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The Mediating Role of Reasoned-Action and Automatic Processes from Past-to-Future Behavior

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Abstract

Objective: Past behavior has been consistently shown to predict and explain future behavior. It has been proposed that past behavior exerts influence on future behavior via both reasoned-action and automatic processes. The current study sought to explore the mediation of past-to-future behavior via these processes across three populations and behaviors: binge drinking in university students, flossing in adults, and parental sun safety behavior of children 2 – 5 years of age. Furthermore, this study sought to use a measure of past behavior that combined long-term, recent, and routine patterns of behavioral engagement. **Methods.** A prospective design with two waves of data collection spaced six weeks apart was adopted. Participants (Total N = 754) completed an initial survey containing measures of past behavior (frequency, recency, and routine), social cognition (attitudes, subjective norms, perceived behavioral control), and behavioral automaticity. Six weeks later, participants (N = 454) completed a self-report measure of behavior and behavioral automaticity. **Results.** Structural equation modelling revealed that automatic, but not reasoned-action processes, mediated the past-to-future relationship, across the three behaviors. Results further revealed that long-term, recent, and routine patterns of behavioral engagement were highly correlated and indicated a second-order past behavior latent variable. **Conclusions.** While both reasoned-action and automatic factors can predict a range of health behaviors, automatic processes appear to explain the effect of past behavior on future behavior. Further investigations should focus on exploring the role of other non-conscious and automatic processes such as counter-intentional habits and implicit beliefs in explaining engagement in heath behaviors.

Data Availability Statement: Data files and analysis output are available online: https://osf.io/2nk3s/?view_only=f959ebced6274964a3c8dc3d5a65fc44

Keywords: past behavior, reasoned action, habit, heath behavior change, heath model

Introduction

To develop effective interventions in order to modify people's behavior one needs to first isolate the mechanisms that guide the behavior and then test the extent to which the mechanisms magnify or diminish behavioral engagement. Previous research has often turned to theories of social cognition to guide investigations aimed at identifying the determinants for health behaviors and, importantly, the processes by which these determinants relate to each other and the behavior. A close examination of the major theories that have been applied to the understanding of health behavior assumes that behavior is determined by a reasoned, intentional process in which an individual invests effort in order to pursue an action. The theory of planned behavior (TPB: Ajzen, 1991), given intention is central to the model, is perhaps the most widely used social–cognitive theory of behavior. According to the model, intention is the most proximal predictor of behavior, with intention determined by three social–cognitive variables: attitude (overall evaluations of performing the behavior), subjective norm (social pressure from important others to perform the behavior), and perceived behavioral control (perceived amount of control over behavioral performance; also more recently theorized as moderating the intention-behavior relationship; Ajzen, 1991). Meta-analytic studies support the use of the TPB in predicting health-related behaviors (e.g., McEachan et al., 2011; Rich et al., 2015)

Social cognition theories such as the TPB tend to focus on a relatively narrow set of determinants that include constructs that represent reasoned, intentional determinants of action. Such approaches tend not to explicitly account for the pervasive effects of past behavior on key constructs of psychological theories and their relations with health behaviors (e.g., Albarracín et al., 2001; Conner et al., 1999; Hagger et al., 2018). However, research has demonstrated that including past behavior in these theories accounts for substantive additional variance in subsequently measured (future) behavior through the *residual* effect of past behavior on future behavior. Inclusion of past behavior has also been shown to attenuate the size of the effects of intention and other social-cognition constructs on future behavior. Some argue that these residual effects are likely an artifact of assessing past behavior and future behavior using the same measure, leading to shared method variance (Ajzen, 1991, 2002). However, research using different measures of past and future behavior has revealed residual effects (Brown et al., 2018; Verplanken, 2006). Others, therefore, argue that the residual effects afforded by past behavior may model non-conscious processes including habits and decisions based on implicit cognition or behavioral ‘scripts’ (Hagger, 2020; Hagger & Chatzisarantis, 2014; Strack & Deutsch, 2004; Triandis, 1977).

In seeking to understand the effects of past behavior in social-cognitive theories, Ouellette and Wood (1998) proposed two pathways by which past behavior relates to future behavior: a direct pathway and an indirect pathway. The direct effect is said to model an automatic process, similar to that proposed in dual-process theories (Strack & Deutsch, 2004). The second, indirect pathway, in which past behavior affects future behavior via conscious, intentional processes, such as those characterized in social-cognition theories (Ajzen, 1991). Ouellette and Wood (1998) hypothesized that well-practiced behaviors, occurring in consistent contexts likely reflect habitual patterns that are expected to be automatically repeated in the future. These automatic behaviors can be intentional and goal-dependent or be perceived as non-volitional and counter-intentional (i.e., outside of an individual’s awareness/control or in opposition to an individual’s intention; Gardner et al., 2015; Ji & Wood, 2007). Conversely, the authors describe how novel or less practiced behaviors are likely governed by conscious, intentional processes. While past behavior has been shown to attenuate the effects of social cognitive variables (Brown et al., 2018), studies suggest that their constructs still account for unique variance in behavior and mediate, at least partially, the effects of past behavior on future behavior (Hagger et al., 2018).

Although previous research has demonstrated support for the direct and indirect effects of past behavior on future behavior in social cognition theories models (Ouellette & Wood, 1998), few studies have tested the effects of other constructs that reflect non-conscious decision making, such as habits, on behavior alongside past behavior (Bamberg et al., 2003; van Bree et al., 2015; Verplanken, 2006). If indirect effects of past behavior on future behavior model automatic, spontaneous processes to behavioral enactment as proposed in dual process theories (Strack & Deutsch, 2004) and, thus, capture the automaticity component of habit they would be expected to mediate the effect of past behavior on subsequent behavior. We aimed to examine these propositions in the present study by testing the TPB in a range of health behaviors and included measures of past behavior and behavioral automaticity across two time-points.

An additional issue with research examining the role of past behavior in social cognition theories is the large variation in arbitrary time frames used to measure past behavior. For example studies have measured past behavior over one week (Mullan et al., 2015), four weeks (Caudwell et al., 2019), and six months (Luszczynska & Cieslak, 2009). Measuring past behavior over arbitrary timeframes may miss patterns of behavioral engagement that could potentially be informative on the mechanisms and processes that determine subsequent health behavior. For example, engagement in sun safety behaviors is likely to be highly seasonal in that they are performed frequently in the summer months and seldom in winter months (Sun et al., 2014; Xiang et al., 2015). A measure of past behavior that refers to sun safety behaviors in close proximity to subsequent behavior is likely to lead to stronger past behavior effects than if the time frame of the past behavior measure extended beyond the current season. Furthermore, Ouellette and Wood (1998) suggested that a different pattern of past behavior effects will occur for infrequently compared to regularly performed behaviors. It would seem reasonable to account for both long-term (i.e., distal) and short-term (i.e., recent) enactments of past behavior as well as the frequency with which the behavior is measured. Perugini and Bagozzi (2001) proposed differentiating between long-term (up to 1 year) and more recent (within the last month) measures of past behavior. Similarly, others have used items relating the extent to which the behavior is routinized to further capture the regularity of daily behavioral performance (Verplanken & Orbell, 2003). Extending this research, the present study tested effects of past behavior using multiple methods that account for the frequency, recency, and routinization of behaviors. Specifically, the measure included items assessing long-term (last year), short-term (last month), and routine patterns of behavior, proposing that these would indicate a multi-component measure of past behavior that would capture the essence of individuals past performance of health behaviors.

The Current Study and Hypotheses

Based on Ouellette and Wood’s (1998) propositions, we propose a set of key hypotheses relating to the effects of reasoned, intentional pathways and non-conscious, automatic pathways to action for three health behaviors in three independent samples: binge drinking in university students, dental flossing in community-dwelling adults, and parental sun safety behaviors of their 2 to 5 year-old children. The proposed model is presented in Figure 1. In the present model, the reasoned, intentional processes are represented by the effects of the social-cognition constructs from the TPB. Specifically, attitude, subjective norm, and perceived behavioral control are expected to significantly and directly predict intentions and intentions and perceived behavioral control are expected to significantly and directly predict the target behaviors. We also expect the effects of the TPB constructs on behavior would be mediated by intentions (Ajzen, 1991).

