Application of the Health Action Process Approach to Social Distancing Behavior During COVID-19

Kyra Hamilton[1], Stephanie R. Smith[1], Jacob J. Keech[2,1], Susette A. Moyers[3] & Martin S. Hagger[3,4]

[1]Griffith University

[2]University of the Sunshine Coast

[3]University of California, Merced

[4]University of Jyväskylä

Full citation: Hamilton, K., Smith, S. R., Keech, J. J., Moyers, S. A. & Hagger, M. S. (in press). Application of the health action process approach to social distancing behavior during COVID-19. *Applied Psychology: Health and Wellbeing*. https://doi.org/10.1111/aphw.12231

Address for Correspondence: Kyra Hamilton, Health and Psychology Innovations (HaPI) Laboratory, School of Applied Psychology, Griffith University, Mt Gravatt Campus, 176 Messines Ridge Road, Mt Gravatt, Queensland, QLD 4122, Australia. Email: kyra.hamilton@griffith.edu.au

Abstract

Background: This study examined the social cognition determinants of social distancing behavior during the COVID-19 pandemic in samples from Australia and US guided by the health action process approach (HAPA). **Methods:** Participants (Australia: N=495, 50.1% women; US: N=701, 48.9% women) completed HAPA social cognition constructs at an initial time-point (T1), and one week later (T2) self-reported their social distancing behavior. **Results:** Single-indicator structural equation models that excluded and included past behavior exhibited adequate fit with the data. Intention and action control were significant predictors of social distancing behavior in both samples, and intention predicted action and coping planning in the US sample. Self-efficacy and action control were significant predictors of intention in both samples, with attitudes predicting intention in the Australia sample and risk perceptions predicting intention in the US sample. Significant indirect effects of social cognition constructs through intentions were observed. Inclusion of past behavior attenuated model effects. Multigroup analysis revealed no differences in model fit across samples suggesting that observed variations in the parameter estimates were relatively trivial. **Conclusion:** Results indicate social distancing is a function of motivational and volitional processes. This knowledge can be used to inform messaging regarding social distancing during COVID-19 and in future pandemics.

Keywords: Health Action Process Approach; Dual-phase model; Social cognition; Action planning; Coping planning; Physical distancing; Self-efficacy.

Data availability statement: Data files and analysis scripts are available online from the Open Science Framework project for this study: https://osf.io/mrzex/

Acknowledgements: Martin S. Hagger's contribution was supported by a Finland Distinguished Professor (FiDiPro) award (Dnro 1801/31/2105) from Business Finland.

Application of the Health Action Process Approach to Social Distancing Behavior During COVID-19

The COVID-19 pandemic has had unprecedented global effects on mortality, way of life, national economies, and physical and mental health not previously experienced in modern times. It has presented governments, healthcare services, and education facilities with wide-scale and complex logistical challenges on how to manage the rapid spread of the disease and minimize the projected human and economic costs. Given that, to date, there is no vaccine to protect against COVID-19, non-pharmacological intervention is the only currently available means to reduce the spread of SARS-CoV-2, the virus that causes COVID-19, and 'flatten the curve' of infection rates. In response, national and statewide governmental measures aimed at minimizing transmission of the virus including 'stay at home' orders, closure of businesses and places of congregation, and travel restrictions have had a substantive impact on mortality rates (Worldometer, 2020). As rates of infection dissipate in some countries, particularly in countries like Australia that have relatively low rates of daily infections, governments are now beginning to ease restrictions. However, preventive behaviors aimed at reducing infection rates remain highly pertinent given concerns over the potential for infection rates to rise again and fears of a 'second wave'. Furthermore, some countries who are easing lockdown measures, such as some states in the US, still have high localized rates of infection, highlighting the imperative of ongoing performance of preventive behaviors to manage infection transmission.

Based on World Health Organization (WHO) recommendations (World Health Organization, 2020) and previous research on behaviors known to reduce virus transmission (Jefferson et al., 2011; Rabie & Curtis, 2006; Smith et al., 2015), two key sets of COVID-19 related behaviors that may apply to the population as a whole have been proposed (Michie et al., 2020). The first set is 'personal protective behaviors' that are aimed at the individual in order to protect themselves or others (e.g., washing hands frequently, practicing respiratory hygiene). The second set involves behaviors aimed at ensuring physical distance between people (e.g., social distancing, stay at home orders). Despite knowledge of these key behaviors in the prevention of virus transmission (e.g., Islam et al., 2020), there is a relative dearth of information on the determinants and mechanisms of action that underpin these preventive behaviors and how to strengthen individuals' capacity to adopt them. In the absence of direct evidence, knowledge to inform practice guidelines that governments and organisations can use to mobilise individuals into performing COVID-19 preventive behaviors has been gleaned from applying general principles from behavioral science and the models of behavior that underpin them (Lunn et al., 2020; Michie et al., 2020; The British Psychological Society, 2020; West et al., 2020) as well as findings of previous empirical investigations in the psychological literature on similar health and risk behaviors (e.g., face mask use, handwashing, distancing; Chu et al., 2020; Reyes Fernández et al., 2016; Zhang, Chung, et al., 2019; Zhang et al., 2020). Although this approach is potentially useful in structuring thinking and recommendations in urgent times, there is a pressing need for direct evidence that identifies the key determinants of these COVID-19 preventive behaviors and the processes involved. This knowledge can then be used to inform development of effective interventions to promote uptake and adherence to these behaviors. This is especially important given individuals' beliefs may affect their adoption of non-pharmacological measures to prevent virus transmission (Teasdale et al., 2014).

Prominent among social cognition theories are dual-phase models which aim to provide a comprehensive theoretical account of health behavior uptake and participation, and the processes involved (Hagger et al., 2020). One such dual-phase theory that has been frequently applied to predict multiple health behaviors is the Health Action Process Approach (HAPA; Schwarzer, 2008; Schwarzer & Hamilton, 2020). The HAPA is an integrated model that combines features of stage and continuum social cognition models. A key feature of the model is the distinction made between motivational (where an individual is in a deliberative mindset while setting a goal – forming an intention) and volitional (where an individual is in an implementation mindset while pursuing their goal) phases involved in behavioral enactment. In the motivational phase, intentions are conceptualized as the most important determinant of behavior. Intentions are proposed to be a function of three sets of belief-based constructs: outcome expectancies (beliefs that the target behavior will lead to outcomes that have utility for the individual, conceptually identical to an individual's *attitudes* toward the behavior), self-efficacy (beliefs in personal capacity to successfully perform the target behavior and overcome challenges and barriers to its performance), and risk perceptions (beliefs in the severity of a health condition that may arise from not performing the target behavior and personal vulnerability toward it).

In the volitional phase of the HAPA, planning and action control strategies are important self-regulatory strategies that determine subsequent enactment of the target behaviour (Schwarzer, 2008; Schwarzer & Hamilton, 2020). Two forms of planning are proposed: action planning, a task-facilitating strategy that relates to how individuals prepare themselves in performing a behavior, and coping planning, a distraction-inhibiting strategy that relates to how individuals prepare themselves in avoiding foreseen barriers and obstacles that may arise when performing a specific behavior, and potentially competing behaviors that may derail the behaviour. In addition, action control, a self-regulatory strategy for promoting behavioral maintenance through the monitoring and evaluation of a behavior against a desired behavioral standard, is also an important direct determinant of behaviour (Hamilton et al., 2018; Reyes Fernández et al., 2016).

Behavioral intention operates as a 'bridge' between the motivational and volitional phases, while planning serves to link intentions with behavior. Previous research has provided support for the HAPA constructs in predicting health preventive behaviors, with prominent roles for outcome expectancies, forms of self-efficacy, planning and action control, with risk perceptions only relevant in certain contexts (see Schwarzer & Hamilton, 2020; Zhang, Zhang, et al., 2019). Furthermore, the model has been used as a basis for effective behavior change interventions aimed at promoting increased participation in health-related behaviors (Schwarzer & Hamilton, 2020).

The Present Study

Given social distancing is a key evidence-based behavior that will minimize transmission of SARS-CoV-2 if performed consistently at the population level, the aim of the present study was to apply the HAPA to identify the social cognition and self-regulatory determinants of this preventive behavior in samples of adults from two countries, Australia and the US. These two countries provided an opportunity to examine the determinants of social distancing because they experienced rapid increases in COVID-19 cases at relatively similar times during the pandemic and introduced public health advice as well as 'lockdown' measures and 'shelter-in-place' orders to minimize transmission, including social distancing. Specifically, the current research aimed to identify potentially modifiable determinants that are reliably related to social distancing intentions and behavior, which may form targets of behavioral interventions to reduce COVID-19 infection rates, and, going forward, other communicable diseases transmitted through person-to-person contact. The value of applying the HAPA is that it provides information on phase-relevant constructs in determining this important behavior. Proposed predictions among model constructs are summarized diagrammatically in Figures 1 and 2. Figure 1 presents the HAPA predictions excluding effects of past social distancing behavior.

Intention to perform social distancing was expected to be predicted by attitude (as a proxy for outcome expectancies), self-efficacy, and risk perceptions, and social distancing behavior was expected to be predicted by self-efficacy, intentions, action planning, coping planning, and action control. Intention was proposed to mediate effects of attitude, self-efficacy, and risk perceptions on behavior. In addition, intention was expected to predict action planning and coping planning such that the planning constructs mediate the intention-behavior relationship. Action control was proposed to predict behavior directly. Although it is strictly a self-regulation technique aimed at facilitating better behavioral enactment, as proposed by the original HAPA (e.g., Schwarzer, 2008), individuals who are effective at action control (i.e., self-monitoring) may also more likely form strong intentions. Action control implies not only the recall of behavior but also the recall of intentions. Self-monitoring of the concurrent behavior, therefore, may make the individual aware of their intention as well as their behavior, focusing on possible discrepancies between the two. It is plausible, then, that action control can be specified as both a predictor of intention and behavior. The co-existence of intention and action control within the same data set allows this key question to be tested; which of the two factors may be more proximal to the behavioral outcome? Action control might not be a time-specific variable, and individuals may self-monitor their behaviors at any point in time (see Zhou et al., 2015), even before goal setting. Actions can be monitored before making intentions, while doing so, or afterwards. Thus, examining the indirect (via intention) and direct effects of action control on behavior is intuitively meaningful, although not supported by the original HAPA, and tested in the present study. Figure 2 outlines the inclusion of past behavior in the model to test its sufficiency. Although model effects were expected to hold with the inclusion of past behavior, it was expected to attenuate the size of the proposed effects consistent with previous studies (Brown et al., 2020). This was expected to be the case in the current study due to the relatively brief one-week follow up. The attenuation effect was proposed to model past decision making and effects of other unmeasured constructs on behavior.

Method

Participants

A sample of Australian ($N = 495$, 50.1% women) and US ($N = 701$, 48.9% women) residents were recruited via an online research panel company. To be eligible for inclusion, participants needed to be aged 18 years or older and were required to not be subject to formal quarantine for COVID-19. In addition to the inclusion criteria, participants were screened on the demographic characteristics of age, gender, and geographical region and quotas were imposed to ensure that the sample comprised similar proportions of these characteristics to the national population of each country. Sample characteristics are presented in Appendix A (supplemental materials). Data were collected in April and May 2020 during which time residents throughout Australia and all states in the US were subject to 'stay at home' orders to reduce transmission of the coronavirus.

