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Title: Effects of habit and intention on behavior : Meta-analysis and test of key moderators

Year: 2023

Version: Accepted version (Final draft)

Please cite the original version:

Hagger, M. S., Hamilton, K., Phipps, D. J., Protogerou, C., Zhang, C.-Q., Girelli, L., Mallia, L., & Lucidi, F. (2023). Effects of habit and intention on behavior : Meta-analysis and test of key moderators. Motivation Science, 9(2), 73-94. https://doi.org/10.1037/mot0000294

Effects of Habit and Intention on Behavior: Meta-Analysis and Test of Key Moderators

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Full citation: Hagger, M. S., Hamilton, K., Phipps, D. J., Protogerou, C., Zhang, C.-Q., Girelli, L., Mallia, L., & Lucidi, F. (2023). Effects of habit and intention on behavior: Meta-analysis and test of key moderators. *Motivation Science*. https://doi.org/10.1037/mot0000294

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Martin Hagger's contribution was supported by a Finnish Distinguished Professor (FiDiPro) award from Business Finland, a Kennedy Y. H. Wong Distinguished Visiting Professorship from Hong Kong Baptist University, and a Visiting Professorship from Sapienza - University of Rome.

Data files, and analysis scripts and output are available online: https://osf.io/zq7c8/

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Abstract

In a meta-analysis of research on measures of the habit construct, we aimed to estimate the size and variability of habit-behavior and intention-behavior relations, and habit as a mediator of past-future behavior relations. Further, we investigated theory-consistent moderators of these relations including opportunity for habit formation and behavioral complexity, and the capacity of different habit measures to detect these effects. We also tested effects of behavior type, behavior measure, and measurement lag as moderators of these effects, and explored convergence in correlations among habit measures and their indication of a single habit factor. A database search identified studies (*k*=267) reporting relations among habit measures (behavioral frequency x context stability, response frequency, self-report measures), behavior, and intention. Data were analyzed using multi-level meta-analytic structural equation modeling. Habit and intention independently predicted behavior, and habit partially mediated past-future behavior relations. Larger habit-behavior relations were observed in studies targeting behaviors with high opportunity for habit formation and lower complexity, but no analogous effects for intention-behavior relations. Similar trends for these moderators were observed across the habit measures, although differences were non-zero for self-reported habit measures only. Habit-behavior relations were larger in studies adopting self-report habit measures that included behavioral frequency items and those with greater measurement lag. Convergence in habit measure correlations, and their indication of a single habit factor, was supported. Findings corroborate and extend prior research on habit, particularly convergence in behavioral effects of the habit measures. Findings are expected to catalyze future habit research using experimental methods and non-self-report measures.

Keywords: automaticity; past behavior; non-conscious processes; habit formation; habit theory

Effects of Habit and Intention on Behavior: Meta-Analysis and Test of Key Moderators

While many rational decision theories (e.g., the theory of planned behavior; Ajzen, 1991; social cognitive theory, Bandura, 1986) assume that human motivated behavior is a function of reflective, deliberative consideration of the anticipated instrumental merits and detriments of performing the behavior in future, theorists contend that such approaches do not provide a sufficient account of behavior and its determinants (e.g., Sheeran et al., 2013). This is predicated on the observation that many common behaviors are enacted with relatively little deliberative anticipatory consideration of outcomes, and are, instead, enacted through more automatic or implicit processes that involve relatively little deliberation (e.g., Strack & Deutsch, 2004).

Theorists have proposed multiple forms of automatic process, with habit identified as one of the most prominent (e.g., Aarts et al., 1998; Verplanken et al., 1998; Wood et al., 2014). Contemporary theoretical perspectives conceptualize habit as a construct that reflects behavioral enactment occurring rapidly and efficiently in response to the presentation of associated contextual features or cues without need for elaborate reasoning or deliberation (Gardner, 2015; Verplanken & Orbell, 2022; Wood, 2017; Wood & Rünger, 2016). A central hypothesis of theory on habit is that habitual behaviors are developed over time, indicated by a gradual shift in control over the behavior from reasoned, deliberative processes, often represented by effects of intention on behavior, to automatic, non-conscious processes, as modeled by effects of measures of the habit construct on behavior (Ouellette & Wood, 1998; Verplanken & Orbell, 2022). Consistent with this premise, as a behavior is developed as a habit, the habit construct should gradually become the predominant determinant of behavior with the effect of intention waning accordingly (Lally et al., 2010; Ouellette, 1996). Researchers have, therefore, aimed to examine the conditions that, according to habit theory, lead to greater habitual control over behavior (Gardner, 2015; Wood & Rünger, 2016).