Based on Ouellette and Wood's (1998) proposed pathways, we expected an indirect effect of past behavior on behavior mediated by the social cognition constructs of the TPB (attitudes, subjective norms, perceived behavioral control) and intentions. This pathway is expected to reflect that individuals' beliefs with respect to future participation in health behaviors is informed by previous decision making and belief formation (Ajzen, 2002). Furthermore, we included a self-report measure of behavioral automaticity at both the initial time point and at follow-up alongside the measure of behavior. Self-reported behavioral automaticity is a meta-cognitive measure, which prompts individuals to reflect on the extent to which the behavior of interest is performed with little cognitive input and in a routine manner. Consistent with the proposal that past behavior represent non-conscious, automatic processes, we expected measures of automaticity to mediate the effects of past behavior on subsequent behavior. We therefore also expected indirect effects of past behavior on subsequent behavior via behavioral automaticity. Finally, the extent to which past behavior is represented by long-term frequency, recency, and routine as proposed by Perugini and Bagozzi (2001), we expect the three measures to be significantly correlated and converge on a higher order factor that captures the essence of the multiple components of past engagement in behavior.

Method

Participants

Participants comprised three samples of Australian residents (total $N = 766$). Sample 1 ($n = 319$) comprised first-year undergraduate students from Griffith University, recruited through the university research participant pool in return for course credit and reported having previously participated in binge drinking, a hazardous pattern of alcohol consumption (NHMRC, 2009). Sample 2 ($n = 251$) comprised adult members of the Australian public, recruited online through social media and university broadcast emails, and focused on dental flossing. Sample 3 (*n* = 184) comprised parents with at least one child aged between 2 and 5 years who usually resided in the same household as the parent, recruited via online advertising (e.g., social media websites such as “Facebook”) and face-to-face (e.g., swim schools), and investigated sun safety behaviors that parents performed for their child. All participants were offered the opportunity to enter a prize draw to win one of three movie vouchers per sample. Sample demographic characteristics for the full sample and separately for each sample are available in Appendix A (supplemental materials).

Design and Procedure

Approval for study procedures was granted prior to data collection from [MASKED] University Human Research Ethics Committee. The study used a two-wave prospective, correlational design with study measures administered to each sample at an initial point in time (T1), with follow-up measures administered at a second point in time, 6-weeks later (T2). At T1, participants completed a survey assessing social cognitive constructs (attitude, subjective norm, perceived behavioral control, and intention), behavioral automaticity, past behavior, and demographic factors. At T2, participants completed a follow-up survey to assess their behavioral automaticity and behavior for the target behaviors performed over the previous six weeks. Survey data was collected online and presented using the Qualtrics™, an online survey tool. Participant data across the time points were de-identified and matched using a unique code identifier created by the participant.

Measures

The social cognition constructs and behavior were measured using multi-item psychometric instruments, that were previously developed and validated using standardized guidelines (Ajzen, 1991; Gardner et al., 2012; Perugini & Bagozzi, 2001; Verplanken & Orbell, 2003). Measures were adapted to refer to the target behaviors in the current study. Participants provided their responses on scales with 7-point response options. Brief details of the measures are provided below, and a full set of items is available in Appendix B (supplemental materials). Items from each instrument were used as indicators of latent variables representing each model construct in a structural equation model. Past behavior was included in the model as a second-order latent variable indicated by first-order latent factors represented by items from frequency, recency, and routine scales.

Target behaviors. The target behaviors were binge drinking ("engaging in binge drinking"), dental flossing ("flossing my teeth on a daily basis"), and sun safety behaviors ("performing sun-protective behaviors for my child"). *Binge drinking* was defined as consuming more than four standard drinks on a single occasion (NHMRC, 2009). A pictorial guide providing examples of a standard drink for common alcoholic beverages was provided to participants. *Dental flossing* was defined as flossing one's teeth on a daily basis (Australian Dental Association, 2017). Parents were asked to think of the sun-protective behaviors they engaged in for their youngest child aged 2 to 5 years every time their child was outdoors in direct sunlight for more than 10 minutes. Parents were told that s*un safety* comprised the following behaviors: (a) applying SPF 30+ sunscreen; (b) wearing sun-protective clothing such as a hat, long-sleeved shirt, and sunglasses; and (c) seeking shade between 10 am and 3 pm (Cancer Council Australia, 2017).

Social cognition constructs. Measures of social cognition constructs from the TPB were assessed at T1 and developed according to published guidelines (Ajzen, 2002). *Intention* was measured by three items each for binge drinking, dental flossing, and sun safety (e.g., "I intend to floss my teeth on a daily basis …"). *Attitude* was measured by three items each for binge drinking and dental flossing, and five items for sun safety (e.g., "For me to binge drink in the next 6 weeks would be …"). *Subjective norm* was measured by four items each for binge drinking, and dental flossing, and five items for sun safety (e.g., "Most people who are important to me think I should perform sun-protective behaviors for my child …"). *Perceived* *behavioral control* was measured by four items each for binge drinking, dental flossing, and sun safety (e.g., “I have complete control over whether I floss my teeth on a daily basis …”).

Behavioral automaticity. Behavioral automaticity at T1 and T2 was measured using the four-item self-reported behavioral automaticity index (Gardner, 2012) (e.g., “Binge drinking is something I do automatically”).

Behavior. *Past behavior* at T1 was measured using items assessing frequency, recency, and routine. *Frequency* was measured using four items that focused on behavior that was performed over the last year (e.g., “How often did you floss your teeth on a daily basis in the past year? …”; Perugini & Bagozzi; 2001). *Recency* was measured using four items that focused on behavior that was performed over the last 4 weeks (e.g., “To what extent did you binge drink in the past four weeks?”; Perugini & Bagozzi, 2001). *Routine* was measured using one item adopted from the Self Report Habit Index (e.g., “Do you agree that performing sun-protective behaviors for your child is something that belongs to my normal routine?”; Verplanken & Orbell, 2003). *Behavior* at T2 was measured using 2 items (e.g., “Think about the past 6 weeks. In general, how often did you floss your teeth on a daily basis?”).

Data Analysis

Variance-based structural equation modelling (VB-SEM) was used to test our hypothesized model. VB-SEM uses a partial least squares estimation method that is based on ranked rather than ordinal data. The analysis is less affected by model complexity or departures from normality than covariance-based methods (Henseler et al., 2009). Models were estimated using the Warp PLS v6.0 software (Kock, 2018). Missing data were treated using hierarchical regression imputation. All proposed paths among constructs detailed in Figure 1 were specified as free parameters in the model. In addition, we statistically controlled for the effects of age, highest educational achievement, and gender by setting these variables as predictors of all other variables in the model.

The validity of the proposed measures was assessed by the measurement aspects of the model. The loading of each indicator on its respective latent factor was expected to exceed .700. Composite reliability coefficients (ρ) and average variance extracted (AVE) statistics, which test the sufficiency of scale items as indicators for the latent variables and whether the items account for sufficient variance in the factor, respectively, were expected to exceed .700 and .500. Discriminant validity was supported if the square-root of the AVE for each latent variable exceeded its correlation coefficient with other latent variables. Overall model fit was evaluated using multiple criteria: the goodness-of-fit (GoF) index with values of .100, .250, and .360 corresponding to small, medium, and large effect sizes, respectively; the average path coefficient (APC) and the average R^2 (ARS), which should both be significantly different from zero for an adequately-fitting model; and the average variance inflation factor for model parameters (AVIF) statistic, which should be less than 5.000 for a well-fitting model (Kock, 2018).

Multi-group analysis was used to make pairwise comparisons of path coefficients for the hypothesized model across the three samples. Multi-group analysis calculates a ratio using the difference in the path coefficients for a hypothesized model path across two samples and the pooled standard errors for the specified path, as outlined in Kock (2018). The ratio produces a test of difference for hypothesized paths across each sample.

Finally, a sensitivity analysis was used to test whether model effects differed according to the method used to treat missing cases. Specifically, we estimated the model effects in each sample with missing data handled either by listwise deletion of cases with missing data or imputed using a linear multiple regression method advocated by Kock (2018).