Design and Procedure

The study adopted a prospective correlational design with self-report measures of HAPA constructs (attitudes, self-efficacy, risk perceptions, intentions, action planning, coping planning, and action control) and past engagement in social distancing behavior administered at an initial time-point (T1) in a survey administered using the Qualtrics™ online survey tool. Participants were informed that they were participating in a survey on their social distancing behavior and provided with an information sheet outlining study requirements. They were also provided with a consent form to which they had to affirm before proceeding with the survey. Participants were also provided with an information sheet providing instructions on how to complete the study measures. They were also provided with 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 meter (3-6 feet) distance from other people)". One-week later (T2), participants were contacted a second time by the panel company and were asked to self-report their social distancing behavior over the previous week using the same behavioral measure administered at T1. Participants received a fixed sum or 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 University Human Research Ethics Committee.

Measures

Study measures were measured on multi-item psychometric instruments developed using published guidelines and adapted for use with the target behavior in the current study (Schwarzer, 2008). Participants provided their responses on scales with seven-point response options. Complete study measures are provided in Appendix B (supplemental materials).

Social cognition constructs. Measures of attitudes, self-efficacy, risk perceptions, intentions, action planning, coping planning, and action control from the HAPA were developed according to guidelines (Schwarzer, 2007). *Attitude* was measured using three semantic differential items in response to a common stem: “My maintaining social distancing in the next week would be...”, followed by a series of bi-polar adjectives (e.g., (1) *worthless* – (7) *valuable*). *Self-efficacy* was measured using four items (e.g., “I am confident that I could maintain social distancing”, scored (1) *strongly disagree* to (7) *strongly agree*). *Risk perception* was measured using two items (e.g., “It would be risky for me to not maintain social distancing”, scored (1) *strongly disagree* to (7) *strongly agree*). *Intention* was measured using three items (e.g., “I intend to maintain social distancing”, scored (1) *strongly disagree* to (7) *strongly agree*). *Action planning* was measured using four items. Participants were required to respond to the stem: “In the next week, I have made a plan regarding...”, followed by the four items of the scale (e.g., “…when to maintain social distancing”) on Likert scales ranging from *strongly disagree* (1) to *strongly agree* (7). *Coping planning* was measured using four items. Participants were required to respond to the stem: “To keep my intention to maintain social distancing in the next week in difficult situations, I have made a plan...”, followed by the four items of the scale (e.g., “…what to do if something interferes with my goal of maintaining social distancing”) on Likert scales ranging from *strongly disagree* (1) to *strongly agree* (7). Action control was measured using three items (e.g., I have consistently monitored when, how often, and how to maintain social distancing”), scored (1) *strongly disagree* to (7) *strongly agree*).

Past behavior and behavior. Participants self-reported their participation in the target behavior maintaining social distancing in relation to others to minimize transmission of the coronavirus that causes COVID-19. The measure comprised two-items prompting participants to report their frequency of social distancing behavior in the previous week: "In the past week, how often did you maintain social distancing", scored (1) *never* to (7) *always* and "In the past week, I maintained social distancing", scored (1) *false* to (7) *true*).

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 facto relationship), annual household income stratified by eleven income levels based on Australia and US national averages, and 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). Binary income (low income vs. middle/high income)[1], highest education level (completed school education only vs. completed post-school education), and ethnicity (white/Caucasian vs. non-white) variables were computed for use in subsequent analyses.

Data Analysis

Hypothesized relations among HAPA constructs in the proposed model were tested in the Australia and US sample separately using single-indicator structural equation models implemented in the lavaan package in R (R Core Team, 2020; Rosseel, 2012). We opted for single-indicator models over a full latent variable structural equation model due to the complexity of the model and the large number of parameters. The single-indicator approach utilizes scale reliabilities to provide an estimate of the measurement error of each variable in the model. Specifically, each variable in the model was indicated by its averaged composite with the error variance fixed at a value based on the reliability estimates using the formula: 1-reliability*scale variance. Simulation studies have demonstrated that

[1]Our cut-off for low vs. medium-to-high income was based on national income data for citizens on low incomes in the US (for a family of four, the low income threshold is US$25,465 per year; Semega et al., 2020) and Australia (for a family of four, the low-income average is $562 per week; AIHW, 2020). Participants reporting incomes of $400-$599 per week ($20,800-$31,199 per year) or below were classified as low income.

parameter estimates and model fit of single-indicator models compare very favorably with full latent variable structural equation models, particularly when sample sizes are small (Savalei, 2019).

We freed parameters between the single-indicator latent variables according to our proposed model. Two models were estimated, one excluding effects of past social distancing behavior (Model 1, Figure 1) and one which controlled for past behavior (Model 2, Figure 2) by freeing parameter estimates from past behavior on each construct in the model. We also controlled for effects of the following demographic variables in each model by freeing paths from each variable to all other model variables: gender, age, ethnicity, income, and education level. Missing data were handled using the full information maximum likelihood (FIML) method. The FIML approach is a preferred approach to handling missing data as simulation studies indicates that it leads to unbiased parameter estimates in structural equation modeling (Enders & Bandalos, 2001; Wothke, 1998).

Model comparisons across the Australia and US samples were conducted using multigroup analyses. An initial configural multisample model for the model excluding past behavior was estimated (Model 3), which provided evidence for the tenability of the model in accounting for the data across both samples. This was followed by a restricted model in which the parameter estimates representing proposed relations among the HAPA constructs and behavior were constrained to equality across the two samples (Model 4). The fit of the constrained model did not differ significantly from the configural model across the two samples, which provided evidence that model parameters did not differ substantially. This was established using a formal likelihood ratio test of the goodness-of-fit chi-square for the configural and constrained models (Byrne et al., 1989). We also examined differences in the CFI; differences of less than .01 between values for the configural and constrained models have also been proposed as indicative of invariance of parameters (Cheung & Rensvold, 2002). The configural (Model 5) and constrained (Model 6) multisample analyses were repeated for the model including past behavior.

Models were implemented using the maximum likelihood estimator with bootstrapped standard errors with 1000 bootstrap replications. Goodness of fit of the models with the data were evaluated using multiple criteria comparing the proposed model with the baseline model including the goodness-of-fit chi-square (χ^2), the comparative fit index (CFI), the standardized root mean-squared of the residuals (SRMR), and the root mean square error of approximation (RMSEA) and its 90% confidence interval (90% CI). Since the chi-square value is often statistically significant in complex models and has been shown to lead to the rejection of adequate models, we focused on the incremental fit indices. Specifically, values for the CFI should exceed .95, values for the SRMR should be less than or equal to .08, and values for the RMSEA should be below .05 with a narrow 90% confidence interval (Hu & Bentler, 1999). Data files, analysis scripts, and output are available online: https://osf.io/mrzex/

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% women; attrition rate 26.27%) and 440 (*M* age = 51.77, *SD* = 16.26; 46.6% women; attrition rate = 37.23%) participants retained at follow-up in the Australia and US samples, respectively. There were no missing data for the social cognition and behavior variables as participants could not advance through the survey without providing a response. 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 as participants could opt not to respond to these items as the represented personal data. Missing data are reported in Appendix C (supplemental materials).

Sample characteristics at follow-up are presented in Appendix A (supplemental materials), and comparisons on study variables between those retained in the study at follow-up and those lost to attrition are presented in Appendix C (supplemental materials). 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 = 0.973, $F(8) = 1.60$, $p = .115$, partial $\eta^2 = .026$). Attrition analyses in the US sample also indicated that participants lost to attrition were younger, and more likely to be men, 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 and past behavior variables among participants lost to attrition and those included at follow-up revealed statistically significant differences (Wilks' Lambda = 0.957, $F(8) = 3.90$, $p < .001$, partial $\eta^2 = .043$). Follow-up tests revealed that mean values for past behavior, attitudes, intentions, and self-monitoring 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 in the small (ds < .23).

Preliminary Analyses

Descriptive statistics for study variables are presented in Appendix D (supplemental materials). Participants reported high levels of intention (Australia sample, $M = 6.54$, $SD = 0.66$; US sample, $M = 6.39$, $SD = 0.85$) and behavior (Australia sample, $M = 6.10$, $SD = 0.67$; US sample, $M = 6.40$, $SD = 0.97$) with respect to social distancing. Internal consistency of the social cognition constructs was estimated using Revelle (2018) omega and internal consistency of the behavior variables and risk perception was estimated using the Spearman-Brown as they comprised two items each. Results are presented in Appendix D (supplemental materials). All constructs in both samples exhibited acceptable internal consistency, and these data were used to estimate measurement error in subsequent single-item structural equation models. Scale variance, descriptive statistics, and computed error variance terms used in structural equation models are also presented in Appendix D. Correlations among the model constructs and behavior and socio-demographic variables are presented in Appendix E (supplemental materials).

Structural Equation Models

The single-indicator structural equation models that excluded (Model 1) and included (Model 2) past behavior exhibited adequate model fit with the data for both the Australia and US samples (see Appendix F, supplemental materials). Standardized parameter estimates and distribution statistics for each model in the Australia and US samples are presented in Tables 1 and 2[2], respectively. Focusing first on the models excluding past behavior, intention and action control were statistically significant predictors of social distancing behavior in both samples, with no significant effects for self-efficacy, action planning, and coping planning. There were also no significant effects of intention on action planning or coping planning in the Australia sample, while intention predicted both planning constructs in the US sample. Self-efficacy and action control were significant predictors of intention in both samples, with attitudes predicting intention in the Australia sample only and risk perceptions predicting intention in the US sample, although the effect in the Australia sample fell short of statistical significance by a trivial margin (p = .077). There were significant indirect effects of self-efficacy on behavior mediated by intention in both samples, and significant indirect effects of risk perceptions and action control on behavior mediated by intentions in the US sample only. Intention and action control had significant total effects on behavior in both samples, with a further total effect of self-efficacy in the US sample.

Inclusion of past behavior led to an attenuation of model effects, consistent with previous research (Brown et al., 2020). Notably, effects of all HAPA constructs on behavior were reduced to a trivial size and were not statistically significant. Effects of constructs on intentions remained with the same pattern as those in the model excluding past behavior for both samples, albeit with smaller effect sizes. The only exception was the action control-intention effect, which was reduced to a trivial

[2]Full parameter estimates for the models in the Australia and US samples are provided in Appendices G and H (supplemental materials), respectively.

size and non-significance in the US sample. Past behavior predicted all model constructs with medium-to-large effect sizes in both samples[3].

Multi-Group Analysis

Comparisons of model fit across the Australia and US samples revealed adequate fit of the configural models excluding (Model 3) and including (Model 5) past behavior, lending support for the tenability of the proposed pattern of model effects across the samples (Appendix F, supplemental materials). Constraining regression coefficients to be invariant for the models including (Model 4) and excluding (Model 6) past behavior resulted in no significant change in model fit according to the goodness-of-fit chi-square and the CFI with differences in the CFI across models less than .01 (Appendix F, supplemental materials). These findings suggested that any observed differences in the parameter estimates of the models across the Australia and US samples were relatively trivial. This is consistent with the highly consistent pattern of effects in the models in each sample with relatively minor sample-specific variation.

Discussion

The empirical literature has highlighted the imperative of non-pharmacological interventions in reducing the transmission of communicable viruses and preventing infection (Jefferson et al., 2011; Rabie & Curtis, 2006; Smith et al., 2015). In the context of the COVID-19 pandemic, participation in behaviors that prevent virus transmission is essential given the absence of a vaccine or clinically-proven pharmacological therapy. Sustained, population-level participation in such behaviors is not only important to reduce infections in the current pandemic phase, but also in the phases of easing restrictions to avoid a potential 'second wave' of infections. There is a pressing need for evidence of

[3]The social distancing behavior and past behavior variables were associated with large skewness and kurtosis values. We checked to see whether the skewness and kurtosis values affected findings. So we re-estimated our structural equation models using a square root transformation of these variables. The reanalysis revealed virtually identical coefficients and the exact pattern of effects found for the analysis using the untransformed behavior variables. Analysis scripts and output for this auxiliary analysis are available online: https://osf.io/mrzex/

potentially modifiable determinants of COVID-19 preventive behaviors, such as social distancing, on which base interventions promoting population level participation in these behaviors.