Numerous means to model habit effects on behavior have been adopted, including inferring them from past behavior (e.g., Chatzisarantis et al., 2004; Hagger et al., 2016; Ouellette & Wood, 1998), or by employing habit measures that capture its key components, including the covariance between behavioral frequency and stability of context cues (e.g., Wood & Neal, 2009), behavioral accessibility (e.g., Verplanken et al., 1994), and experiences of the behavior as automatic, unthinking, and routine (e.g., Verplanken & Orbell, 2003). For example, researchers have examined the relative effects of past behavior and measures of the habit construct on subsequent behavior alongside measures of intention (e.g., Conroy et al., 2013; Orbell et al., 2001; Ouellette & Wood, 1998; Verplanken & Aarts, 1999). Such research affords the opportunity to confirm the extent to which habit accounts for unique variance in behavior relative to intention, and its relative contribution compared to intention (for reviews see Gardner et al., 2011; Wood, 2017). Importantly, it also enables identification of key conditions likely to determine the size of habit and intention effects on future behavior according to theory including the propensity of the behavior to be formed as a habit (e.g., Ouellette & Wood, 1998; Webb & Sheeran, 2006), as well as habit strength (e.g., Gardner et al., 2011; Ji & Wood, 2007) and degree of behavioral complexity (e.g., McCloskey & Johnson, 2019; Verplanken, 2006).

However, a number of key questions pervade in habit research. Studies have examined the simultaneous effects of habit measures and intention on behavior, and the extent to which past behavior effects are subsumed by habit measures (van Bree et al., 2015; Verplanken, 2006), supporting the typically-expected pattern of effects of these constructs on the target behavior and population (Gardner et al., 2011). However, to date, no research has systematically examined these effects across the extant research on habit and, importantly, compared these effects across different habit measures. Studies have also examined the conditions that determine the relative size of habit-behavior and intention-behavior effects consistent with habit theory, such as the opportunity for the behavior to be formed as a habit (e.g., Ouellette & Wood, 1998), behavioral complexity (e.g., Verplanken, 2006), or the extent to which the behavior is rewarding (e.g., McCloskey & Johnson, 2019). Syntheses of habit research may provide robust corroboration of these effects. In addition, these patterns of effects may also vary according to habit measure type, and the research methods adopted, such as whether self-report measures of habit include or exclude behavioral frequency items, whether behavior is measured by self-report or non-self-report methods, or whether the behavior is measured in close or distal proximity to the habit measure. Research syntheses testing the effects of these moderators may extend current knowledge of the conditions impacting habit-behavior effects.

In the present analysis, we aimed to address these issues though a meta-analytic synthesis of studies examining effects of measures of the habit construct and intention on subsequent behavior. Such an analysis enabled us to corroborate prior research by estimating the average size and variability of the effects of habit measures and intention on future behavior across studies, and the extent to which habit measures mediate past behavior effects. We also expected substantive heterogeneity in the averaged effect sizes for habit and intention given they represent aggregated effects across studies targeting different behaviors and in varied contexts. We therefore aimed to identify the conditions that affect habit-behavior and intention-behavior relations according habit theory by testing effects of key moderator variables in our analysis. Prominent candidate moderators were habit measure type, propensity for the behavior to be developed as a habit, and behavioral complexity, and their interaction. We also tested the effects of other moderators such as behavior type, inclusion of frequency items in habit measures, behavior measure type, and the time lag between measures of habit and behavior. We expected our analysis to advance knowledge on the relative effects of habit and intention on behavior and, importantly, provide further evidence on the conditions impacting these effects. Next, we outline the conceptual bases for our predicted effects, with a summary provided in Table 1.