Results

Participants and attrition analysis

Demographic characteristics of the three samples and descriptive statistics of the study variables at both time points are presented in Appendix A (supplemental materials). One hundred and forty-two participants dropped out at follow-up in sample 1, 67 dropped out in sample 2, and 92 dropped out in sample 3. Attrition analysis for sample 1 indicated no significant differences in age ($t(315) = 1.12$, $p = .263$, $d = 0.13$), educational achievement ($t(293) = -.567$, $p = .571$, $d = 0.07$), or gender ($t(294) = 1.089$, $p = .277$, $d = 0.14$) between participants who dropped out and those who remained in the study at T2. Also, no differences were observed on the psychological and behavioral variables (Wilks' Lambda = .985, $F(6,274) = .712$, $p = .640$, $\eta_p^2 = .015$). Attrition analysis for sample 2 indicated no significant differences in age ($t(180) = .746$, $p = .457$, $d = 0.10$) or educational achievement ($t(168) = 1.102$, $p = .272$, $d = 0.14$) between participants who dropped out and those who remaining in the study. There was, however, a significantly higher proportion of females among participants who dropped out than those who remained in the study at T2 ($t(210) = -2.679$, $p = .008$, $d = 0.33$). No differences were found in psychological and behavioral variables (Wilks' Lambda = .957, $F(6,206) = 1.554$, $p = .162$, $\eta_p^2 = .043$). Attrition analysis for sample 3 indicated no significant differences in age ($t(188) = -.030$, $p = .979$, $d = 0.00$) or educational achievement ($t(175) = -.650$, $p = .517$, $d = 0.09$). There was a greater proportion of males among participants who dropped out than those who remained in the study at T2 ($t(166) = -2.665$, $p = .008$, $d = 0.38$). Last, no differences were found in the psychological and behavioral variables (Wilks' Lambda = .988, $F(6,154) = .314$, $p = .929$, $\eta_p^2 = .012$).

Preliminary analysis

Measurement components of the VB-SEM confirmed that the latent variables met or approached the criteria for construct and discriminant validity and had good model fit, see Table 1. Factor loadings for the latent factors approached or exceeded the .700 criterion, supporting construct validity of the factors. Importantly, the second-order factor loadings for the frequency, recency, and routine indicators of the past behavior latent variable were large (>.884) and statistically significant ($p < .001$) for all behaviors. Composite (ρ) reliability coefficients, AVE, and intercorrelations for model variables are presented in Appendix C (supplemental materials). Reliability coefficients exceeded the .700 criterion, and AVE values exceeded the recommended .500 criterion. Correlations among the latent variables also indicated no problems with discriminant validity. Missing values analysis using Little's (1988) missing completely at random (MCAR) test revealed a significant value for the flossing behavior sample (χ^2 = 437.599, df = 357, p = .002), but not for the binge drinking behavior (χ^2 = 431.810, df = 416, p = .286) or parent sun safety behaviors (χ^2 = 296.450, df = 385, p = 1.000) samples.

Model Effects

Standardized parameter estimates for the hypothesized relations among factors are presented in Figure 1 and as a table in Appendix D (supplemental materials). Overall, the model accounted for 68.8%, 64.0%, and 61.6% of the variance in intention to binge drink, floss, and adopt safe sun behaviors, respectively, and 39.4%, 77.6%, and 27.9% of the variance in the binge drinking, flossing, and sun-safe behaviors, respectively. Results revealed statistically significant effects of attitudes on intentions to engage in binge drinking and flossing, but not for sun safety behaviors. There was a statistically significant effect of subjective norms on intentions for flossing, but not for the other behaviors. Perceived behavior control significantly predicted intention for binge drinking and flossing but not for sun safety behaviors. Intention statistically predicted flossing, but no effect was found for binge drinking and sun safety behaviors. There was a statistically significant effect of perceived behavioral control on behavior for sun safety behaviors, but not for the other behaviors. Automaticity at T1 predicted automaticity 6-weeks later (T2), and automaticity at

T2 predicted behavior, for each of the three behaviors. Statistically significant effects were found from past behavior on attitude, subjective norms, perceived behavioral control, intentions, and automaticity at T1 and T2 for all behaviors. There was a statistically significant effect of past behavior on behavior for binge drinking, but not for flossing or sun safety behaviors.

Focusing on the indirect effects, we found no indirect effect of attitudes, subjective norms, or perceived behavioral control on behavior mediated by intention. We did find indirect effects of T1 automaticity on behavior mediated by T2 automaticity for all behaviors. We found no indirect effects of past behavior on behavior through attitudes, subjective norms, perceived behavioral control, and intention in each of the models. There was, however, a statistically significant indirect effect of past behavior on behavior via T1 automaticity, and via T2 automaticity for all behaviors.

Multi-group analyses identified a few differences in effects across the three samples, although the differences reflected the relative size of the effects across samples, rather than differences reflecting effects that were different from zero and those that were indistinguishable from zero. Effects of attitudes and perceived behavioral control on intentions, and intentions on behavior, were significantly smaller in the sun safety sample relative to the binge drinking and flossing samples. Effects of perceived behavioral control on intention and behavior were significantly larger in the sun safety sample relative to the binge drinking and flossing sample. The effect of past behavior on attitude was significantly larger in the binge drinking sample than the sun safety sample. Similarly, the effect of past behavior on subjective norms was significantly greater in the binge drinking sample than the flossing sample. The effects of past behavior on T1 and T2 automaticity were significantly greater in the flossing sample compared to the binge drinking sample. The effect of past behavior on intention was significantly smaller in the binge drinking and flossing samples relative to the sun safety sample. Relative to the sun safety sample, the effect of past behavior on behavior was larger in the binge drinking sample

For completion, we compared model effects without imputation of missing values, using listwise deletion of data with missing cases instead. The model estimated with listwise-deleted data did not result in substantive differences in the pattern of effects across the samples. Full results of these analyses are presented in Appendix D (supplemental materials).

Discussion

Social cognition theories tend to focus on a narrow range of determinants of health behaviors. As a consequence, they may not account for effects of other variables that could be potentially informative when it comes to predicting health behaviors. One potential variable whose effects within social cognition models may provide important information on the determinants of behavior is past behavior. There is already a substantive body of research examining past behavior effects within social cognition theories. Studies including frequency of past behavior within these theories have consistently shown that past behavior attenuates effects of intention and other social cognition constructs on subsequently measured (future) behavior. However, there is some debate over what such effects represent. Some researchers have argued that past behavior may model non-conscious and automatic processes, such as habit (Ouellette & Wood, 1998). Others have argued that past behavior effects should be mediated by constructs from social cognition theories if the theory is to be considered sufficient as an account for further behavior (Ajzen, 1991, 2002). Drawing on Ouellette and Wood’s (1998) propositions, we tested a set of key hypotheses related to reasoned action and automatic processes in a social cognition model including past behavior in three health behaviors, with three, independent samples: binge drinking in university students, dental flossing in community-dwelling adults, and sun safety behaviors by parents for their 2 to 5 year-old children. Furthermore, we adopted a comprehensive measure of past behavior, which encompassed frequency, recency, and routine patterns of previous behavior.

Results revealed a consistent pattern of effects for the proposed model in the binge drinking and dental flossing behavior samples consistent with the TPB. These findings suggest that individuals are more likely to engage in these behaviors when they have positive attitudes toward performing the behavior in future and believe doing so is within their control. Subjective norms did not predict any of the behaviors, suggesting a lesser role for the perceived influence of significant others for these behaviors. Importantly, behavior was also predicted by automaticity in all three samples, suggesting, that the very least, all three behaviors were somewhat determined by habits or routine. These findings suggest that constructs representing both reasoned and automatic processes determine behavior simultaneously. A possible interpretation of this pattern of effects, provided by Hagger et al. (2016), is that these behaviors are determined by constructs representing one or the other of the processes for groups of participants within the sample, each with sufficient strength so as to be presented as statistically significant overall. The key challenge for future research is to identify the moderator variables that determine when each pattern of effect pervades.

In contrast with previous studies (Hamilton, Kirkpatrick, Rebar, & Hagger, 2017), none of the TPB variables predicted parents' intentions, and intentions did not predict behavior for parental sun safety behaviors. One possible reason for this pattern of effects may be that these behaviors are highly routinized and habitual, particularly in an Australian context where exposure to the sun is both likely and regular. A means to test this hypothesis would be to examine effects of the constructs representing the reasoned process predict behavior when effects of constructs representing the automatic process are removed. We therefore re-estimated the model removing effects of automaticity in the model for this behavior. As predicted, results revealed intentions predicted parental sun safety behavior (β =

.227, $p < .01$). This attenuation effect has been observed consistently in previous studies (see Hagger et al., 2016, 2018), and suggests automaticity is the pervading determinant of behavior in this context.

Research has suggested that past behavior-future behavior relations effectively represent habits (Hagger, 2019; Hagger et al., 2016, 2018; Ouellette & Wood, 1998). We reasoned that if this was the case, residual effects of past behavior on future behavior should be mediated by automaticity, to the extent that individual's reflections on automaticity sufficiently capture a key component of habit. Consistent with previous research (van Bree et al., 2015), our results revealed consistent indirect effects of past behavior on future behavior through automaticity at both time points. This result substantiates one of the propositions set by Ouellette and Wood (1998), that effects of past behavior model habitual or automatic actions.