The current study aimed to address this need by identifying the theory based social cognition determinants of social distancing behavior, and the processes involved, in samples from Australia and the US. The study adopted a correlational prospective survey design guided by the HAPA. Consistent with HAPA predictions, intention and action control were identified as significant direct predictors of social distancing behavior in both samples, while intention predicted action planning and coping planning in the US sample. Further, self-efficacy and action control were identified as significant predictors of intention in both samples. Attitudes and risk perceptions were additional predictors in the Australia and US samples, respectively. Significant indirect effects were also observed; self-efficacy predicted behavior mediated by intention in both samples, and risk perceptions and action control were found to predict behavior mediated by intentions in the US sample only. Despite these limited differences, it should be noted that comparisons of the models across the Australia and US samples suggested that observed differences in parameter estimates across the samples were relatively trivial. Findings are consistent with the auxiliary assumption promulgated in the HAPA, and social cognition theories more generally, that the effects of the belief-based constructs reflect generalized processes that have consistent pattern of effects across contexts, populations, and behaviors. In sum, current findings indicate that individuals' social distancing behavior is a function of both motivational and volitional processes, and this provides formative data on potential targets for behavioral interventions aimed at promoting participation in this preventive behavior.

Theoretical Implications

Results of this study provide qualified support for the application of the HAPA, with its focus on constructs that represent dual phases of action. Findings demonstrate a prominent role for self-efficacy as the key determinant of intentions, and intentions as the key determinant of behavior across both samples. These findings are in line with applications of the HAPA in multiple health behavioral contexts (Zhang, Zhang, et al., 2019), as well as research on social cognition constructs more broadly (Hamilton et al., 2020; McEachan et al., 2011). Confidence in engaging in health behaviors and capacity to overcome setbacks and barriers have been consistently linked with future behavioral performance (Warner & French, 2020). The pervasive effect of intention on behavior is also aligned with a substantive literature on social cognition theories demonstrating intentions as the preeminent determinant of behaviour (Hamilton et al., 2020; McEachan et al., 2011). Overall, these effects suggest that social distancing behavior should be conceptualized as a reasoned action.

However, the current study also demonstrated a prominent role for constructs representing volitional processes in the enactment of behavior. In particular, action control, a construct reflecting individuals' application of key self-regulatory skills to enact behavior, was a consistent predictor of both intentions and behavior across the samples. Individuals possessing these skills are not only more likely to form intentions to perform social distancing behaviors, but are also more likely to engage in the behavior through, for example, an automatic process. Specifically, the direct effect not mediated by intentions suggests that individuals with good action control might be more effective in structuring their environment or forming habits that promote enactment of social distancing without the need for extensive deliberation or weighing up of options. Over time, these individuals are likely to form habits, that is, performance of behaviors that are activated through cues and contexts independent of the goals and intentions that originally gave rise to them (Aarts et al., 1998; Verplanken & Orbell, 2003; Wood, 2017). Research has suggested that individuals possessing these skills are effective in controlling their actions more broadly, but also that such skills can be acquired or learned (Gardner, 2015; Gardner et al., 2020), which provides a potential avenue for intervention: training people to be more effective in regulating their own actions.

Interestingly, current research shows that risk perceptions have small effects on intentions and subsequent behavior. Risk perceptions had small but significant effects in the US sample, and a small effect which fell short of statistical significance in the Australia sample. This pattern of effects is consistent with applications of the HAPA and other social cognition models like protection motivation theory, which found relatively modest or null effects of risk perceptions on intentions and behaviour (Zhang et al., 2019). In the context of COVID-19 prevention and social distancing behavior, it is common knowledge that the infection will not have serious consequences for the majority of the population, and is likely only to be serious for those with underlying conditions or impaired immunity, or the elderly. As a consequence, perceived risk may not be a major influence on decisions to act. Instead, it seems that self-efficacy and action control are more pervasive and consistent determinants of behavior, and these may be more pertinent targets for intervention.

Action and coping planning were expected to mediate intention-behavior effects in the current model, such that planning is an important part of the process of intention enactment for social distancing. However, findings indicated that neither form of planning mediated intention effects on behavior, contrary to HAPA predictions. These findings are not, however, unique, and previous research has demonstrated considerable variability in the role of planning in intention enactment, and effect sizes are often small (Rhodes et al., 2020; Zhang, Zhang, et al., 2019). Taken together, it seems that volitional processes such as action control are far more pervasive in promoting social distancing intentions and behavior.

Introduction of past behavior in the current model had marked influences on the size of model effects, rendering effects of almost all model constructs on intentions and behavior trivial and not statistically significant. One interpretation of these findings is that the current model is not sufficient in accounting for social distancing over time. However, it was not unexpected that past behavior will have pervasive effects on subsequent behavior over such short range prediction and, given the high stability of social distancing behavior, it is unsurprising that it accounts for model effects over time. It must also be stressed that past behavior alone is not a construct and does not, therefore, offer any information other than on the stability of social distancing behavior (Ouellette & Wood, 1998). Some have proposed that past behavior is indicative of habitual influences on behaviour, but research examining habit as a construct suggests that it is more than performing a behavior frequently, and that the quality of the behavioral experience, such as experiencing it as automatic or without explicit thought, better characterizes habitual processes (Aarts et al., 1998; Verplanken & Orbell, 2003). Nevertheless, the residual effect of past behavior may provide some indication of unmeasured constructs on subsequent behavior, particularly those that bypass effects of intentions and are more likely rooted in non-conscious processes that lead to behavior, such as implicit attitudes or motives.

Practical Implications

Research applying social cognition models like the HAPA provide useful guidance for the development of future behavioral interventions aimed at promoting social distancing behaviors. Although participants intentions toward, and actual participation in, social distancing behavior were relatively high, scores and variability estimates suggest that some participants were reporting lapses in their social distancing behavior. Such lapses present considerable risks to coronavirus transmission, particularly in areas of high prevalence where the likelihood of contact with infected persons is substantially elevated. Our research provides some indication of the constructs that should be targeted for change and also the types of behavior change techniques that make up the content of interventions (Hagger et al., 2020; Kok et al., 2016). Based on current findings, strategies to promote self-efficacy should be foremost in potential targets of interventions to promote intentions and behavior. Interventions that have manipulated mastery experience (i.e., practicing a behavior) and vicarious experience (i.e., observing a model performing the behavior) have been shown to be successful in strengthening self-efficacy, as have interventions that provide feedback on past or others' performance (Warner & French, 2020). Tailoring of these strategies could also be considered and targeted at uptake of the behavior for those that have not already adopted the behavior (e.g., demonstration of appropriate social distance when in line to purchase goods) or at maintenance of the behaviour (e.g., developing a rule of thumb on keeping an appropriate social distance every time when in line to purchase goods).

Action control was another key determinant of intentions and behavior. This suggests that it is important that individuals acquire monitoring and self-regulatory strategies with respect to their social distancing behavior. For example, action control involves consistent monitoring as to whether an individual follows through on their intentions for the target behavior (Schwarzer & Hamilton, 2020). Monitoring helps identify discrepancies in behavior (e.g., not being at an appropriate social distance when in line to purchase goods), and noting a discrepancy can trigger taking additional action to ensure goals are achieved (e.g., adjusting the distance), or for disengaging from the goal (e.g., abandoning the goods and leaving the shop) (Webb & de Bruin, 2020). In order to promote better action control, interventions may prompt self-monitoring (e.g., through self-observation of social distancing behavior) or be monitored by others (e.g., shop attendant prompts an individual to increase their social distance).

Given that constructs such as attitudes and risk perceptions were not strong, consistent determinants of social distancing behavior, strategies targeting change in these constructs may not be at the forefront of behavioral interventions to promote social distancing. However, context-specific interventions that target change in attitudes for individuals in Australia and risk perceptions, particularly for individuals in the US may assist in promoting stronger intentions. Strategies aimed at promoting attitude change and increased risk perceptions usually involve information provision (e.g., providing information about health consequences, highlighting the pros over the cons of social distancing) and communication-persuasion (e.g., using credible sources to deliver messages, using framing/reframing methods) about the importance of maintaining social distancing (Hamilton & Johnson, 2020). However, reviews suggest that such strategies relate more to short-term change rather than sustained, longer-term impact on behavior (Jepson et al., 2010). Another approach could be the use of fear appeals which seek to arouse negative emotional reactions in order to promote self-protective motivation and action (Kok et al., 2016). However, caution is needed when using fear appeals to attempt to change behavior as excessively heightened fear may be counterproductive in motivating individuals to engage in preventive behaviors (Kok et al., 2018; Lin, 2020), and may even be counter-productive because they responses aimed at mitigating fear, such as avoidance or denial, neither of which may manage the risk itself (Hagger et al., 2017; Leventhal et al., 1998). There is evidence that messages that highlight risk but also provide coping information to increase self-efficacy (Kok et al., 2018) and that use positive prosocial language (Heffner et al., 2020) may be effective because they are more readily accepted and prevent defensive and avoidant reactions. However, current evidence suggests that interventions targeting change in attitudes and risk perception are unlikely to be enough to promote social distancing.

Strengths, Limitations, and Avenues for Future Research

The present research has a number of strengths including focus on social distancing, a key preventive behavior aimed at reducing transmission of SARS-CoV-2 to prevent COVID-19 infections; adoption of a fit-for-purpose theoretical model, the HAPA, that provides a set of a priori predictions on the motivational and volitional determinants of the target behavior; recruitment of samples from two countries, Australia and the US, with key demographic characteristics that closely match those of the population; and the use of prospective study design and structural equation modelling techniques. A number of limitations to the current data should be also noted. That there was substantive attrition at follow-up in both samples is an important limitation. Non-trivial attrition could result in selection bias. For example, participants who are more motivated or engaged may be overrepresented in the sample. In the current study, participants were provided with multiple reminders to complete measures at follow-up, but more intensive recruitment and incentivization of non-responders may have further minimized attrition rates. It should be noted that participant drop out affected the demographic profile of the samples, particularly among underrepresented groups. This is particularly relevant to the current context given data indicating that COVID-19 infection and mortality rates are higher in underrepresented minority and socioeconomic groups (CDC, 2020). A potential solution would be to oversample in underrepresented groups in which attrition rates are likely to be high and should be considered in future research. Furthermore, our recruitment strategy was focused on producing a sample with characteristics that corresponded with those of the national population on gender and state. However, the samples were not stratified by salient demographic or socio-economic variables. The current samples cannot be characterized as representative of the Australian or US population. Taking these biases into account, current findings should not be considered directly generalizable to the broader population.