Effects of Past Behavior, Habit, and Intention on Behavior

Initial research on the effects of habit on behavior inferred them from frequency measures of past behavior, predicated on the assumption that repeated experience with a behavior heightens the opportunity for it to become routinized and formed as a habit (Aarts et al., 1998; Ouellette & Wood, 1998; Triandis, 1977). Studies have consistently demonstrated independent effects of past behavior and intention on behavior, suggestive of the propensity for behaviors to be controlled by both habitual and reasoned decision-making processes (e.g., Albarracín et al., 2001; Conner et al., 1999). These findings, however, did not provide indication of the conditions determining when habit or intention was the predominant determinant. To resolve this, researchers examined effects of the likelihood of a behavior to formed as a habit, indicated by a greater opportunity for it to be repeated often and in consistent contexts (e.g., in the same location, with the same people), as a moderator of past behavior effects. This pattern of effects is consistent with theories of habit, which predict that habits should be the primary determinant of behaviors that are routinely performed in conjunction with stable cues or conditions, while intention should be the predominant determinant of behaviors performed less frequently or in varying contexts, or both (Ouellette & Wood, 1998; Triandis, 1977;

Verplanken, 2006; Wood et al., 2014). Ouellette and Wood (1998) supported this proposed pattern in their seminal meta-analysis in which studies targeting behaviors classified as performed regularly in stable contexts (e.g., class attendance, alcohol consumption) reported larger past behavior-behavior relations and smaller intention-behavior relations relative to those targeting behaviors performed less regularly (e.g., blood donation, voting), or in widely varying contexts (e.g., attending music concerts, visiting the family physician), or both. Analogously, a further meta-analysis reported larger intention-behavior relations in studies classified as unlikely to be formed as habits (Webb & Sheeran, 2006). These analyses provided converging evidence for the theoretically-derived pattern of effects of past behavior and intention on behavior according to the likelihood of the behavior to be formed as a habit.

The observed convergence in these findings notwithstanding, frequency measures of past behavior are considered somewhat unsatisfactory as means to model habit effects. Theorists have consistently argued that past behavior is not a psychological construct, and that past behavior measures do not capture other essential components of habit as a construct beyond behavioral frequency (Ajzen, 2002; Ouellette & Wood, 1998; Verplanken, 2006). For example, Verplanken (2006) demonstrated that measures capturing other components of habit, such as automaticity, lack of awareness, and behavioral complexity, predicted behavior independent of behavioral frequency measures. In addition, past behavior effects on behavior may not be exclusively attributable to habit – they may model effects of other unmeasured constructs. For example, Ajzen (2002) suggested that any construct purported to have affected behavior previously could feasibly continue to affect current behavior and account for past behavior effects. Corroborating this, studies have demonstrated that past behavior effects on behavior are partially mediated by personality constructs (e.g., Conner & Abraham, 2001). As a consequence, researchers have developed habit measures that encompass other components of the construct in keeping with its definition to facilitate greater precision in habit research.

Habit Measurement and Overall Habit-Behavior and Intention-Behavior Effects

Three habit measures have featured prominently in habit research, each capturing key components of the construct: the behavioral frequency x context stability measure (Wood & Neal, 2009), the response frequency measure (Verplanken et al., 1994), and self-report habit measures (Verplanken & Orbell, 2003). The behavioral frequency x context stability measure is a multiplicative composite score of measures of behavioral frequency and the stability of the contextual features or situational cues present when it is performed (e.g., Wood & Neal, 2009). This measure recognizes the importance of context stability as an essential component of habit beyond performance frequency. By contrast, response frequency measures capitalize on the assumption that habitual behaviors are the most salient and accessible choice in any given behavioral context. Individuals are presented with a hypothetical scenario and prompted to identify the most likely behavioral response as rapidly as possible from a list of alternatives. This measure has been largely applied in contexts such as travel mode choice (e.g., Klöckner et al., 2003; Verplanken et al., 1994) and technology use (Naab & Schnauber, 2016a). Finally, self-report habit measures capture a range of components of the habit construct based on subjective experiences of the behavior, and typically comprise scaled items prompting respondents to reflect on the extent to which a target behavior is experienced as frequent, routine, automatic, and self-relevant (e.g., LaRose & Eastin, 2004; Limayem & Hirt, 2003; Verplanken & Orbell, 2003).