However, contrary to previous research (Hagger et al., 2016, 2018) and the proposals by Oullette and Wood, effects of past behavior were not found to be mediated by the social cognition constructs in the current model. Ajzen (2002) suggested that the TPB constructs should account for the effects of past behavior if it is to provide a sufficient account of behavior. He suggested that indirect effects may reflect having made similar decisions in the past or the effect of past experience in informing beliefs regarding future performance of the behavior. However, it seems that for the current set of behaviors, beliefs regarding future participation jn behavior are not based on past experience. One possible interpretation is that a minority of individuals in these samples perhaps have low levels of previous experience and, thus, their beliefs toward performing the behaviors in future are not based on their past experience. However, for the majority, these behaviors are likely determined by habits. For example, it is well documented that university students frequently engage in hazardous binge drinking (Davoren et al., 2015), even compared to their non-student peers (Kypri et al., 2005). Similarly, sun safety practices is a relevant behavior for most parents in an Australian context (Hamilton et al., 2016; Hamilton, Kirkpatrick, Rebar, White, et al., 2017). It is therefore likely that the behaviors are likely those that are largely habitually determined.

Unlike other proposed models that include deliberative and automatic pathways (Caudwell et al., 2019; Hamilton, Kirkpatrick, Rebar, & Hagger, 2017; van Bree et al., 2015), a novel aspect of the current research is the measurement of automaticity over two time points, this may have contributed to the full mediation of past behavior effects by automaticity for the dental flossing and parental sun safety behavior samples. A residual effect of past behavior was still observed in the binge-drinking sample, which suggest that automaticity may not fully account for effects of automatic, non-conscious behaviors. For example, it could suggest that individuals self-report of automaticity for binge drinking may not be entirely precise because they do not take into account of ‘in-the-moment’ decision making. Other constructs that reflect automatic evaluations of binge drinking behavior such as implicit attitudes toward alcohol, impulsivity, and implicit alcohol identity may be further important mediators of past behavior effects (Caudwell & Hagger, 2014; Houben & Wiers, 2009).

An innovative contribution of the current study is the use of a second-order latent variable of past behavior that included long-term frequency of performance, recent performance (up to 1 month), and routine performance of the target behavior. Typically, past behavior is measured using an arbitrary time frame, such as 1 week. Such measures may miss previous patterns of behavior that may be important in the determination of future behavior. Bagozzi and Warsaw (1990) in their theory of trying, and later Perugini and Bagozzi (2001) in their model of goal-directed behaviors, argued that past behavior should be separated into long-term and recent components. They argued that while the two components may be related, they are conceptually different and therefore add important independent information in the prediction of behavior. For example, an individual may have only recently taken up an activity (e.g., flossing after advice from their dentist), or could have regularly engaged in an activity over a long period, but has not been able to recently (e.g., an individual who usually binge drinks each weekend but has recently reduced spending to save for their university text-books). Perugini and Bagozzi (2001) proposed that recency of behavioral engagement may influence future behavior by anchoring biases that may carry implicit information about intentions to a degree higher than by what is consciously available. Furthermore, consistent with Ouellette and Wood's (1998) premise, they suggest that long-term frequency of behavioral engagement likely maps to habitual occurrences of the behavior. Despite these premises, we found that these conceptually distinct components of past behavior were highly correlated and served as indicators of a second-order past behavior latent variable. These findings suggest that all three components are captured by an overall past behavior construct. Measures of the different past behavior components tend to converge in large samples, and separation of the different components do not offer additional information in terms of the prediction of future behavior. In fact, separation of the different components would likely confound analyses due to multi-collinearity due to the high intercorrelations. Nevertheless, justification for separating past behavior into separate components may be justified when studying past behavior effects of infrequently performed behaviors, like blood donation, or new behaviors that have only just been initiated.

The pervasive effects of habit on the health behaviors in the current study have important implications for practitioners and clinicians. Findings suggest that once an individual has adopted a health-behavior, such as applying sun-safe practices to their children or flossing, they should focus their efforts on building behavioral automaticity to maintain the health-behavior. Strategies that promote habits such as increasing behavioral performance in the presence of a cue could therefore be adopted. Furthermore, previous research has demonstrated that habit formation follows an asymptotic curve; automaticity grows fastest in the initial weeks of habit formation, and then plateaus (Lally et al., 2010). This pattern may mean that while it can take several months for a habit to fully form (Lally et al., 2010), the more intensive work to build the habit (e.g., focusing on building a response to a stable and applicable cue) can be performed in the initial few weeks of an intervention before sufficient self-regulatory actions (e.g., development of self-monitoring charts) could enable persistent repetition of the habitual action. In addition, interventions may need to focus on building the awareness of when an unhealthy habit is being cued. The focus of interventions may be to break or swap a habitual response, for example, if an individual regularly begins binge-drinking after work on a Friday, they may change their response to the cue (i.e., 'finishing work on a Friday) with something more healthy (e.g., eating at a restaurant that does not serve alcohol or by engaging in physical exercise). This work requires effortful, conscious reflection and decisions, and therefore future interventions may also need to use techniques that focus on the social–cognitive aspect of the current model (i.e., focus on building perceived behavioral control and positive attitudes to change).

Strengths, Limitations, and Research Directions

The current study has a number of strengths, including a comprehensive test of a model that included constructs representing reasoned and automatic processes in three distinct behaviors: dental flossing, binge drinking, and parents' sun safety behaviors for their children. Importantly, this is the first study, to the authors' knowledge, to use a measure of three distinct components of past-behavior: frequency, recency, and routine. The research is also innovative as it explores the extent to which effects of the past behavior factor on future behavior were accounted for by measures of behavioral automaticity, a key component of habit. Also unique was the measurement of automaticity at two points in time, which takes the temporal stability of this construct into account.

However, this study is not without limitations, which we outline next along with directions for future research. The current study used a prospective correlational design, so the direction of relations can only be inferred from the proposed relationships outlined in the relevant theories. Cross-lagged panel and experimental designs are needed to confirm the direction of causality (Chan et al., 2020; Liska, 1984). The current study primarily recruited relatively homogenous samples of participants that was low on diversity, which places limits on the generalizability of the results (Henrich et al., 2010). Another limitation is the reliance on self-report measures of behavior. Given one of the behaviors could be socially undesirable (i.e., binge drinking), and another could be seen as an evaluation of positive parenting practices (i.e., the use of sun safety behaviors on your child), social desirability effects have unduly inflated reports of these behaviors. Future studies should focus on collecting behavioral data that does not rely on self-reports which may obviate these biases (Buller & Borland, 1999). In addition, the parental sun safety behavior was defined as a collection of behaviors, which may have had unintended consequences in the way some participants reflected on the automaticity of the behavior. For example, it is plausible that different sun safety behaviors may vary in their degree of automaticity, which may have made it problematic for participants to respond to the measure. However, given each of these behaviors are likely cued in the same way (e.g., going outside during the day) and that the collection of behaviors have been advocated to occur together in a long-standing public health campaign in Australia (Montague et al., 2001), it is likely that each has a similar level of automaticity. Last, automatic processes in the current model were represented by self-reported automaticity alone. Future research should consider including other measures that tap into these processes, such as counter-intentional habits (Gardner et al., 2015) and implicit beliefs (Hagger & Chatzisarantis, 2014; Strack & Deutsch, 2004). These additional constructs may play an important role in accounting for effects of past behavior (Hagger et al., 2017).

Conclusion

The current study tested a social cognition model that encompassed constructs representing reasoned action and automatic processes to predict three health behaviors in three separate samples: binge drinking in university students, dental flossing in community-dwelling adults, and parental sun safety behaviors for their 2 to 5 year-old children. Results indicated that constructs representing the reasoned action and automatic processes significantly predicted flossing, whereas binge drinking and sun safety behaviors were generally predicted by constructs representing automatic behaviors. The current investigation also found support for the mediation of the past behavior-future behavior relationship by automaticity. The current study fills a knowledge gap in the current literature on the multiple processes that guide behavior and provide further evidence that constructs that represent automatic processes play a key role. Future research should focus on exploring the role of other constructs that represent automatic processes such as counter-intentional habits and implicit beliefs.

Figure 1. Relations among proposed model constructs including standardized parameter estimates. Estimates on the upper, center, and lower lines are estimates for the binge drinking, flossing, and sun safety behaviors, respectively. Effects of age, gender, and education on each model construct have been omitted for clarity.