In addition, the current study adopted a prospective design, which provided a basis for the temporal ordering of constructs in the model. However, the correlational design of the current study means that inferences of causality are based on theory rather than the data. Furthermore, the current design did not permit modeling of the stability or change in model constructs over time. The latter represents an important caveat when utilizing current data as a basis for intervention. Future research should aim to adopt cross-lagged panel designs that model change in constructs over time, and utilize intervention or experimental designs that target change in model constructs and observe their effects on behavior. Also, the study was conducted over a one-week period. Although this is a relatively brief follow-up period, it was considered appropriate given the high speed of virus transmission and the need for prompt adoption of social distancing in the population to prevent widespread infection. Current results, however, do not confirm the extent to which model constructs predict social distancing over a longer period, and long-term follow-up would be necessary to support the application of the HAPA in accounting for maintenance of social distancing, which is especially important as lockdown restrictions ease in order to prevent a ‘second wave’ of infection. The present study also relied exclusively on self-report measures which may introduce additional error variance through recall bias and socially-desirable responding. Future studies may consider verification of behavioral data with non-self-report data such the use of GPS mapping of mobile phones or using observation to verify rates of social distancing behavior in particular contexts (e.g., workplaces, grocery stores). It might also be useful for future studies to investigate the role of social factors, as suggested in the HAPA, on social distancing behavior. This is particularly important given the considerable potential for 'social' influences to affect individuals' behavior in minimizing person-to-person contact with others outside the individual's immediate household. Precedence for these effects comes from previous research which has found pressure from important others and moral obligation toward others predicts adherence to COVID-19 preventive behaviors, including social distancing (Hagger, 2020; Lin et al., 2020). Finally, this research was conducted during a period when it is likely that participants were already engaging in social distancing and, thus, already had substantive experience with the behavior, indicated by the high scale mean scores for past behavior (M = 6.5 on a 7-point scale) in both samples. This likely explains the substantive effect of past behavior in attenuating model effects and the need for longitudinal designs or using methods such as ecological momentary assessment that capture moment-by-moment changes over time in behavior.

Conclusion

Given the urgent need for populations to adopt COVID-19 preventive behaviors, such as social distancing, the present study applied the HAPA to predict key motivational and volitional determinants of social distancing behavior in samples across two different countries, Australia and the US. Overall, current findings provide qualified support for some of the core proposed effects among the motivational and volitional factors in the model, as well as their effects on individuals' social distancing behavior. The current study fills a knowledge gap in the literature on the social psychological processes that guide social distancing behavior in an unprecedented context of a pandemic and suggests that the motivational and volitional constructs of self-efficacy, intention and action control, in particular, may have utility in explaining this important COVID-19 preventive behavior. Despite the correlational design, current findings suggest multiple potential routes to behavioral performance that can serve as a basis for the development of intervention and enable further testing of effects of the techniques on both behavior change and the targeted theory constructs.

References

Aarts, H., Verplanken, B., & van Knippenberg, A. (1998). Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of Applied Social Psychology, 28*(15), 1355-1374. https://doi.org/10.1111/j.1559-1816.1998.tb01681.x

AIHW (2020). *Australia's children*. Australian Insitute of Health and Welfare. Retrieved August 25 from https://www.aihw.gov.au/reports/children-youth/australias-children/contents/income-finance-and-employment-snapshots/family-economic-situation

Brown, D. J., Hagger, M. S., & Hamilton, K. (2020). The mediating role of reasoned-action and automatic processes from past-to-future behavior across three health behaviors. *Social Science and Medicine, 258*. https://doi.org/10.1016/j.socscimed.2020.113085

Byrne, B. M., Shavelson, R. J., & Muthén, B. (1989). Testing for the equivalence of factor covariance and means structures: The issue of partial measurement invariance. *Psychological Bulletin, 105*, 456-466. https://doi.org/10.1037/0033-2909.105.3.456

CDC. (2020). *COVID-19 in racial and ethnic minority groups*. Retrieved June 25 from https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/racial-ethnic-minorities.html

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*, 233-255. https://doi.org/10.1207/S15328007SEM0902_5

Chu, D. K., Akl, E. A., Duda, S., Solo, K., Yaacoub, S., Schünemann, H. J., Chu, D. K., Akl, E. A., El-harakeh, A., Bognanni, A., Lotfi, T., Loeb, M., Hajizadeh, A., Bak, A., Izcovich, A., Cuello-Garcia, C. A., Chen, C., Harris, D. J., Borowiack, E., … Schünemann, H. J. (2020). Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. *The Lancet*. https://doi.org/10.1016/S0140-6736(20)31142-9

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling, 8*(3), 430-457. https://doi.org/10.1207/S15328007SEM0803_5

Gardner, B. (2015). A review and analysis of the use of 'habit' in understanding, predicting and influencing health-related behaviour. *Health Psychology Review, 9*(3), 277-295. https://doi.org/10.1080/17437199.2013.876238

Gardner, B., Rebar, A., & Lally, P. (2020). Habit interventions. In M. S. Hagger, L. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *Handbook of behavior change* (pp. 599-616). Cambridge University Press.

Hagger, M. S., Cameron, L., Hamilton, K., Hankonen, N., & Lintunen, T. (Eds.). (2020). *Handbook of behavior change*. Cambridge University Press. https://doi.org/10.1017/9781108677318.

Hagger, M. S., Koch, S., Chatzisarantis, N. L. D., & Orbell, S. (2017). The common sense model of self-regulation: Meta-analysis and test of a process model. *Psychological Bulletin, 143*(11), 1117-1154. https://doi.org/10.1037/bul0000118

Hagger, M. S., Smith, S. R., Keech, J. J., Moyers, S. A., & Hamilton, K. (2020). Predicting social distancing behavior during the COVID-19 pandemic: An integrated social cognition model. *Annals of Behavioral Medicine*. https://doi.org/10.1093/abm/kaaa073

Hamilton, K., Cornish, S., Kirkpatrick, A., Kroon, J., & Schwarzer, R. (2018). Parental supervision for their children's toothbrushing: Mediating effects of planning, self-efficacy, and action control. *British Journal of Health Psychology, 23*(2), 387-406. https://doi.org/10.1111/bjhp.12294

Hamilton, K., & Johnson, B. T. (2020). Attitude and persuasive communication interventions. In M. S. Hagger, L. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *Handbook of behavior change* (pp. 445-460). Cambridge University Press. https://doi.org/10.1017/97811086773180.031

Hamilton, K., van Dongen, A., & Hagger, M. S. (2020). An extended theory of planned behavior for parent-for-child health behaviors: A meta-analysis. *Health Psychology*. https://doi.org/10.1037/hea0000940

Heffner, J., Vives, M., & FeldmanHall, O. (2020). Emotional responses to prosocial messages increase willingness to self-isolate during the COVID-19 pandemic. PsyArXiv Preprint. https://doi.org/10.31234/osf.io/qkxvb

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Islam, N., Sharp, S. J., Chowell, G., Shabnam, S., Kawachi, I., Lacey, B., Massaro, J. M., D'Agostino, R. B., & White, M. (2020). Physical distancing interventions and incidence of coronavirus disease 2019: natural experiment in 149 countries. *BMJ, 370*, m2743. https://doi.org/10.1136/bmj.m2743

Jefferson, T., Del Mar, C. B., Dooley, L., Ferroni, E., Al-Ansary, L. A., Bawazeer, G. A., van Driel, M. L., Nair, N. S., Jones, M. A., Thorning, S., & et al. (2011). Physical interventions to interrupt or reduce the spread of respiratory viruses. *Cochrane Database of Systematic Reviews*(7). https://doi.org/10.1002/14651858.CD006207.pub4

Jepson, R. G., Harris, F. M., Platt, S., & Tannahill, C. (2010). The effectiveness of interventions to change six health behaviours: a review of reviews. *BMC Public Health, 10*(1), 538. https://doi.org/10.1186/1471-2458-10-538

Kok, G., Gottlieb, N. H., Peters, G.-J. Y., Mullen, P. D., Parcel, G. S., Ruiter, R. A., Fernández, M. E., Markham, C., & Bartholomew, L. K. (2016). A taxonomy of behaviour change methods: an Intervention Mapping approach. *Health Psychology Review, 10*(3), 297-312. https://doi.org/10.1080/17437199.2015.1077155

Kok, G., Peters, G.-J. Y., Kessels, L. T. E., ten Hoor, G. A., & Ruiter, R. A. C. (2018). Ignoring theory and misinterpreting evidence: the false belief in fear appeals. *Health Psychology Review, 12*(2), 111-125. https://doi.org/10.1080/17437199.2017.1415767

Leventhal, H., Leventhal, E. A., & Contrada, R. J. (1998). Self-regulation, health, and behavior: A perceptual-cognitive approach. *Psychology & Health, 13*(4), 717-733. https://doi.org/10.1080/08870449808407425

Lin, C.-Y. (2020). Social reaction toward the 2019 novel coronavirus (COVID-19) [Editorial]. *Social Health and Behavior, 3*(1), 1-2. https://doi.org/10.4103/shb.Shb_11_20

Lin, C.-Y., Imani, V., Rajabi Majd, V., Ghasemi, Z., Griffiths, M. D., Hamilton, K., Hagger, M. S., & Pakpour, A. H. (2020). Using an integrated social cognition model to predict COVID-19 preventive behaviors. *British Journal of Health Psychology*. https://doi.org/10.1111/bjhp.12465

Lunn, P. D., Timmons, S., Barjaková, M., Belton, C. A., Julienne, H., & Lavin, C. (2020). *Motivating social distancing during the COVID-19 pandemic: An online experiment*. https://www.esri.ie/pubs/WP658.pdf

McEachan, R. R. C., Conner, M., Taylor, N. J., & Lawton, R. J. (2011). Prospective prediction of health-related behaviours with the Theory of Planned Behaviour: a meta-analysis. *Health Psychology Review, 5*(2), 97-144. https://doi.org/10.1080/17437199.2010.521684

Michie, S., West, R., Rogers, M. B., Bonell, C., Rubin, G. J., & Amlôt, R. (2020). Reducing SARS-CoV-2 transmission in the UK: A behavioural science approach to identifying options for increasing adherence to social distancing and shielding vulnerable people. *British Journal of Health Psychology*. https://doi.org/10.1111/bjhp.12428

R Core Team. (2020). *R: A language and environment for statistical computing. R Foundation for Statistical Computing.* R Foundation for Statistical Computing. https://www.R-project.org/

Rabie, T., & Curtis, V. (2006). Handwashing and risk of respiratory infections: a quantitative systematic review. *Tropical Medicine and International Health, 11*(3), 258-267. https://doi.org/10.1111/j.1365-3156.2006.01568.x

Revelle, W. (2018). *psych: Procedures for psychological, psychometric, and personality research.* https://cran.r-project.org/web/packages/psych/index.html

Reyes Fernández, B., Knoll, N., Hamilton, K., & Schwarzer, R. (2016). Social-cognitive antecedents of hand washing: Action control bridges the planning–behaviour gap. *Psychology & Health, 31*(8), 993-1004. https://doi.org/10.1080/08870446.2016.1174236

Rhodes, R., Grant, S., & de Bruin, G.-J. (2020). Planning and implementation intention interventions. In M. S. Hagger, L. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *Handbook of behavior change* (pp. 572-585). Cambridge University Press.

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1-36. https://doi.org/http://www.jstatsoft.org/v48/i02/

Savalei, V. (2019). A comparison of several approaches for controlling measurement error in small samples. *Psychological Methods, 24*, 352-370. https://doi.org/10.1037/met0000181

Schwarzer, R. (2007). *The Health Action Process Approach (HAPA): Assessment Tools*. http://www.hapa-model.de/

Schwarzer, R. (2008). Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology: An International Review, 57*(1), 1-29. https://doi.org/10.1111/j.1464-0597.2007.00325.x

Schwarzer, R., & Hamilton, K. (2020). Changing behaviour using the health action process approach. In M. S. Hagger, L. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *Handbook of behavior change* (pp. 89-103). Cambridge University Press. https://doi.org/10.1017/97811086773180.031

Semega, J., Kollar, M., Creamer, J., & Mohanty, A. (2020). *Income and Poverty in the United States: 2018.* United States Census Bureau.