Studies adopting these measures have provided support for their predictive validity in that they account for unique variance in behavior beyond intention and other constructs representing deliberative, reasoned decision making (e.g., Conroy et al., 2013 van Bree, 2015 #8964; Friedrichsmeier et al., 2013; Gardner et al., 2011). This has been corroborated in a meta-analysis of effects of habit measures on physical activity participation, albeit confined to self-reported habit measures and a single behavior (Gardner et al., 2011). Studies supporting these overall effects of habit and intention have value in that they identify the pattern of effects a researcher might expect for each construct for a given behavior and population (Gardner et al., 2011).

However, the observation that habit and intention have simultaneous effects on behavior appears, on the surface, to conflict with habit theory, which stipulates that habitual behaviors should be predicted by habit measures with small or null effects for intention with the opposite pattern expected for behaviors not formed habits. Based on the assumption that habit formation is a relatively slow process indicated by a gradual shift from intention to habitual control (Lally et al., 2010), one interpretation of this pattern of effects is that in any given population the extent to which individuals have formed the target behavior as a habit would be expected to vary. This would be manifested in the observation of simultaneous effects of both constructs on behavior.

Our first step in the current study, therefore, was to corroborate this simultaneous pattern of effects of measures of habit and intention on behavior across the research literature. Specifically, we aimed to provide meta-analytic estimates of the average size and variability of the effects of the habit (H1, Table 1) and intention (H2, Table 1) constructs on behavior across studies adopting these three habit measures, and expected non-zero averaged effects for each construct consistent with prior research. Corroborating these effects adds to current knowledge by providing overall estimates of the expected habit-behavior and intention-behavior effects in simultaneous tests across available studies.

Acknowledging that habit measures were developed in part because past behavior is somewhat inadequate in capturing the essential characteristics of habit, researchers have sought to examine the extent to which past behavior effects are accounted for by habit measures. For example, predictive studies have demonstrated that habit measures are efficacious in mediating the effect of past behavior on subsequent behavior (e.g., Phipps et al., 2020; van Bree et al., 2015; Verplanken, 2006), although the mediated effect is often partial with a substantive residual past behavior effect. Such effects may indicate the extent to which past behavior effects can be attributed to habit as opposed to constructs representing other automatic processes, but it may also be a measurement artifact in that some habit measures encompass frequency measures of behavior as an integral component. The current meta-analysis provided us with the opportunity to replicate the observed mediation effect across the extant research on habit. Based on prior findings, we expected a non-zero indirect effect of past behavior on behavior mediated by habit (H3a, Table 1), but also anticipated the mediation would be partial and, therefore, expected to observe a non-zero residual effect of past behavior (H3b, Table 1).

Moderators of Habit Effects

Although observing simultaneous averaged effects of habit and intention on behavior across studies may be informative of the expected overall effects of each within a given population, such effects are uninformative of the conditions that determine whether a behavior is under intentional or habitual control. Our current analysis provided opportunity to identify these conditions, and test them as moderators of habit and intention effects on behavior across studies. In this section we outline a series of candidate moderator variables and provide bases for their hypothesized effects. We segregate our discussion into conceptual moderators that test predictions aligned with habit theory, and methodological moderators that have implications for measurement and study design in habit research. A summary of the proposed moderator effects is presented in Table 1.