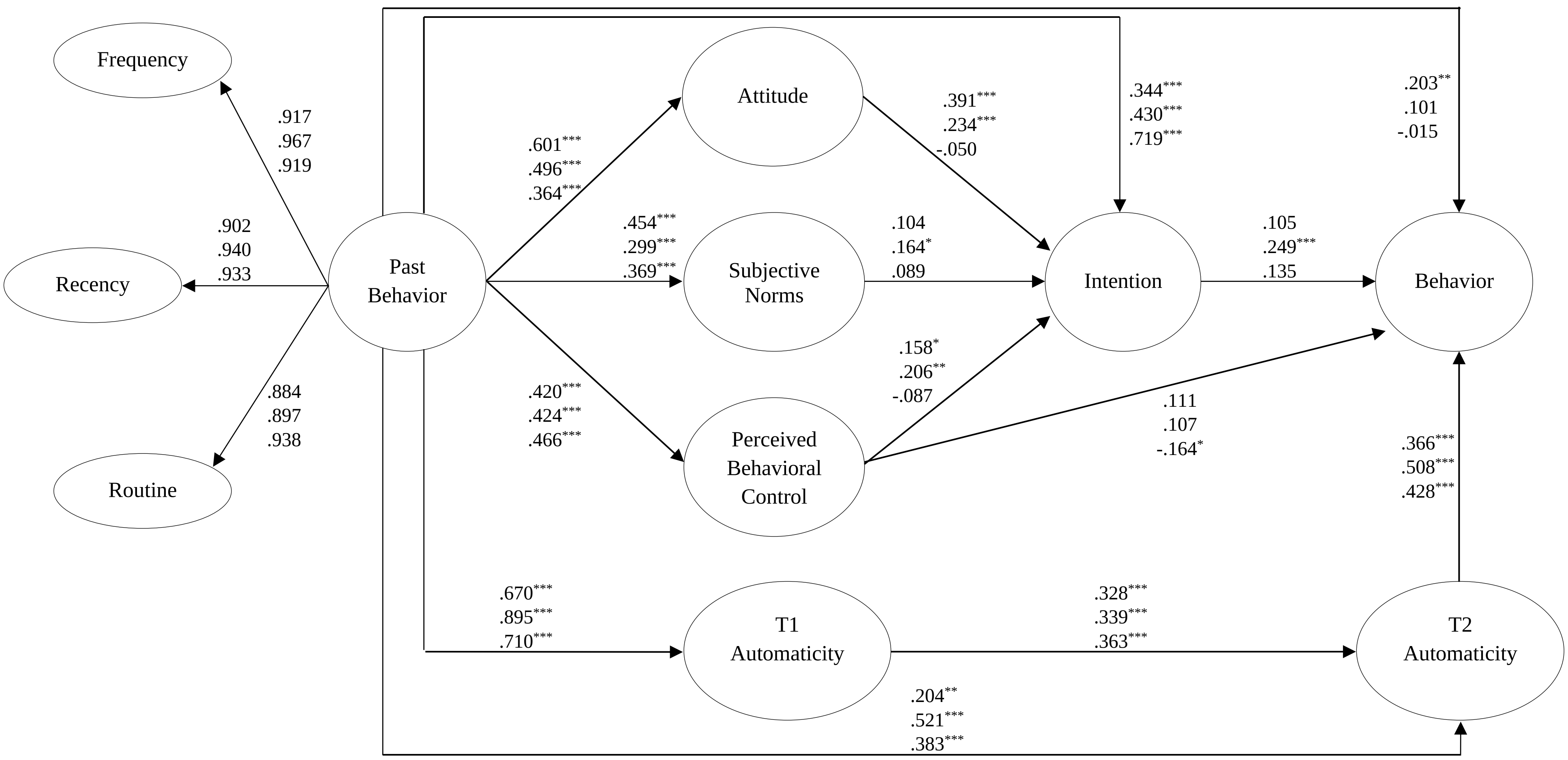

Table 1

Model Fit and Quality Indices for Structural Equation Models for Binge Drinking, Flossing, and Sun Safety

Index	Binge drinking	Flossing	Sun safety
GoF	.575	.672	.592
AR^2	$.382^{***}$	$.508^{***}$	$.382^{***}$
APC	$.164^{**}$	$.186^{**}$	$.201^{**}$
AVIF	1.272	1.581	1.342

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

Appendix A

Table 1.

Characteristics of Study Participants Who Completed the Initial Survey (Time 1) and Who Completed the Initial and Follow-Up Survey (Time 2) by Behavior

Variable	Total sample		Binge drinking		Flossing		Sun safety	
	Time 1	Time 2	Time 1	Time 2	Time 1	Time 2	Time 1	Time 2
Participants, *N*	754	454	319	177	251	177	184	100
Age, *M* years (*SD*)	29.05 (10.34)	29.55 (10.77)	23.01 (7.48)	23.47 (7.87)	32.02 (12.11)	32.50 (12.58)	35.10 (5.12)	35.12 (5.07)
Gender (%)								
Male	20.10	18.80	23.50	20.90	17.50	20.30	19.00	12.00
Female	78.20	81.00	75.90	78.50	82.10	79.70	81.00	88.00
Other/non-disclosed	0.40	0.20	0.60	0.60	0.40	-	-	-
Education level (%)								
Junior/senior school	33.20	32.00	57.10	56.50	22.70	22.00	8.70	6.00
TAFE/Diploma	21.90	22.70	25.70	28.80	21.50	19.20	18.50	19.00
UG degree	23.70	24.70	14.70	12.40	29.10	30.50	32.10	36.00
PG degree	19.20	20.30	2.20	2.30	26.70	28.20	38.60	38.00

Note. UG = Undergraduate; PG = Postgraduate.

Table 2.

Descriptive Statistics Across Behaviors for Study Variables for Those Who Completed the Initial Survey (Time 1) and Those Who Completed the Initial and Follow-Up Survey (Time 2)

Variable	Binge drinking		Flossing		Sun safety	
	Time 1	Time 2	Time 1	Time 2	Time 1	Time 2
Attitude	2.99 (1.74)	3.06 (1.82)	6.03 (1.12)	6.04 (1.15)	6.41 (1.01)	6.37 (1.09)
Subjective norm	2.54 (1.49)	2.63 (1.47)	4.86 (1.54)	4.81 (1.50)	6.45 (0.71)	6.42 (0.79)
Perceived behavioral control	5.12 (1.52)	5.27 (1.42)	6.06 (1.10)	6.12 (1.08)	6.29 (0.75)	6.32 (0.75)
Intention	3.03 (2.08)	3.05 (2.04)	4.98 (1.87)	5.02 (1.86)	6.55 (0.87)	6.55 (0.91)
T1 automaticity	2.49 (1.67)	2.38 (1.52)	2.90 (2.05)	2.84 (2.02)	5.23 (1.39)	5.15 (1.36)
Past behavior	2.58 (1.52)	2.61 (1.56)	3.95 (2.04)	4.01 (1.99)	6.35 (0.82)	6.34 (0.93)
T2 automaticity	–	2.34 (1.49)	–	2.95 (2.06)	–	5.04 (1.40)
Behavior	–	2.16 (1.35)	–	4.12 (2.46)	–	5.16 (1.67)

Appendix B

Scale Items for Constructs of the Hypothesised Model

Variable	Item	Scale
Intention	It is likely I will [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	I intend to [behaviour]	
	I expect to [behaviour]	
Attitude	For me to [behaviour] in the next six weeks it would be:	1 = “bad”, 7 = “good”
		1 = “unpleasant”, 7 = “pleasant”
		1 = “worthless”, 7 = “valuable” [ac]
		1 = “unfavourable”, 7 = “favourable” [b]
		1 = “unwise”, 7 = “wise” [b]
		1 = “awful”, 7 = “nice” [b]
Subjective norm	Those people who are important to me would want me to [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	Most people who are important to me would approve of me [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	Most people who are important to me think I should [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	Those people who are important to me do [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	Other parents I know think that [behaviour]is a good thing to do [b]	1 = “strongly disagree”, 7 = “strongly agree”
	Other parents I know [behaviour] [b]	
Perceived behavioural control	I have complete control over whether I [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	I am confident that I could [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	It is mostly up to me whether I [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
	It would be easy for me to [behaviour]	1 = “strongly disagree”, 7 = “strongly agree”
Behavioural Automaticity	I do automatically	1 = “strongly disagree”, 7 = “strongly agree”
	I do without having to consciously remember	1 = “strongly disagree”, 7 = “strongly agree”
	I do without thinking	1 = “strongly disagree”, 7 = “strongly agree”
	I start doing before I realise I’m doing it	1 = “strongly disagree”, 7 = “strongly agree”
Frequency	Do you agree that [behaviour] is something I do frequently	1 = “strongly disagree”, 7 = “strongly agree
	Do you agree that [behaviour] is something I have been doing for a long time	1 = “strongly disagree”, 7 = “strongly agree
	How often did you [behaviour] in the past year?*	1 = “never”, 7 = “very many times”
	To what extent did you [behaviour] in the past year?*	1 = “never”, 7 = “very many times”