Smith, S. M. S., Sonego, S., Wallen, G. R., Waterer, G., Cheng, A. C., & Thompson, P. (2015). Use of non-pharmaceutical interventions to reduce the transmission of influenza in adults: A systematic review. *Respirology, 20*(6), 896-903. https://doi.org/10.1111/resp.12541

Teasdale, E., Santer, M., Geraghty, A. W. A., Little, P., & Yardley, L. (2014). Public perceptions of non-pharmaceutical interventions for reducing transmission of respiratory infection: systematic review and synthesis of qualitative studies. *BMC Public Health, 14*(1), 589. https://doi.org/10.1186/1471-2458-14-589

The British Psychological Society. (2020). *Behavioural science and disease prevention: Psychological guidance*. https://www.bps.org.uk/sites/www.bps.org.uk/files/Policy/Policy%20-%20Files/Behavioural%20science%20and%20disease%20prevention%20-%20Psychological%20guidance%20for%20optimising%20policies%20and%20communication.pdf

Verplanken, B., & Orbell, S. (2003). Reflections on past behavior: A self-report index of habit strength. *Journal of Applied Social Psychology, 33*(6), 1313-1330. https://doi.org/10.1111/j.1559-1816.2003.tb01951.x

Warner, L. M., & French, D. P. (2020). Confidence and self-efficacy interventions. In M. S. Hagger, L. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *Handbook of behavior change* (pp. 461-478). Cambridge University Press. https://doi.org/10.1017/97811086773180.032

Webb, T. L., & de Bruin, M. (2020). Monitoring interventions. In M. S. Hagger, L. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *Handbook of behavior change* (pp. 537-553). Cambridge University Press.

West, R., Michie, S., Rubin, G. J., & Amlôt, R. (2020). Applying principles of behaviour change to reduce SARS-CoV-2 transmission. *Nature Human Behaviour, 4*(5), 451-459. https://doi.org/10.1038/s41562-020-0887-9

Wood, W. (2017). Habit in personality and social psychology. *Personality and Social Psychology Review, 21*(4), 389-403. https://doi.org/10.1177/1088868317720362

World Health Organization. (2020). *Coronavirus disease (COVID-19) advice for the public*. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public

Worldometer. (2020). *Worldometer COVID-19 Coronavirus Pandemic*. https://www.worldometers.info/coronavirus/

Wothke, W. (1998). Longitudinal and multi-group modeling with missing data. In K. U. S. J. B. T. D. Little (Ed.), *Modeling longitudinal and multiple group data: Practical issues, applied approaches and specific examples* (pp. 2019-2240). Lawrence Erlbaum Publishers.

Zhang, C.-Q., Chung, P.-K., Liu, J.-D., Chan, D. K. C., Hagger, M. S., & Hamilton, K. (2019). Health beliefs of wearing facemasks for Influenza A/H1N1 prevention: A qualitative investigation of Hong Kong older adults. *Asia Pacific Journal of Public Health, 31*(3), 246-256. https://doi.org/10.1177/1010539519844082

Zhang, C.-Q., Fang, R., Zhang, R., Hagger, M. S., & Hamilton, K. (2020). Predicting hand washing and sleep hygiene behaviors among college students: Test of an integrated social-cognition model. *International Journal of Environmental Research and Public Health, 17*, 1209. https://doi.org/10.3390/ijerph17041209

Zhang, C.-Q., Zhang, R., Schwarzer, R., & Hagger, M. S. (2019). A meta-analysis of the health action process approach. *Health Psychology, 38*(7), 623-637. https://doi.org/10.1037/hea0000728

Zhou, G., Gan, Y., Miao, M., Hamilton, K., Knoll, N., & Schwarzer, R. (2015). The role of action control and action planning on fruit and vegetable consumption. *Appetite, 91*, 64-68. https://doi.org/10.1016/j.appet.2015.03.022

Table 1

Standardized Path Coefficients for Direct and Indirect Effects for the Single-Indicator Structural Equation Model of the Health Action Process Approach in the Australian Sample

Effect	Model excluding past behavior				Model including past behavior			
	β	*p*	CI_{95}		β	*p*	CI_{95}	
			LL	UL			LL	UL
Direct effects								
Int→Beh	.261	.026	0.027	0.445	-.077	.542	-0.327	0.125
AP→Beh	.040	.712	-0.082	0.144	.004	.966	-0.094	0.110
CP→Beh	-.041	.606	-0.084	0.043	-.078	.371	-0.103	0.029
AC→Beh	.276	.024	0.036	0.303	.174	.148	-0.033	0.241
SE→Beh	.060	.546	-0.087	0.168	.051	.566	-0.081	0.157
PB→Beh	–	–	–	–	.725	<.001	0.416	1.109
Att→Int	.182	.001	0.042	0.182	.135	.023	0.009	0.160
SE→Int	.314	<.001	0.135	0.326	.241	<.001	0.099	0.258
RP→Int	.150	.077	0.005	0.225	.083	.290	-0.032	0.168
AC→Int	.232	.006	0.046	0.256	.158	.019	0.020	0.182
PB→Int	–	–	–	–	.370	<.001	0.223	0.532
Int→AP	.074	.338	-0.133	0.388	.038	.594	-0.185	0.326
PB→AP	–	–	–	–	.357	<.001	0.378	0.928
Int→CP	-.212	<.001	-0.746	-0.243	-.244	<.001	-0.868	-0.293
PB→CP	–	–	–	–	.421	<.001	0.680	1.388
PB→Att	–	–	–	–	.326	<.001	0.319	0.807
PB→SE	–	–	–	–	.359	<.001	0.322	0.832
PB→RP	–	–	–	–	.417	<.001	0.458	0.892
Indirect effects								
Att→Int→Beh	.048	.082	0.002	0.062	-.010	.545	-0.026	0.015
SE→Int→Beh	.082	.042	0.006	0.108	-.019	.548	-0.057	0.025
RP→Int→Beh	.039	.262	-0.001	0.076	-.006	.694	-0.028	0.013
AC→Int→Beh	.061	.082	0.004	0.079	-.012	.598	-0.042	0.012
Int→AP→Beh	.003	.806	-0.012	0.030	.000	.984	-0.012	0.020
Int→CP→Beh	.009	.628	-0.022	0.045	.019	.428	-0.016	0.068
Int→Plan→Beh[a]	.012	.633	-0.026	0.061	.019	.468	-0.018	0.077
Total effects[b]								
Int→Beh	.273	.015	0.053	0.453	-.058	.621	-0.289	0.131
SE→Beh	.142	.100	-0.013	0.208	.032	.691	-0.092	0.126
AC→Beh	.336	.007	0.063	0.336	.162	.176	-0.058	0.226

Note. [a]Sum of indirect effects of both action planning and coping planning on behavior; β = Standardized parameter estimate; CI_{95} = 95% bootstrapped confidence interval of parameter estimate (unstandardized); LL = Lower limit of CI_{95}; UL = Upper limit of CI_{95}. Int = Intention; Beh = Behavior; AP = Action planning; CP = Coping planning; AC = Action control; SE = Self-efficacy; PB = Past behavior; Att = Attitude; RP = Risk perceptions.

Table 2

Standardized Path Coefficients for Direct and Indirect Effects for the Single-Indicator Structural Equation Model of the Health Action Process Approach in the US Sample

Effect	Model excluding past behavior				Model including past behavior			
	β	*p*	CI_{95}		β	*p*	CI_{95}	
			LL	UL			LL	UL
Direct effects								
Int→Beh	.382	<.001	0.152	0.602	.054	.647	-0.181	0.283
AP→Beh	-.046	.566	-0.138	0.074	-.106	.193	-0.191	0.033
CP→Beh	-.012	.914	-0.136	0.116	.035	.678	-0.073	0.135
AC→Beh	.479	.001	0.159	0.573	.182	.112	-0.028	0.308
SE→Beh	.026	.665	-0.084	0.149	.016	.785	-0.103	0.137
PB→Beh	–	–	–	–	.747	<.001	0.548	1.054
Att→Int	.082	.184	-0.030	0.159	.015	.780	-0.071	0.096
SE→Int	.371	<.001	0.247	0.506	.347	<.001	0.232	0.487
RP→Int	.239	.001	0.082	0.297	.156	.017	0.028	0.219
AC→Int	.244	.001	0.082	0.294	.079	.242	-0.034	0.156
PB→Int	–	–	–	–	.424	<.001	0.273	0.624
Int→AP	.190	.004	0.074	0.458	.145	.105	-0.050	0.458
PB→AP	–	–	–	–	.439	<.001	0.432	0.930
Int→CP	-.167	.004	-0.493	-0.106	-.161	.023	-0.531	-0.072
PB→CP	–	–	–	–	.561	<.001	0.748	1.268
PB→Att	–	–	–	–	.521	<.001	0.548	0.807
PB→SE	–	–	–	–	.377	<.001	0.292	0.527
PB→RP	–	–	–	–	.582	<.001	0.682	0.956
Indirect effects								
Att→Int→Beh	.031	.292	-0.010	0.086	.001	.910	-0.009	0.015
SE→Int→Beh	.142	.005	0.056	0.256	.019	.652	-0.065	0.107
RP→Int→Beh	.091	.024	0.019	0.140	.008	.657	-0.026	0.034
AC→Int→Beh	.093	.023	0.021	0.137	.004	.775	-0.010	0.036
Int→AP→Beh	-.009	.613	-0.049	0.022	-.015	.299	-0.045	0.014
Int→CP→Beh	.002	.922	-0.039	0.043	-.006	.729	-0.046	0.025
Int→Plan→Beh[a]	-.007	.836	-0.074	0.054	-.021	.397	-0.075	0.027
Total effects[b]								
Int→Beh	.376	<.001	0.177	0.577	.033	.766	-0.185	0.256
SE→Beh	.168	.007	0.041	0.287	.034	.512	-0.071	0.140
AC→Beh	.572	<.001	0.251	0.619	.186	.105	-0.022	0.313

Note. [a]Sum of indirect effects of both action planning and coping planning on behavior; β = Standardized parameter estimate; CI_{95} = 95% bootstrapped confidence interval of parameter estimate (unstandardized); LL = Lower limit of CI_{95}; UL = Upper limit of CI_{95}. Int = Intention; Beh = Behavior; AP = Action planning; CP = Coping planning; AC = Action control; SE = Self-efficacy; PB = Past behavior; Att = Attitude; RP = Risk perceptions.

Figure 1. Proposed model illustrating effects among health action process approach (HAPA) constructs excluding past behavior.