Conceptual Moderators

Assuming that any given population is likely to comprise individuals who are at varying stages of developing the target behavior as a habit, it follows that the extent to which the behavior is amenable to habit formation is likely to impact the relative size of the observed habit-behavior and intention-behavior effects. Therefore, consistent with the premises of habit theory, the propensity of a given behavior to be formed as a habit is expected to be a key moderator of these effects. Specifically, effects of habit on behavior are expected to be larger, relative to effects of intention, in behaviors with greater propensity to be formed as habit, that is, those that generally performed regularly and in stable contexts. By contrast, the opposite pattern is expected for behaviors that have low propensity for habit formation, that is, those generally performed rarely or in varying contexts, or both. General support for this pattern of prediction has been observed in studies adopting specific habit measures (Verplanken et al., 1994; Verplanken & Orbell, 2003; Wood & Neal, 2009), which have mirrored findings of meta-analytic research adopting past behavior as a proxy for habit (Ouellette & Wood, 1998) and examining intention-behavior relations (Webb & Sheeran, 2006). However, to date, no study has systematically examined this pattern of effects across studies on habit. The current analysis permitted the opportunity to address this evidence gap across research on habit. Specifically, we hypothesized that studies targeting behaviors affording greater opportunity to be formed as a habit would exhibit larger habit-behavior (H4a, Table 1) and smaller intention-behavior (H4b, Table 1) effects, with an opposite pattern expected in studies targeting behaviors less likely to be formed as a habit.

A further important question is the extent to which the theory consistent pattern of habit-behavior and intention-behavior effects hold across different habit measures. Given that habit measures are purported to capture the same underlying habit construct, it would be reasonable to predict consistency in the effects of habit on behavior regardless of the measure used. However, an alternative perspective is that a focus on different characteristics of habit within each measure may lead to observed variability in habit-behavior effects (e.g., Friedrichsmeier et al., 2013; McCloskey & Johnson, 2019; Naab & Schnauber, 2016a; Norman & Cooper, 2011). In the current meta-analysis, we therefore proposed to initially test whether the relative size of the habit-behavior (H5a, Table 1) and intention-behavior (H5b, Table 1) effects varied according to the type of habit measure adopted by study authors: the behavioral frequency x context stability, response frequency, and self-reported habit measures. Importantly, we also aimed to estimate the extent to which the relative effects of habit and intention on behavior varied according to the likelihood of habit formation and habit measure type, effectively a test of the interactive effects of these two moderators. Again, as each habit measure is purported to tap the same underlying construct, we assumed within-measure consistency in the habit (H6a) and intention (H6b) effects on behavior and, therefore, that the interaction analysis of moderators would corroborate the main effects of these moderators. We expected this analysis to provide important information on the sensitivity of each measure to detect the theoretically prescribed patterns of effects for habit and intention on behavior under conditions of opportunity for habit formation.

Another candidate moderator of habit and intention effects is the relative complexity of the target behavior. Behaviors lower in complexity, defined as those that do not involve extensive planning or cognitive processing to perform, do not require adaptation in response to new information during performance, and comprise relatively few sub-actions, have been proposed as having a greater propensity to be developed as habits (Gardner, 2015; Lally & Gardner, 2013; Lin et al., 2016; Phillips & More, 2022; Wood et al., 2002). By contrast, behaviors higher in complexity, defined as those involving substantive cognitive processing and planning, requiring ongoing responsivity to new information as it arises, and comprising multiple sub-actions, are less likely to be acquired as habits. As a consequence, and consistent with habit theory, researchers have examined the relative size of the habit-behavior and intention-behavior effects according target behavior complexity. For example, studies have demonstrated that behaviors identified as lower in complexity, or behaviors experimentally manipulated to appear lower in complexity, are more likely to be expressed as habitual than those classified as, or manipulated to be, higher in complexity (Verplanken, 2006; Wood et al., 2002). However, given few studies have tested complexity as a moderator of these effects, we aimed to provide further corroboration in the current meta-analysis. We hypothesized that studies focusing on behaviors considered higher in complexity would be more likely to demonstrate smaller habit-behavior (H7a, Table 1) and larger intention-behavior (H7b, Table 1) effects relative to studies focusing on behaviors considered lower in complexity.

