.119	
PB→Beh.	_	_	_	.030	0.573	.567	
Att.→Int.	020	-0.362	.717	014	-0.254	.800	
$SN\rightarrow Int.$	.041	0.753	.451	.021	0.386	.700	
$MN \rightarrow Int.$	007	-0.130	.896	016	-0.298	.766	
$AR \rightarrow Int.$	003	-0.055	.956	018	-0.326	.744	
PBC→Int.	042	-0.781	.435	040	-0.744	.457	
Hab. $(T1)\rightarrow Int$ .	.004	0.074	.941	.000	0.000	1.000	
PB→Int.	_	_	_	.050	0.930	.353	
Int.→AP	.024	0.458	.647	010	-0.189	.425	
$PB \rightarrow AP$	_	_	_	.027	0.502	.616	
PB→Att.	_	_	_	.019	0.359	.720	
PB→SN	_	_	_	.063	1.189	.235	
$PB \rightarrow MN$	_	_	_	.058	1.904	.274	
$PB \rightarrow AR$	_	_	_	.043	0.821	.412	
PB→PBC	_	_	_	.022	0.415	.678	
PB→Hab. (T1)	_	_	_	.021	0.396	.692	
Hab. (T1)→Hab. (T2)	004	-0.078	.938	004	-0.078	.938	

*Note.* Diff. = Absolute difference in standardized parameter estimate; t = t-value from test of mean difference in parameter estimates using the Satterthwaite method; Int. = Intention; Beh. = Behavior; PBC = Perceived behavioral control; Hab. (T1) = Self-reported habit measured at baseline (T1); Hab. (T2) = Self-reported habit measured at follow-up (T2); AP = Action planning; PB = Past behavior; Att. = Attitude; SN = Subjective norm; MN = Moral norm; AR = Anticipated regret.