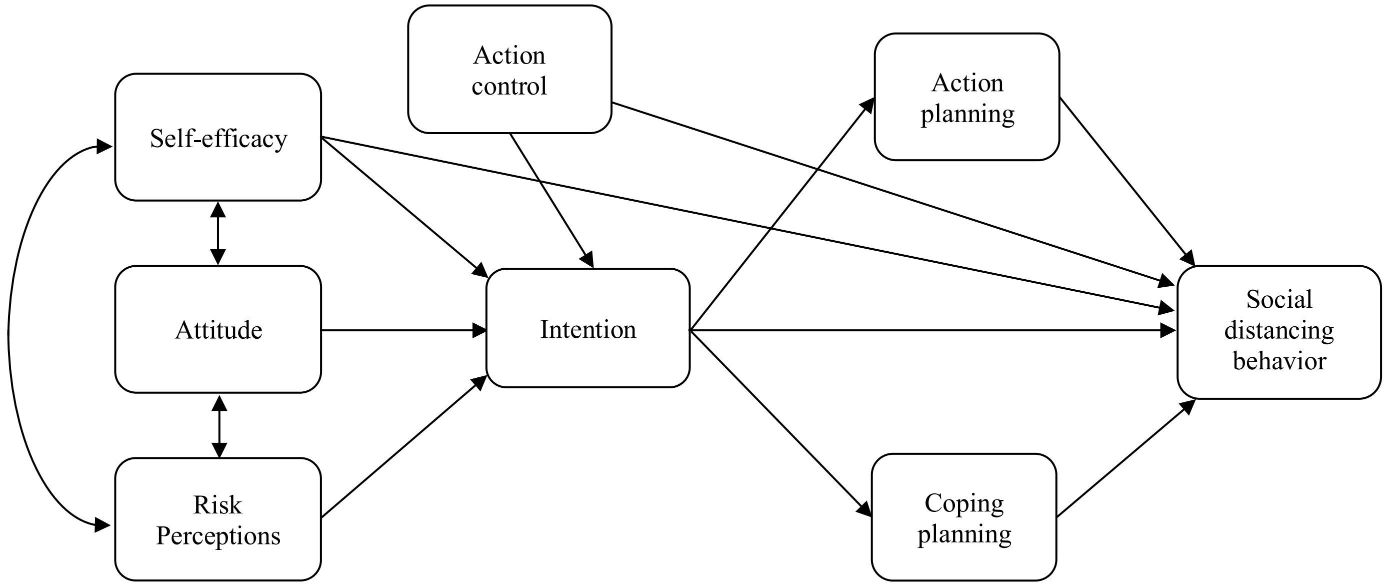
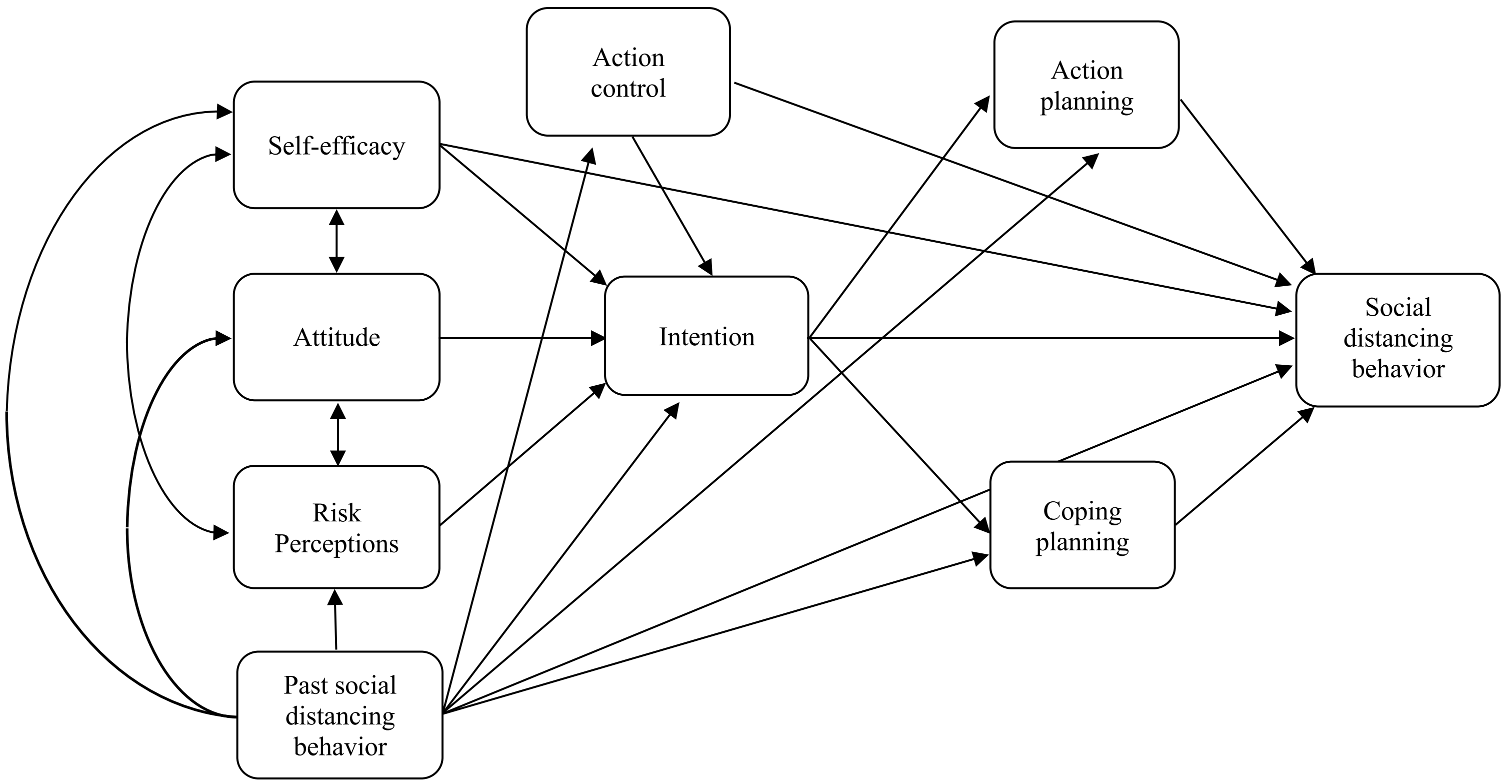


Figure 2. Proposed model illustrating effects among health action process approach (HAPA) constructs including past behavior



Appendix A

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

Variable	Australia sample		US sample	
	Baseline	Follow-up	Baseline	Follow-up
Participants	495	365	701	440
Age, *M* years (SD)	47.09 (17.11)	49.78 (16.89)	45.55 (17.40)	51.77 (16.26)
Gender, *n* (%)[a]				
Women	252 (51.1)	182 (50.1)	352 (48.9)	205 (46.6)
Men	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* (%)[b]				
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 witout pay/furloughed	27 (5.5)	16 (4.4)	28 (4.0)	13 (3.0)
Marital status, *n* (%)[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* (%)[d]				
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* (%)[e]				
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* (%)				
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. [a]Two participants in the Australia sample did not report their gender, four participants in the US sample not report their gender; [b]Four participants in the US sample did not report their employment status; [c]Four participants in the US sample did not report their marital status; [d]Four participants in the US sample did not report their ethnicity; [e]Thirty-one participants in the Australia sample did not report their income and four participants in the US sample did not report their income.

Appendix B

Items and Response Scales for Health Action Process Approach Variables

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
Self-efficacy	In the next week, do you agree that… It is mostly up to me whether I maintain social distancing 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	1 = strongly disagree, 7 = strongly agree
Risk perception	In the next week, do you agree that… It would be risky for me to not maintain social distancing If I did not maintain social distancing there would be risk involved	1 = strongly disagree, 7 = strongly agree
Intention	In the next week… It is likely that I will maintain social distancing I intend to maintain social distancing I plan to maintain social distancing	1 = strongly disagree, 7 = strongly agree
Action planning	In the next week, I have made a plan... When to maintain social distancing Where to maintain social distancing How often to maintain social distancing How to maintain social distancing	1 = strongly disagree, 7 = strongly agree
Coping planning	To keep my intention to maintain social distancing in the next week in difficult situations, I have made a plan... What to do if something interferes with my goal of maintaining social distancing How to cope with possible setbacks What to do in difficult situations in order to stick to my intentions When I have to pay extra attention to prevent lapses	1 = strongly disagree, 7 = strongly agree
Action control	During the past week... I have consistently monitored when, how often, and how to maintain social distancing Social distancing has always been on my mind I have really tried hard to maintain social distancing	1 = strongly disagree, 7 = strongly agree
Past behavior/ behavior	In the past week, how often did you maintain social distancing In the past week, I maintained social distancing	1 = never, 7 = always 1 = false, 7 = true

Appendix C

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

Variable	Australia 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)	$t(493) = 6.05$, $p < .001$, $d = 0.54$	0 (0.0)	51.77 (16.26)	35.16 (13.95)	$t(695) = 13.75$, $p < .001$, $d = 0.73$	4 (0.9)
Gender, *n* (%)[a]	182 (36.92) 181 (36.71)	70 (14.20) 60 (12.17)	$\chi^2(1) = 0.39$, $p = .533$, $d = 0.06$	2 (0.5)	205 (29.58%) 231 (33.33%)	147 (21.21%) 110 (15.87%)	$\chi^2(1) = 6.30$, $p = .012$, $d = 0.19$	4 (0.9)
Income, *n* (%)[a]	63 (14.06) 270 (60.27)	27 (603) 88 (19.64)	$\chi^2(1) = 0.84$, $p = .359$, $d = 0.08$	32 (8.8)	122 (19.52%) 290 (46.40%)	83 (13.28%) 130 (20.80%)	$\chi^2(1) = 5.16$, $p = .023$, $d = 0.19$	28 (6.4)
Education, *n* (%)[a]	115 (23.23) 250 (50.51)	36 (7.27) 94 (18.99)	$\chi^2(1) = 0.49$, $p = .484$, $d = 0.06$	0 (0.0)	132 (18.83%) 308 (43.94%)	139 (19.83%) 122 (17.40%)	$\chi^2(1) = 36.39$, $p < .001$, $d = 0.47$	0 (0.0)
Ethnicity, *n* (%)[a]	61 (12.32) 304 (61.41)	42 (8.48) 88 (17.78)	$\chi^2(1) = 13.22$, $p < .001$, $d = 0.33$	0 (0.0)	60 (8.61%) 376 (53.95%)	71 (10.19%) 190 (27.26%)	$\chi^2(1) = 18.46$, $p < .001$, $d = 0.33$	4 (0.9)
Past behavior, *M* (*SD*)	6.50 (0.70)	6.37 (0.75)	$F(1,493) = 3.57$, $p = .059$, $d = 0.17$	0 (0.0)	6.46 (0.89)	6.22 (1.13)	$F(1,699) = 9.28$, $p = .002$, $d = 0.23$	0 (0.0)
Attitude, *M* (*SD*)	5.90 (1.11)	5.94 (1.19)	$F(1,493) = 0.09$, $p = .765$, $d = 0.03$	0 (0.0)	5.87 (1.18)	5.54 (1.48)	$F(1,699) = 10.61$, $p = .001$, $d = 0.25$	0 (0.0)
Self-efficacy, *M* (*SD*)	6.02 (0.95)	5.84 (1.07)	$F(1,493) = 3.16$, $p = .076$, $d = 0.16$	0 (0.0)	5.98 (0.92)	5.84 (1.16)	$F(1,699) = 3.13$, $p = .077$, $d = 0.13$	0 (0.0)
Intention, *M* (*SD*)	6.54 (0.66)	6.40 (0.69)	$F(1,493) = 4.04$, $p = .045$, $d = 0.18$	0 (0.0)	6.39 (0.85)	6.15 (1.19)	$F(1,699) = 9.90$, $p = .002$, $d = 0.24$	0 (0.0)
RP, *M* (*SD*)	6.26 (1.06)	6.08 (1.17)	$F(1,493) = 2.70$, $p = .101$, $d = 0.15$	0 (0.0)	5.87 (1.37)	5.88 (1.39)	$F(1,699) < 0.01$, $p = .946$, $d < 0.01$	0 (0.0)
AP, *M* (*SD*)	5.83 (1.28)	5.90 (1.18)	$F(1,493) = 0.30$, $p = .582$, $d = 0.02$	0 (0.0)	5.76 (1.43)	5.71 (1.42)	$F(1,699) = 0.22$, $p = .641$, $d = 0.04$	0 (0.0)
CP, *M* (*SD*)	4.94 (1.51)	4.94 (1.46)	$F(1,493) < 0.01$, $p = .983$, $d < 0.01$	0 (0.0)	4.90 (1.62)	4.82 (1.59)	$F(1,699) = 0.45$, $p = .504$, $d = 0.05$	0 (0.0)
AC, *M* (*SD*)	5.82 (1.19)	5.68 (1.10)	$F(1,493) = 1.31$, $p = .253$, $d = 0.10$	0 (0.0)	5.58 (1.36)	5.28 (1.51)	$F(1,699) = 7.41$, $p = .007$, $d = 0.21$	0 (0.0)
Behavior, *M* (*SD*)	6.10 (0.67)	–	–	0 (0.0)	6.40 (0.97)	–	–	0 (0.0)

Note. [a]Statistics presented on the upper line are for women, low income, lower education level, and non-white ethnicity and statistics presented on the lower line are for men, high income, higher education, and white ethnicity. Missing = Number and proportion of missing cases; RP = Risk perception; AP = Action planning; CP = Coping planning; AC = Action control.