We also recognized the importance of evaluating the capacity of different habit measures to detect the theory-derived pattern of habit-behavior and intention-behavior effects across levels of behavioral complexity. We therefore resolved in the current analysis to systematically test the interactive effects of the behavioral complexity and habit measure type moderator variables on the habit-behavior and intention-behavior relations. As with the opportunity for habit formation moderator, we based our predictions on the assumption that each habit measure tapped the same underlying construct. So, we hypothesized that the predicted pattern of habit-behavior (H8a, Table 1) and intention-behavior (H8b, Table 1) effects at each level of the complexity moderator would hold regardless of the habit measure adopted.

Other behavioral characteristics may moderate the effects of habit and intention on behavior. For example, inherently rewarding behaviors, such as those readily reinforced through dopamine-mediated processes (e.g., alcohol or snack consumption), will have greater propensity to develop as habits (e.g., Bouton, 2014). The reinforced behavior is likely to be repeated often and in stable contexts, the exact conditions conducive to developing a habit. By contrast, behaviors for which inherent reinforcing contingencies are minimal or absent (e.g., clinic attendance, conserving electricity) will have lower propensity to develop as habits (e.g., Churchill & Jessop, 2011). Habit is, therefore, more likely to be the predominant predictor of highly rewarding behaviors, while intention is likely to be the pervading predictor of behaviors that are not inherently rewarding. We aimed to conduct a systematic test of these effects across studies targeting behaviors identified as more or less rewarding in the current analysis. Specifically, we grouped studies into behavior categories consistent with prior research (McEachan et al., 2011), namely, dietary behaviors, physical activity, alcohol behaviors, protection behaviors, and transport use behaviors, and compare the size of the effects of habit and intention on behavior in sets of studies in each group. We predicted that studies targeting behaviors likely to be highly rewarding (e.g., dietary behaviors, alcohol consumption) would exhibit larger habit-behavior (H9a, Table

1) and smaller intention-behavior (H9b, Table 1) effects relative to studies on behaviors that are not inherently rewarding (e.g., physical activity, transport use).

Methodological Moderators

We also expected other variables relating to study methods to serve as candidate moderators of habit effects on behavior in our analysis, such as the item content of self-report habit measures, the type of behavior measure adopted, and time lag between measures of habit and intention and measures of subsequent behavior. Studies adopting self-report measures of habit that include behavioral frequency items may by more likely to exhibit larger habit-behavior relations than those adopting measures that exclude frequency items. This is because frequency is a central component of habit and measures encompassing such items are likely to have close correspondence with behavioral measures which often rely on frequency measures (Labrecque & Wood, 2015). Alternatively, it could be hypothesized that similar patterns should emerge regardless of measure type based on the assumption that the different measures tap the same underlying habit construct. However, this prediction has not been systematically tested. In the current analysis we aimed to test these predictions among studies adopting self-reported habit measures. We hypothesized (H10, Table 1) that habit-behavior effects in studies using measures that included behavioral frequency items (e.g., Verplanken & Orbell, 2003) would be larger compared to those adopting measures excluding frequency items (e.g., Gardner et al., 2012; Sczesny et al., 2015).

Alongside this, studies adopting self-report measures of behavior may also lead to effect size inflation when estimating habit-behavior and intention-behavior relations. The inflated effects can be attributed to the high likelihood of shared variance arising from the common use of self-report methods in the habit, intention, and behavior measures. In addition, time lag between habit and behavior measures may also inflate habit-behavior relations. A shorter, more proximal measurement lag is likely to lead to larger habit-behavior and intention-behavior effects as it affords less opportunity for new information, or changes in behavioral circumstances, to come to light and affect habit or intention. In the current analysis we aimed to test effects of these moderators, and hypothesized larger habit-behavior (H11a; H12a, Table 1) and intention-behavior (H11b; H12b, Table 1) effects in studies adopting self-report behavior measures and a proximal measurement lag, based on the premise that the common use of self-report methods to tap these constructs and behavior, and measurement of these constructs and behavior in close proximity, will tend to inflate relations. This analysis is expected to provide salient information for researchers on the method and design of future studies on habit.