Recency	Do you agree that [behaviour] is something you have done recently	1 = "strongly disagree", 7 = "strongly agree
	Do you agree that [behaviour] is something you have done in the past four weeks	1 = "strongly disagree", 7 = "strongly agree
	How often did you [behaviour] in the past four weeks?[*]	1 = "never", 7 = "very many times"
	To what extent did you [behaviour] in the past four weeks?[*]	1 = "never", 7 = "very many times"
Routine	Do you agree that [behaviour] is something that belongs to my normal routine	1 = "strongly disagree", 7 = "strongly agree
T2	Think about the past 6 weeks. In general, how often did you [behaviour]?	1 = "never", 7 = "always"
Behaviour	Think about the past 6 weeks. In general, to what extent did you [behaviour]?	1 = "never", 7 = "a large extent"

Note. [a]Item only administered in the binge drinking survey. [b]Item only administered in the sun safety survey. [c] Item only administered in the flossing survey. [*]These items were given values for their intermediate scale points: 1 = "never", 2 = "almost never", 3 = "a very few times", 4 = "occasionally", 5 = "often", 6 = "quite often", 7 = "very many times".

Appendix C

Table 1

Factor Intercorrelations, Composite Reliabilities, and Average Variance Extracted for Latent Variables in the Structural Equation Model in Each Sample

	ρ	AVE	R^2	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Attitude	.954	.873	.390	.934													
	.886	.724	.286	.851													
	.926	.716	.380	.846													
2. Sub. norm	.932	.775	.211	.620***	.880												
	.826	.665	.139	.388***	.815												
	.914	.683	.283	.348**	.826												
3. PBC	.834	.557	.216	.344***	.345***	.746											
	.814	.646	.199	.282***	.209**	.804											
	.815	.527	.347	.147	.312**	.726											
4. Intention	.969	.914	.688	.729***	.580***	.451***	.956										
	.952	.913	.640	.593***	.360***	.503***	.955										
	.973	.923	.616	.271**	.342***	.316**	.961										
5. T2 Behavior	.937	.881	.394	.339***	.226**	.221**	.421***	.938									
	.954	.956	.776	.425***	.242**	.483***	.721***	.978									
	.983	.967	.279	.211*	.057	.176	.471***	.983									
6. T1 Habit	.935	.782	.469	.313***	.293***	.317***	.516***	.301***	.884								
	.964	.904	.811	.389***	.219**	.329***	.593***	.703***	.951								
	.948	.821	.578	.195	.158	.296**	.572***	.388***	.906								
7. T2 Habit	.942	.802	.305	.276***	.225**	.168*	.302***	.430***	.431***	.896							
	.965	.905	.708	.332***	.263**	.404***	.619***	.814***	.794***	.951							
	.947	.816	.550	.174	.115	.292**	.572***	.525***	.673***	.903							
8. Age	-	-	-	-.136	-.110	-.098	-.206**	-.173*	-.140	-.154*	1.000						
	-	-	-	.154*	-.102	.074	.199**	.307***	.195*	.227**	1.000						
	-	-	-	-.115	-.053	-.053	-.233*	-.174	-.179	-.141	1.000						
9. Gender	-	-	-	.052	.004	-.024	.050	-.042	.096	.095	-.029	1.000					
	-	-	-	.142	-.115	-.132	.003	-.012	-.029	-.073	-.041	1.000					
	-	-	-	.157	.147	.271**	.010	-.056	.046	-.051	.149	1.000					
10. Education	-	-	-	.019	-.032	.007	-.074	-.062	-.026	.070	.443***	.047	1.000				
	-	-	-	.115	.147	-.038	.075	.105	.079	.079	.488***	-.071	1.000				
	-	-	-	-.045	.130	.160	.077	.038	-.190	-.152	.235*	.098	1.000				
11.Frequency	.954	.839	-	.541***	.435***	.420***	.685***	.425***	.692***	.417***	-.141	.028	.054	.916			
	.963	.900	-	.478***	.197**	.405***	.673***	.774***	.846***	.802***	.336***	.008	.121	.949			

	.924	.754	-	.272**	.404***	.469***	.725***	.402***	.705***	.656***	-.063	-.009	.052	.868			
12. Recency	.968	.883	-	.492***	.354***	.322***	.623***	.493***	.499***	.320***	-.228**	-.071	-.121	.758***	.940		
	.978	.937	-	.504***	.251***	.427***	.712***	.759***	.760***	.735***	.316***	.083	.127	.906***	.968		
	.949	.822	-	.410***	.322**	.222*	.743***	.442***	.602***	.577***	-.155	-.039	-.044	.776***	.907		
13.Routine	-	-	-	.514***	.312***	.168*	.511***	.397***	.550***	.300***	-.027	-.099	.097	.716***	.679***	1.000	
	-	-	-	.431***	.201**	.288***	.582***	.664***	.750***	.700***	.249***	-.034	.104	.800***	.725***	1.000	
	-	-	-	.406**	.262**	.326***	.727***	.404***	.647***	.590***	-.019	.042	.009	.791***	.826***	1.000	
14. Past behavior	.928	.812	-	.572***	.408***	.338***	.674***	.487***	.645***	.384***	-.147	-.052	.011	-	-	-	.901
	.928	.877	-	.496***	.232**	.401***	.702***	.784***	.841***	.798***	.322***	.021	.126	-	-	-	.935
	.951	.865	-	.356***	.354***	.364***	.787***	.447***	.700***	.653***	-.085	-.002	.006	-	-	-	.930

Note. ρ = Composite reliability coefficient; AVE = Average variance extracted; Values on principal diagonal are square-root of average variance extracted (AVE); Sub. Norm = Subjective norm; PBC = Perceived behavioral control; PB = Past behavior; Coefficients for binge drinking, flossing, and sun safety behaviors are depicted on the first, second, and third lines, respectively.
$^{***}p < .001$ $^{**}p < .01$ $^{*}p < .05$.

Composite reliability coefficients (ρ) and average variance extracted (AVE) statistics test the sufficiency of scale items as indicators for the latent variables and whether the items account for sufficient variance in the factor, respectively. They were expected to exceed .700 and .500, respectively.

Appendix D

Table 1

Standardized Path Coefficients (β) and 95% Confidence Intervals from Structural Equation Models for Binge Drinking, Flossing, and Sun Safety