Appendix D

Factor Loadings, Reliability Estimates, ErrorVariances, and Descriptive Statistics for the Health Action Process Approach Variables

Construct	Australian sample						US sample					
	λ	Rel.	Var.	EV	*M*	*SD*	λ	Rel.	Var.	EV	*M*	*SD*
Past behavior[a]	.856	.734	0.510	.136	6.467	0.714	.920	.846	0.983	.151	6.369	0.991
Attitude[b]	.906	.823	1.279	.226	5.910	1.131	.910	.828	1.714	.295	5.752	1.309
Self-efficacy[b]	.915	.841	0.972	.155	5.968	0.986	.934	.872	1.038	.133	5.925	1.019
Intention[b]	.965	.933	0.449	.030	6.504	0.670	.971	.944	0.988	.055	6.301	0.994
Risk perception[a]	.905	.820	1.199	.216	6.212	1.095	.925	.857	1.897	.271	5.871	1.377
Action planning[b]	.916	.841	1.574	.250	5.848	1.254	.983	.966	2.032	.069	5.741	1.426
Coping planning[b]	.975	.951	2.231	.109	4.939	1.494	.976	.952	2.575	.124	4.872	1.605
Action control[b]	.883	.781	1.358	.297	5.780	1.165	.910	.828	2.032	.349	5.472	1.425
Behavior[a]	.859	.750	0.450	.112	6.096	0.671	.944	.877	0.942	.116	6.397	0.971

Note. [a]Reliability coefficient for this factor is Spearman-Brown coefficient between two items; [b]Reliability coefficient for this factor is Revelle's omega (ω) coefficient between items; λ = Factor loading from single indicator structural equation model; Rel. = Reliability coefficient; EV= Fixed error variance of factor based on reliability coefficient computed and parameter variance.

Appendix E

Intercorrelations Among Model Variables Used in Single-Indicator Structural Equation Models

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Past behavior	–	.521***	.377***	.705***	.582***	.541***	.448***	.658***	.869***	.053	.163***	.022	-.007	.139***
2. Attitude	.326***	–	.485***	.520***	.535***	.400***	.423***	.572***	.501***	.003	.104**	.083*	-.038	-.001
3. Self-efficacy	.359***	.384***	–	.595***	.380***	.341***	.402***	.424***	.385***	.007	.086*	.075*	.002	-.030
4. Intention	.605***	.442***	.512***	–	.590***	.529***	.406***	.621***	.662***	.041	.121**	-.008	.073	.140***
5. Risk perceptions	.417***	.383***	.286***	.473***	–	.498***	.498***	.689***	.564***	.038	.096*	.087*	.000	.042
6. Action planning	.380***	.293***	.301***	.427***	.523***	–	.694***	.703***	.486***	.111**	.020	.065	-.016	-.014
7. Coping planning	.273***	.223***	.359***	.222***	.434***	.557***	–	.753***	.461***	.025	.065	.083*	-.056	-.031
8. Action control	.441***	.337***	.349***	.507***	.674***	.636***	.541***	–	.666***	.057	.102**	.047	.011	.057
9. Behavior	.754***	.280***	.323***	.469***	.370***	.340***	.236***	.434***	–	.075	.069	.106*	.049	.114***
10. Gender	.048	.095*	.076	.138**	.123**	.232***	.047	.094*	.065	–	-.275***	-.019	-.014	-.130***
11. Age	.129**	.164***	.205***	.171***	.091*	.058	.073	.156**	.135*	-.141**	–	-.207***	.068	.237***
12. Ethnicity	-.039	.002	-.061	-.061	.005	.003	.064	-.060	.007	.004	-.373***	–	-.093*	-.050
13. Income	-.015	-.004	-.064	-.019	-.009	-.085	-.168***	-.149**	-.119*	-.108*	-.033	-.039	–	.210***
14. Education	-.031	-.038	-.037	.003	.040	.021	.027	.062	-.004	.002	-.072	.199***	.045	–

Note. Coefficients below the principal diagonal are for the Australia sample, coefficients above the principal diagonal are for the US sample; Correlations among social cognition constructs from the HAPA (variables 1-9) are model-implied latent variable correlations, correlations among socio-demographic variables and HAPA constructs are non-latent composite variables.

$^{***}p < .001$ $^{**}p < .01$ $^{*}p < .05$.

Appendix F

Goodness-of-Fit Statistics for the Single-Indicator Structural Equation Model of the Health Action Process Approach in the Australian and US Samples and Multigroup Models with Comparisons

Model	χ^2	df	CFI	RMSEA	CI_{90} RMSEA		SRMSR	$\Delta\chi^2$	Δdf	ΔCFI
					LL	UL				
Model 1: HAPA excl. past behavior (Australia)	36.619***	7	.976	.092	.064	.123	.049	–	–	–
Model 2: HAPA incl. past behavior (Australia)	40.974***	12	.980	.070	.047	.094	.040	–	–	–
Model 1: HAPA excl. past behavior (US)	28.251***	7	.992	.066	.042	.092	.027	–	–	–
Model 2: HAPA incl. past behavior (US)	49.357***	12	.988	.067	.048	.086	.038	–	–	–
Model 3: HAPA excl. past behavior MG model (configural)	64.870***	14	.987	.078	.059	.098	.032	–	–	–
Model 4: HAPA excl. past behavior MG model (β invariant)	103.209***	49	.986	.043	.031	.054	.035	38.339	35	.001
Model 5: HAPA incl. past behavior MG model (configural)	90.331***	24	.986	.068	.053	.083	.039	–	–	–
Model 6: HAPA incl. past behavior MG model (β invariant)	136.451***	66	.985	.042	.032	.052	.042	46.120	42	.001

Note. HAPA = Health action process approach; χ^2 = Model goodness-of-fit chi-square; df = Degrees of freedom of model chi-square; CFI = Comparative fit index; RMSEA = Root mean square error of approximation; CI_{90} RMSEA = 90% confidence interval of the RMSEA; SRMSR = Standardized root mean square of the residuals; $\Delta\chi^2$ = Change in goodness-of-fit chi-square when restricting regression coefficients to be equal across samples; Δdf = Change in chi-square degrees of freedom when restricting regression coefficients to be equal across samples; Δdf = Change in compariative fit index when restricting regression coefficients to be equal across samples.

$^{*}p < .050$ $^{**}p < .010$ $^{***}p < .001$

Appendix G

Standardized Path Coefficients for Direct and Indirect Effects for the Single-Indicator Structural Equation Model of the Health Action Process Approach in the Australian Sample

Effect	Model excluding past behavior				Model including past behavior			
	β	p	CI_{95}		β	p	CI_{95}	
			LL	UL			LL	UL
Direct effects								
Int→Beh	.261	.026	0.027	0.445	-.077	.542	-0.327	0.125
AP→Be	.040	.712	-0.082	0.144	.004	.966	-0.094	0.110
CP→Beh	-.041	.606	-0.084	0.043	-.078	.371	-0.103	0.029
AC→Beh	.276	.024	0.036	0.303	.174	.148	-0.033	0.241
SE→Beh	.060	.546	-0.087	0.168	.051	.566	-0.081	0.157
PB→Beh	–	–	–	–	.725	<.001	0.416	1.109
Gender→Beh	.012	.854	-0.146	0.163	.045	.461	-0.089	0.182
Age→Beh	.108	.112	-0.001	0.008	.118	.063	-0.001	0.008
Ethnicity→Beh	.099	.115	-0.044	0.303	.102	.068	-0.015	0.289
Income→Beh	-.072	.183	-0.252	0.052	-.078	.122	-0.268	0.027
Education→Beh	-.008	.897	-0.159	0.158	.040	.491	-0.085	0.204
Att→Int	.182	.001	0.042	0.182	.135	.023	0.009	0.160
SE→Int	.314	<.001	0.135	0.326	.241	<.001	0.099	0.258
RP→Int	.150	.077	0.005	0.225	.083	.290	-0.032	0.168
AC→Int	.232	.006	0.046	0.256	.158	.019	0.020	0.182
PB→Int	–	–	–	–	.370	<.001	0.223	0.532
Gender→Int	.069	.069	-0.010	0.180	.075	.046	0.005	0.197
Age→Int	.031	.442	-0.002	0.004	.029	.455	-0.002	0.004
Ethnicity→Int	-.021	.627	-0.179	0.092	-.017	.684	-0.152	0.092
Income→Int	.040	.207	-0.033	0.165	.036	.259	-0.038	0.158
Education→Int	.008	.820	-0.085	0.117	.017	.610	-0.070	0.118
Int→AP	.074	.338	-0.133	0.388	.038	.594	-0.185	0.326
PB→AP	–	–	–	–	.357	<.001	0.378	0.928
Gender→AP	.197	.000	0.240	0.652	.197	<.001	0.260	0.650
Age→AP	.013	.780	-0.005	0.007	.005	.904	-0.005	0.006
Ethnicity→AP	.047	.290	-0.118	0.373	.044	.342	-0.141	0.392
Income→AP	.008	.791	-0.147	0.218	.004	.899	-0.170	0.195
Education→AP	-.019	.664	-0.256	0.173	-.012	.773	-0.239	0.182
Int→CP	-.212	<.001	-0.746	-0.243	-.244	<.001	-0.868	-0.293
PB→CP	–	–	–	–	.421	<.001	0.680	1.388
Gender→CP	.027	.555	-0.168	0.355	.024	.580	-0.172	0.319
Age→CP	.066	.149	-0.002	0.013	.054	.260	-0.003	0.013
Ethnicity→CP	.113	.009	0.106	0.700	.109	.009	0.107	0.701
Income→CP	-.079	.038	-0.553	0.001	-.085	.025	-0.571	-0.047
Education→CP	-.022	.620	-0.349	0.195	-.013	.763	-0.332	0.202
PB→Att	–	–	–	–	.326	<.001	0.319	0.807
Gender→Att	.111	.018	0.029	0.412	.104	.028	0.023	0.401
Age→Att	.188	<.001	0.005	0.017	.170	.001	0.005	0.016
Ethnicity→Att	.107	.054	0.003	0.548	.102	.069	-0.010	0.548
Income→Att	.062	.240	-0.073	0.450	.053	.314	-0.115	0.413
Education→Att	-.072	.118	-0.368	0.040	-.061	.193	-0.336	0.062
PB→SE	–	–	–	–	.359	<.001	0.322	0.832
Gender→SE	.082	.077	-0.024	0.301	.074	.110	-0.027	0.298