Convergence in Habit Measures

Relatively few studies on habit have adopted more than one habit measure in the same study and examined their interrelations. Those that have report substantive non-zero correlations among the measures (e.g., Friedrichsmeier et al., 2013; McCloskey & Johnson, 2019; Naab & Schnauber, 2016a; Norman & Cooper, 2011). However, to date, there has been no systematic investigation of the correlations among these measures, and currently available data do not provide definitive conclusions on the expected extent of their convergence. This represents a prominent gap in the extant literature. We proposed to test the extent of shared variance among these habit measures in the current meta-analysis by estimating the size and variability of correlations among the measures in studies including more than one habit measure. On the one hand, it would be reasonable to expect a high degree of convergence in the averaged correlations among the measures given each is purported to tap the same underlying habit construct, on the other the correlations may be suppressed because each measure encompasses different habit components. We therefore expected medium-to-large sized non-zero effects among the behavioral frequency x context stability, response frequency, and self-reported measures across studies (H13a-H13c, Table 1). We also proposed a further test of measurement convergence by conducting a meta-analytic confirmatory factor analysis of the measures, which tests the viability of the measures as indicators of a single latent habit construct. To date, such a test has not been conducted in any primary research study, and we expected that large non-zero factor loadings would provide further evidence of habit measurement convergence.

Summary and Overview

The current study reports a meta-analytic synthesis of habit research aimed at testing a series of key hypotheses relating to habit and intention effects on behavior, the theory-based conditions that determine the relative size of these effects, and the convergence in relations among habit measures. Our approach involved initially identifying studies reporting relations between measures of habit, intention, and behavior in a systematic search of the extant literature. Next, we conducted a multi-level multivariate meta-analysis of correlations among these measures extracted from the identified studies, and tested structural equation models specifying our hypothesized effects using the pooled meta-analytically-derived correlation matrices as input. Specifically, we estimated a model specifying simultaneous effects of measures of the habit and intention constructs on behavior (Figure 1, panel a, bold arrowed lines), and also estimated an identical model that included effects of past behavior (Figure 1, panel b).

Our analysis enabled us to estimate the average size and variability of the simultaneous effects of habit and intention on behavior across studies, consistent with prior research (e.g., Danner et al., 2008; Gardner et al., 2011; Verplanken et al., 1994; Verplanken & Orbell, 2003), and the extent to which habit mediated past behavior effects on future behavior (e.g., van Bree et al., 2015; Verplanken, 2006). Our analysis also enabled us to test the effects of key moderator variables by comparing habit-behavior and intention-behavior effects in models estimated in groups of studies at each level of the moderator (Figure 1, broken arrowed lines). Key conceptual moderators were the propensity of the target behavior to be formed as a habit and behavioral complexity. We expected larger habit-behavior effects relative to intention-behavior effects in studies targeting behaviors more likely to be formed as habits and those lower in complexity, corroborating like effects in prior meta-analyses (Ouellette & Wood, 1998; Webb & Sheeran, 2006). Our analysis also permitted exploration of whether the effects of these moderators held regardless of habit measure type. In addition, we were able to test whether studies targeting behaviors more likely to be rewarding (e.g., dietary behaviors, alcohol consumption) exhibited larger habit-behavior effects relative to intention-behavior effects in studies targeting those less likely to be rewarding (e.g., physical activity, transport use). We were also able to test effects of key methodological moderators on habit-behavior and intention-behavior effects, including whether or not studies adopting self-report habit measures included frequency items, type of behavior measure (self-report vs. non-self-report), and measurement lag between habit and intention measures and behavior measures. Finally, we also tested convergence in the different habit measures, particularly the size and variability of the meta-analytically derived intercorrelations among the habit measures, and the propensity of each measure to adequately indicate a latent overall habit factor in a meta-analytic confirmatory factor analysis.