Effect	Binge Drinking			Flossing			Sun Safety		
	β	CI_{95}		β	CI_{95}		β	CI_{95}	
		LL	UL		LL	UL		LL	UL
Direct effects									
Attitude→Intention	.391^{***c}	0.256	0.526	.234^{***b}	0.093	0.375	-.050^{bc}	-0.244	0.144
Subjective norms→Intention	.104	-0.041	0.249	.164*	0.021	0.307	.089	-0.103	0.281
Perceived behavioral control→Intention	.158^{*c}	0.015	0.301	.206^{**b}	0.065	0.347	-.087^{bc}	-0.279	0.105
T1 automaticity→T2 automaticity	.328***	0.191	0.465	.339***	0.202	0.476	.363***	0.185	0.541
Intention→Behavior	.105	-0.040	0.250	.249***	0.110	0.388	.135	-0.053	0.323
Perceived behavioral control→Behavior	.111^{c}	-0.032	0.254	.107^{b}	-0.038	0.252	-.164^{*bc}	-0.352	0.024
T2 automaticity→Behavior	.366***	0.229	0.503	.508***	0.375	0.641	.428***	0.254	0.602
Past behavior→Attitude	.601^{***c}	0.472	0.730	.496***	0.363	0.629	.364^{***c}	0.186	0.542
Past behavior→Subjective norm	.454***	0.319	0.589	.299***	0.160	0.438	.369***	0.193	0.545
Past behavior→Perceived behavioral control	.420***	0.285	0.555	.424***	0.289	0.559	.466***	0.294	0.638
Past behavior→T1 automaticity	.670^{***a}	0.541	0.799	.895^{***a}	0.772	1.018	.710***	-0.897	2.317
Past behavior→Intention	.344^{***c}	0.207	0.481	.430^{***b}	0.295	0.565	.719^{***bc}	0.558	0.880
Past behavior→T2 automaticity	.204^{**a}	0.063	0.345	.521^{***a}	0.388	0.654	.383***	0.207	0.559
Past behavior→Behavior	.203**	0.062	0.344	.101	-0.044	0.246	-.015	-0.211	0.181
Past behavior→Frequency[d]	.917			.967			.919		
Past behavior→Recency[d]	.902			.940			.933		
Past behavior→Routine[d]	.884			.897			.938		
Indirect Effects									
Attitude→Intention→Behavior	.050	-0.054	0.154	.058	-0.046	0.162	-.010	-0.149	0.129
Subjective norms→Intention→Behavior	.034	-0.070	0.138	.041	-0.063	0.145	.015	-0.122	0.152
Perceived behavioral control→Intention→Behavior	.022	-0.082	0.126	.051	-0.053	0.155	-.014	-0.151	0.123
T1 automaticity→T2 automaticity→Behavior	.120*	0.018	0.222	.172***	0.072	0.272	.155*	0.022	0.288
Past behavior→Attitude→Intention→Behavior	.030	-0.054	0.114	.029	-0.055	0.113	-.004	-0.118	0.110
Past behavior→Subjective norms→Intention→Behavior	.015	-0.069	0.099	.012	-0.072	0.096	.006	-0.108	0.120
Past behavior→Perceived behavioral control→Intention→Behavior	.009	-0.075	0.093	.022	-0.062	0.106	-.006	-0.120	0.108

Past behavior→T1 automaticity→T2 automaticity→Behavior	$.080^{*}$	-0.004	0.164	$.154^{***}$	0.072	0.236	$.110^{*}$	0.000	0.220
Total effect									
Past behavior→Behavior	$.477^{***a}$	.344	.610	$.735^{***ab}$	0.608	0.862	$.276^{**b}$	.094	.458

Note. [a]Significant difference ($p < .05$) between path in flossing data and binge drinking data in multi-group analysis; [b]Significant difference ($p < .05$) between flossing data and sun safety data in multi-group analysis; [c]Significant difference ($p < .05$) between binge drinking data and sun safety data in multi-group analysis; [d]Paramter estimate represents a second-order factor loading. β = Standardized path coefficient; CI_{95} = 95% confidence interval of path coefficient.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Table 2

Standardized Path Coefficients (β) and 95% Confidence Intervals from Structural Equation Models for Binge Drinking, Flossing, and Sun Safety with Listwise Deletion of Missing Data

Effect	Binge Drinking			Flossing			Sun Safety		
	β	CI_{95}		β	CI_{95}		β	CI_{95}	
		LL	UL		LL	UL		LL	UL
Direct effects									
Attitude→Intention	.382***	0.239	0.525	.250***	0.103	0.397	-.044	-0.250	0.162
Subjective norms→Intention	.090	-0.065	0.245	.130*	-0.021	0.281	.092	-0.112	0.296
Perceived behavioral control→Intention	.146*	-0.005	0.297	.198**	0.049	0.347	-.089	-0.293	0.115
T1 automaticity→T2 automaticity	.309***	0.164	0.454	.313***	0.168	0.458	.310**	0.120	0.500
Intention→Behavior	.098	-0.055	0.251	.283***	0.136	0.430	.233*	0.037	0.429
Perceived behavioral control→Behavior	.116	-0.035	0.267	.124	-0.027	0.275	.282**	0.090	0.474
T2 automaticity→Behavior	.392***	0.249	0.535	.522***	0.383	0.661	.292**	0.100	0.484
Past behavior→Attitude	.594***	0.457	0.731	.487***	0.346	0.628	.317***	0.127	0.507
Past behavior→Subjective norm	.447***	0.306	0.588	.260***	0.113	0.407	.386***	0.200	0.572
Past behavior→Perceived behavioral control	.425***	0.284	0.566	.404***	0.261	0.547	.429***	0.245	0.613
Past behavior→T1 automaticity	.679***	0.544	0.814	.891***	0.762	1.020	.717***	0.546	0.888
Past behavior→Intention	.366***	0.223	0.509	.449***	0.308	0.590	.723***	0.554	0.892
Past behavior→T2 automaticity	.196**	0.047	0.345	.545***	0.406	0.684	.421***	0.237	0.605
Past behavior→Behavior	.216**	0.067	0.365	.034	-0.121	0.189	.025	-0.183	0.233
Indirect Effects									
Attitude→Intention→Behavior	.044	-0.066	0.154	.071	-0.037	0.179	-.014	-0.161	0.133
Subjective norms→Intention→Behavior	.030	-0.080	0.140	.037	-0.073	0.147	.027	-0.120	0.174
Perceived behavioral control→Intention→Behavior	.018	-0.092	0.128	.056	-0.054	0.166	-.025	-1.495	1.445
T1 automaticity→T2 automaticity→Behavior	.121*	0.013	0.229	.163**	0.057	0.269	.091	-0.052	0.234
Past behavior→Attitude→Intention→Behavior	.026	-0.064	0.116	.034	-0.056	0.124	-.004	-0.124	0.116
Past behavior→Subjective norms→Intention→Behavior	.013	-0.077	0.103	.010	-0.080	0.100	.010	-0.110	0.130
Past behavior→Perceived behavioral control→Intention→Behavior	.008	-0.082	0.098	.023	-0.067	0.113	-.011	-0.131	0.109
Past behavior→T1 automaticity→T2 automaticity→Behavior	.082*	-0.006	0.170	.146***	0.058	0.234	.065	-0.053	0.183
Total effects									

Past behavior→Behavior	.493***	.354	.632	.708***	0.575	0.841	.499***	.319	.679

Note. β = Standardized path coefficient; CI_{95} = 95% confidence interval of path coefficient; $^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

References

Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes*, *50*, 179–211. https://doi.org/doi:10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Residual Effects of Past on Later Behavior: Habituation and Reasoned Action Perspectives. *Personality and Social Psychology Review*, *6*(2), 107–122. https://doi.org/10.1207/S15327957PSPR0602_02

Albarracín, D., Johnson, B. T., Fishbein, M., & Muellerleile, P. A. (2001). Theories of Reasoned Action and Planned Behavior as Models of Condom Use: A Meta-Analysis. *Psychological Bulletin*, *127*(1), 142–161. https://doi.org/10.1037//0033-2909.127.1.142

Australian Dental Association. (2017). *Flossing (18-30yrs)—Your Dental Health | Australian Dental Association*. https://www.ada.org.au/Your-Dental-Health/Younger-Adults-18-30/flossing

Bagozzi, R. P., & Warshaw, P. R. (1990). Trying to Consume. *Journal of Consumer Research*, *17*(2), 127–140. https://doi.org/10.1086/208543

Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. *Basic and Applied Social Psychology*, *25*(3), 175–187. https://doi.org/10.1207/S15324834BASP2503_01

Brown, D. J., Hagger, M. S., Morrissey, S., & Hamilton, K. (2018). Predicting fruit and vegetable consumption in long-haul heavy goods vehicle drivers: Application of a multi-theory, dual-phase model and the contribution of past behaviour. *Appetite*, *121*, 326–336. https://doi.org/10.1016/j.appet.2017.11.106

Buller, D. B., & Borland, R. (1999). Skin cancer prevention for children: A critical review. *Health Education & Behavior*, *26*(3), 317–343. https://doi.org/10.1177/109019819902600304

Cancer Council Australia. (2017). *Sun Protection*. https://wiki.cancer.org.au/skincancerstats/Sun_protection

Caudwell, K. M., & Hagger, M. S. (2014). Pre-drinking and alcohol-related harm in undergraduates: The influence of explicit motives and implicit alcohol identity. *Journal of Behavioral Medicine*, *37*(6), 1252–1262. https://doi.org/10.1007/s10865-014-9573-6

Caudwell, K. M., Keech, J. J., Hamilton, K., Mullan, B. A., & Hagger, M. S. (2019). Reducing alcohol consumption during pre-drinking sessions: Testing an integrated behaviour-change model. *Psychology & Health*, 1–22. https://doi.org/10.1080/08870446.2018.1518527