Age→SE	.199	<.001	0.005	0.015	.179	<.001	0.004	0.014
Ethnicity→SE	.036	.487	-0.146	0.289	.030	.541	-0.135	0.277
Income→SE	-.007	.875	-0.208	0.211	-.017	.714	-0.250	0.168
Education→SE	-.052	.287	-0.294	0.093	-.041	.396	-0.265	0.112
PB→RP	–	–	–	–	.417	<.001	0.458	0.892
Gender→RP	.096	.035	0.013	0.361	.090	.033	0.018	0.345
Age→RP	.048	.286	-0.002	0.008	.032	.490	-0.003	0.007
Ethnicity→RP	.063	.135	-0.053	0.350	.059	.150	-0.057	0.336
Income→RP	.089	.039	0.022	0.429	.081	.080	-0.016	0.436
Education→RP	-.006	.886	-0.188	0.159	.004	.934	-0.181	0.188
Indirect effects								
Att→Int→Beh	.048	.082	0.002	0.062	-.010	.545	-0.026	0.015
SE→Int→Beh	.082	.042	0.006	0.108	-.019	.548	-0.057	0.025
RP→Int→Beh	.039	.262	-0.001	0.076	-.006	.694	-0.028	0.013
AC→Int→Beh	.061	.082	0.004	0.079	-.012	.598	-0.042	0.012
Int→AP→Beh	.003	.806	-0.012	0.030	.000	.984	-0.012	0.020
Int→CP→Beh	.009	.628	-0.022	0.045	.019	.428	-0.016	0.068
Int→Plan→Beh[a]	.012	.633	-0.026	0.061	.019	.468	-0.018	0.077
Total effects[b]								
Int→Beh	.273	.015	0.053	0.453	-.058	.621	-0.289	0.131
SE→Beh	.142	.100	-0.013	0.208	.032	.691	-0.092	0.126
AC→Beh	.336	.007	0.063	0.336	.162	.176	-0.058	0.226
Correlations								
Att↔SE	.367	<.001	0.207	0.428	.281	<.001	0.110	0.310
Att↔RP	.377	<.001	0.223	0.522	.279	.001	0.105	0.375
Att↔AP	.261	<.001	0.142	0.443	.172	.010	0.042	0.291
Att↔CP	.296	<.001	0.285	0.638	.203	<.001	0.129	0.430
Att↔AC	.344	<.001	0.223	0.486	.208	.002	0.073	0.320
SE↔RP	.288	<.001	0.144	0.360	.160	.016	0.026	0.206
SE↔AP	.271	<.001	0.129	0.404	.176	.023	0.026	0.270
SE↔CP	.441	<.001	0.405	0.769	.360	<.001	0.257	0.592
SE↔AC	.354	<.001	0.213	0.438	.209	.002	0.071	0.296
RP↔AP	.499	<.001	0.330	0.751	.420	<.001	0.227	0.575
RP↔CP	.508	<.001	0.537	0.995	.420	<.001	0.342	0.745
RP↔AC	.680	<.001	0.487	0.902	.544	<.001	0.308	0.717
AP↔CP	.603	<.001	0.747	1.288	.549	<.001	0.558	1.048
AP↔AC	.630	<.001	0.466	0.966	.513	<.001	0.355	0.782
CP↔AC	.612	<.001	0.732	1.189	.486	<.001	0.505	0.935

Note. [a]Sum of indirect effects of both action planning and coping planning on behavior; β = Standardized parameter estimate; CI_{95} = 95% bootstrapped confidence interval of parameter estimate (unstandardized); LL = Lower limit of CI_{95}; UL = Upper limit of CI_{95}. Int = Intention; Beh = Behavior; AP = Action planning; CP = Coping planning; AC = Action control; SE = Self-efficacy; PB = Past behavior; Att = Attitude; RP = Risk perceptions.

Appendix H

Standardized Path Coefficients for Direct and Indirect Effects for the Single-Indicator Structural Equation Model of the Health Action Process Approach in the US Sample

Effect	Model excluding past behavior				Model including past behavior			
	β	*p*			β	*p*		
			LL	UL			LL	UL
Direct effects								
Int→Beh	.382	<.001	0.152	0.602	.054	.647	-0.181	0.283
AP→Beh	-.046	.566	-0.138	0.074	-.106	.193	-0.191	0.033
CP→Beh	-.012	.914	-0.136	0.116	.035	.678	-0.073	0.135
AC→Beh	.479	.001	0.159	0.573	.182	.112	-0.028	0.308
SE→Beh	.026	.665	-0.084	0.149	.016	.785	-0.103	0.137
PB→Beh	–	–	–	–	.747	<.001	0.548	1.054
Gender→Beh	.049	.249	-0.067	0.243	.009	.806	-0.118	0.155
Age→Beh	.050	.197	-0.001	0.007	-.011	.755	-0.004	0.003
Ethnicity→Beh	.060	.136	-0.047	0.340	.033	.366	-0.101	0.243
Income→Beh	-.015	.707	-0.190	0.131	.016	.628	-0.108	0.165
Education→Beh	.054	.276	-0.088	0.294	.014	.689	-0.113	0.168
Att→Int	.082	.184	-0.030	0.159	.015	.780	-0.071	0.096
SE→Int	.371	<.001	0.247	0.506	.347	<.001	0.232	0.487
RP→Int	.239	.001	0.082	0.297	.156	.017	0.028	0.219
AC→Int	.244	.001	0.082	0.294	.079	.242	-0.034	0.156
PB→Int	–	–	–	–	.424	<.001	0.273	0.624
Gender→Int	.032	.336	-0.054	0.184	.008	.772	-0.083	0.128
Age→Int	-.006	.835	-0.003	0.003	-.033	.230	-0.005	0.001
Ethnicity→Int	-.069	.025	-0.314	-0.018	-.063	.029	-0.294	-0.017
Income→Int	.043	.187	-0.042	0.227	.052	.075	-0.012	0.217
Education→Int	.127	<.001	0.127	0.374	.085	.005	0.052	0.285
Int→AP	.190	.004	0.074	0.458	.145	.105	-0.050	0.458
PB→AP	–	–	–	–	.439	<.001	0.432	0.930
Gender→AP	.063	.025	0.027	0.329	.055	.053	-0.002	0.305
Age→AP	-.020	.559	-0.007	0.004	-.033	.357	-0.008	0.003
Ethnicity→AP	.035	.250	-0.097	0.329	.031	.311	-0.113	0.319
Income→AP	-.019	.540	-0.242	0.132	-.013	.677	-0.209	0.145
Education→AP	-.053	.081	-0.317	0.028	-.062	.034	-0.341	-0.011
Int→CP	-.167	.004	-0.493	-0.106	-.161	.023	-0.531	-0.072
PB→CP	–	–	–	–	.561	<.001	0.748	1.268
Gender→CP	-.011	.715	-0.195	0.147	-.019	.528	-0.233	0.119
Age→CP	.029	.376	-0.003	0.009	.015	.643	-0.005	0.007
Ethnicity→CP	.046	.150	-0.073	0.448	.044	.156	-0.087	0.403
Income→CP	-.035	.276	-0.322	0.085	-.031	.328	-0.303	0.098
Education→CP	-.050	.115	-0.348	0.054	-.063	.049	-0.386	0.019
PB→Att	–	–	–	–	.521	<.001	0.548	0.807
Gender→Att	-.007	.852	-0.187	0.174	-.025	.517	-0.231	0.125
Age→Att	.089	.035	0.000	0.012	.059	.135	-0.001	0.009
Ethnicity→Att	.080	.051	-0.013	0.473	.074	.053	-0.013	0.458
Income→Att	-.032	.480	-0.304	0.138	-.023	.595	-0.265	0.160
Education→Att	-.042	.353	-0.310	0.114	-.069	.107	-0.375	0.033
PB→SE	–	–	–	–	.377	<.001	0.292	0.527
Gender→SE	.002	.958	-0.142	0.139	-.011	.797	-0.183	0.127

Age→SE	.086	.041	0.000	0.009	.065	.100	-0.001	0.008
Ethnicity→SE	.078	.082	-0.055	0.395	.073	.081	-0.047	0.368
Income→SE	.015	.706	-0.138	0.188	.021	.597	-0.113	0.203
Education→SE	-.074	.058	-0.286	0.017	-.093	.020	-0.337	-0.021
PB→RP	–	–	–	–	.582	<.001	0.682	0.956
Gender→RP	.025	.506	-0.125	0.253	.007	.827	-0.161	0.171
Age→RP	.063	.091	-0.001	0.010	.034	.328	-0.003	0.008
Ethnicity→RP	.078	.021	0.040	0.467	.072	.021	0.021	0.428
Income→RP	.000	.998	-0.182	0.224	.008	.812	-0.160	0.208
Education→RP	.002	.959	-0.182	0.192	-.025	.462	-0.240	0.107
Indirect effects								
Att→Int→Beh	.031	.292	-0.010	0.086	.001	.910	-0.009	0.015
SE→Int→Beh	.142	.005	0.056	0.256	.019	.652	-0.065	0.107
RP→Int→Beh	.091	.024	0.019	0.140	.008	.657	-0.026	0.034
AC→Int→Beh	.093	.023	0.021	0.137	.004	.775	-0.010	0.036
Int.→AP→Beh	-.009	.613	-0.049	0.022	-.015	.299	-0.045	0.014
Int.→CP→Beh	.002	.922	-0.039	0.043	-.006	.729	-0.046	0.025
Int→Plan→Beh[a]	-.007	.836	-0.074	0.054	-.021	.397	-0.075	0.027
Total effects[b]								
Int→Beh	.376	<.001	0.177	0.577	.033	.766	-0.185	0.256
SE→Beh	.168	.007	0.041	0.287	.034	.512	-0.071	0.140
AC→Beh	.572	<.001	0.251	0.619	.186	.105	-0.022	0.313
Correlations								
Att↔SE	.477	<.001	0.403	0.639	.356	<.001	0.209	0.407
At↔RP	.529	<.001	0.592	0.995	.329	<.001	0.173	0.497
Att↔AP	.326	<.001	0.297	0.711	.134	.027	0.022	0.295
Att↔CP	.465	<.001	0.692	1.181	.265	<.001	0.211	0.551
Att↔AC	.578	<.001	0.690	1.079	.271	<.001	0.203	0.496
SE↔RP	.372	<.001	0.310	0.568	.205	<.001	0.086	0.278
SE↔AP	.245	<.001	0.149	0.453	.113	.062	-0.012	0.229
SE↔CP	.459	<.001	0.559	0.936	.331	<.001	0.272	0.566
SE↔AC	.423	<.001	0.391	0.652	.191	<.001	0.120	0.311
RP↔AP	.420	<.001	0.446	0.909	.234	.001	0.112	0.446
RP↔CP	.550	<.001	0.906	1.444	.355	<.001	0.318	0.696
RP↔AC	.692	<.001	0.919	1.347	.378	<.001	0.330	0.680
AP↔CP	.684	<.001	1.157	1.802	.599	<.001	0.767	1.206
AP↔AC	.645	<.001	0.810	1.343	.398	<.001	0.416	0.792
CP↔AC	.796	<.001	1.464	2.048	.529	<.001	0.780	1.186

Note. [a]Sum of indirect effects of both action planning and coping planning on behavior; β = Standardized parameter estimate; CI_{95} = 95% bootstrapped confidence interval of parameter estimate (unstandardized); LL = Lower limit of CI_{95}; UL = Upper limit of CI_{95}. Int = Intention; Beh = Behavior; AP = Action planning; CP = Coping planning; AC = Action control; SE = Self-efficacy; PB = Past behavior; Att = Attitude; RP = Risk perceptions.