Chan, D. K. C., Zhang, L., Lee, A. S. Y., & Hagger, M. S. (2020). Reciprocal relations between autonomous motivation from self-determination theory and social cognition constructs from the theory of planned behavior: A cross-lagged panel design in sport injury prevention. *Psychology of Sport and Exercise*, 101660. https://doi.org/10.1016/j.psychsport.2020.101660

Conner, M., Warren, R., Close, S., & Sparks, P. (1999). Alcohol Consumption and the Theory of Planned Behavior: An Examination of the Cognitive Mediation of Past Behaviorid. *Journal of Applied Social Psychology*, *29*(8), 1676–1704. https://doi.org/10.1111/j.1559-1816.1999.tb02046.x

Davoren, M. P., Shiely, F., Byrne, M., & Perry, I. J. (2015). Hazardous alcohol consumption among university students in Ireland: A cross-sectional study. *BMJ Open*, *5*(1), e006045–e006045. https://doi.org/10.1136/bmjopen-2014-006045

Gardner, B., Abraham, C., Lally, P., & de Bruijn, G.-J. (2012). Towards parsimony in habit measurement: Testing the convergent and predictive validity of an automaticity subscale of the Self-Report Habit Index. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 102. https://doi.org/10.1186/1479-5868-9-102

Gardner, B., Corbridge, S., & McGowan, L. (2015). Do habits always override intentions? Pitting unhealthy snacking habits against snack-avoidance intentions. *BMC Psychology*, *3*(1), 8. https://doi.org/10.1186/s40359-015-0065-4

Hagger, M. S. (2020). Redefining habits and linking habits with other implicit processes. *Psychology of Sport and Exercise*, *46*, 101606. https://doi.org/10.1016/j.psychsport.2019.101606

Hagger, M. S., Chan, D. K., Protogerou, C., & Chatzisarantis, N. L. (2016). Using meta-analytic path analysis to test theoretical predictions in health behavior: An illustration based on meta-analyses of the theory of planned behavior. *Preventive Medicine*, *89*, 154–161. https://doi.org/10.1016/j.ypmed.2016.05.020

Hagger, M. S., & Chatzisarantis, N. L. D. (2014). An Integrated Behavior Change Model for Physical Activity: *Exercise and Sport Sciences Reviews*, *42*(2), 62–69. https://doi.org/10.1249/JES.0000000000000008

Hagger, M. S., Polet, J., & Lintunen, T. (2018). The reasoned action approach applied to health behavior: Role of past behavior and tests of some key moderators using meta-analytic structural equation modeling. *Social Science & Medicine*, *213*, 85–94. https://doi.org/10.1016/j.socscimed.2018.07.038

Hagger, M. S., Trost, N., Keech, J. J., Chan, D. K. C., & Hamilton, K. (2017). Predicting sugar consumption: Application of an integrated dual-process, dual-phase model. *Appetite*, *116*, 147–156. https://doi.org/10.1016/j.appet.2017.04.032

Hamilton, K., Cleary, C., White, K. M., & Hawkes, A. L. (2016). Keeping kids sun safe: Exploring parents' beliefs about their young child's sun-protective behaviours: Parents' beliefs about their young child's sun-protective behaviours. *Psycho-Oncology*, *25*(2), 158–163. https://doi.org/10.1002/pon.3888

Hamilton, K., Kirkpatrick, A., Rebar, A., & Hagger, M. S. (2017). Child sun safety: Application of an Integrated Behavior Change model. *Health Psychology*, *36*(9), 916–926. https://doi.org/10.1037/hea0000533

Hamilton, K., Kirkpatrick, A., Rebar, A., White, K. M., & Hagger, M. S. (2017). Protecting young children against skin cancer: Parental beliefs, roles, and regret. *Psycho-Oncology*, *26*(12), 2135–2141. https://doi.org/10.1002/pon.4434

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. *Nature*, *466*(7302), 29. https://doi.org/10.1038/466029a

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing* (pp. 277–319). Emerald Group Publishing Limited.

Houben, K., & Wiers, R. W. (2009). Response inhibition moderates the relationship between implicit associations and drinking behavior. *Alcoholism: Clinical and Experimental Research*, *33*(4), 626–633. https://doi.org/10.1111/j.1530-0277.2008.00877.x

Ji, M. F., & Wood, W. (2007). Purchase and consumption habits: Not necessarily what you intend. *Journal of Consumer Psychology*, *17*(4), 261–276. https://doi.org/10.1016/S1057-7408(07)70037-2

Kock, N. (2018). *WarpPLS User Manual: Version 6.0*. ScriptWarp Systems.

Kypri, K., Cronin, M., & Wright, C. S. (2005). Do university students drink more hazardously than their non-student peers? *Addiction*, *100*(5), 713–714. https://doi.org/10.1111/j.1360-0443.2005.01116.x

Lally, P., van Jaarsveld, C. H. M., Potts, H. W. W., & Wardle, J. (2010). How are habits formed: Modelling habit formation in the real world. *European Journal of Social Psychology*, *40*(6), 998–1009. https://doi.org/10.1002/ejsp.674

Liska, A. E. (1984). A critical examination of the causal structure of the Fishbein/Ajzen attitude-behavior model. *Social Psychology Quarterly*, 61–74. https://doi.org/10.2307/3033889

Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association*, *83*(404), 1198–1202. https://doi.org/10.2307/2290157

Luszczynska, A., & Cieslak, R. (2009). Mediated Effects of Social Support for Healthy Nutrition: Fruit and Vegetable Intake Across 8 Months After Myocardial Infarction. *Behavioral Medicine*, *35*(1), 30–38. https://doi.org/10.3200/BMED.35.1.30-38

McEachan, R., 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

Montague, M., Borland, R., & Sinclair, C. (2001). Slip! Slop! Slap! And SunSmart, 1980-2000: Skin cancer control and 20 years of population-based campaigning. *Health Education & Behavior*, *28*(3), 290–305. https://doi.org/10.1177/109019810102800304

Mullan, B., Allom, V., Sainsbury, K., & Monds, L. A. (2015). Examining the predictive utility of an extended theory of planned behaviour model in the context of specific individual safe food-handling. *Appetite*, *90*, 91–98. https://doi.org/10.1016/j.appet.2015.02.033

NHMRC. (2009). Australian guidelines to reduce health risks from drinking alcohol. *National Health & Medical Research Council, Ed*.

Ouellette, J. A., & Wood, W. (1998). Habit and Intention in Everyday Life: The Multiple Processes by Which Past Behavior Predicts Future Behavior. *Psychological Bulletin*, *124*, 54–74. https://doi.org/10.1037/0033-2909.124.1.54

Perugini, M., & Bagozzi, R. P. (2001). The role of desires and anticipated emotions in goal-directed behaviours: Broadening and deepening the theory of planned behaviour. *British Journal of Social Psychology*, *40*(1), 79–98. https://doi.org/10.1348/014466601164704

Rich, A., Brandes, K., Mullan, B., & Hagger, M. S. (2015). Theory of planned behavior and adherence in chronic illness: A meta-analysis. *Journal of Behavioral Medicine*, *38*(4), 673–688. https://doi.org/10.1007/s10865-015-9644-3

Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review*, *8*(3), 220–247. https://doi.org/10.1207/s15327957pspr0803_1

Sun, J., Lucas, R., Harrison, S., van der Mei, I., Armstrong, B. K., Nowak, M., Brodie, A., & Kimlin, M. G. (2014). The relationship between ambient ultraviolet radiation (UVR) and objectively measured personal UVR exposure dose is modified by season and latitude. *Photochemical & Photobiological Sciences*, *13*(12), 1711–1718. https://doi.org/10.1039/c4pp00322e

Triandis, H. C. (1977). *Interpersonal behavior*. Brooks/Cole Pub. Co.

van Bree, R. J. H., van Stralen, M. M., Mudde, A. N., Bolman, C., de Vries, H., & Lechner, L. (2015). Habit as mediator of the relationship between prior and later physical activity: A longitudinal study in older adults. *Psychology of Sport and Exercise*, *19*, 95–102. https://doi.org/10.1016/j.psychsport.2015.03.006

Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology*, *45*(3), 639–656. https://doi.org/10.1348/014466605X49122

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

Xiang, F., Harrison, S., Nowak, M., Kimlin, M., Van der Mei, I., Neale, R. E., Sinclair, C., & Lucas, R. M. (2015). Weekend personal ultraviolet radiation exposure in four cities in Australia: Influence of temperature, humidity and ambient ultraviolet radiation. *Journal of Photochemistry and Photobiology B: Biology*, *143*, 74–81. https://doi.org/10.1016/j.jphotobiol.2014.12.029