Method

Search Strategy and Study Selection

We conducted independent searches of four online databases (Web of Science, Scopus, PsycARTICLES, PubMed) to locate studies reporting relations among measures of habit and/or measures of intention or behavior with a date range from 1994, the date of publication of Verplanken et al.'s (1994) response frequency measure of habit, to December 2019[1]. In addition, we conducted a cited reference search of the source articles of each habit measure (Verplanken et al., 1994; Verplanken & Orbell, 2003; Wood et al., 2005) and their derivatives (e.g., Gardner et al., 2012; LaRose & Eastin, 2004; Limayem et al., 2007). We also searched for unpublished 'fugitive literature' (Rosenthal, 1994) by contacting prominent authors in the field. The pool of articles identified in the searches was subjected to initial title and abstract screening against inclusion criteria by four trained researchers. Articles retained after screening were subjected to detailed full-text screening against inclusion criteria by the lead researcher supported by the other researchers. The screening protocol and associated training program was validated across each researcher and the lead researcher through double screening of a subset of the articles, with good agreement across researchers (average $\kappa = .842$). Inconsistencies were discussed, resolved through consensus, and the screening protocol updated accordingly. Where articles that met inclusion criteria did not report sufficient data for effect size computation, we contacted the corresponding author via email to request the relevant data. A flowchart outlining the search and inclusion and exclusion procedures is presented in the supplemental materials (Figure S1).

Inclusion Criteria

Studies were included in the current analysis if they reported quantitative relations between at least one measure of habit, and either a measure of intention or behavior[2]. Studies need not to have measured all constructs in our proposed model – our analytic techniques adopted means to handle missing correlations. Three measures of habit were considered: behavioral frequency x context stability measures (Wood et al.,

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[1]Our search also identified studies measuring relations between habit measures and constructs from typical social cognition theories (e.g., attitude, social norms, self-efficacy). Those data are not included in the current analysis. Full search strings are provided in the supplemental materials.
[2]Studies that reported only correlations between habit and social cognition constructs without a measure of intention or behavior were omitted from the current analysis.

2005); response frequency measures (Verplanken et al., 1994); and the self-reported habit index (Verplanken & Orbell, 2003) including modified versions (e.g., Gardner et al., 2012) and derivatives (e.g., LaRose & Eastin, 2004; Limayem et al., 2007). Studies reporting qualitative research, conceptual reviews, and study protocols were excluded. The study protocol was registered in advance on the PROSPERO international register of systematic reviews (see https://www.crd.york.ac.uk/PROSPERO/display_record.asp?ID=CRD42016041950).

Characteristics of Included Studies

Our search procedure identified 243 articles that met inclusion criteria. A list of included articles is provided in the supplemental materials. Some articles reported data from multiple studies or samples, which yielded additional independent samples (referred to herein as "studies") for inclusion (*k* = 44). In addition, a few articles reported using the same data set (*k* = 20). Details of articles reporting data from multiple samples and multiple studies using the same data set are outlined in the supplemental materials (Tables S1 and S2). The final sample comprised 267 independent studies with a total sample size of 107,813. Summary characteristics of studies included in the analysis are presented in the supplemental materials (Table S3)[3]. A diverse range of target behaviors was represented in the sample of studies with dietary behaviors (*k* = 70), physical activity (*k* = 68), transport use and travel-related behaviors (*k* = 37), technology use (e.g., mobile telephone use, text messaging) (*k* = 29), protection behaviors (e.g., cancer screening, sunscreen use) (*k* = 28), alcohol-related behaviors (*k* = 18), smoking tobacco and cannabis (*k* = 10), medication adherence (*k* = 8), and conservation behaviors (e.g., conserving electricity, saving water) (*k* = 7) the most common. Approximately half of the studies were conducted on student samples (*k* = 134), and a large majority had an approximately equal ratio of female and male participants (*k* = 205)[4]. The majority of studies included a follow-up measure of behavior (*k* = 136)

[3]A spreadsheet providing full details of studies including sample demographics, detailed descriptions of constructs measured and target behaviors, operationalization of the target behavior, and moderator coding is provided online: https://osf.io/zq7c8/

[4]Studies reporting samples comprising between 25% and 75% females were considered 'balanced' while samples comprising >75% females were considered 'majority female' and samples comprising <25% females considered 'majority male'. See the covariate coding section for details.

with the remainder including a measure of concurrent or past behavior only (*k* = 119), or no behavior measure (*k* = 14)[5].

Effect Size Data Extraction and Classification of Constructs

Data Extraction

We extracted available effect size and sample data for relations among measures of habit, intention, and/or behavior from the included studies. As the majority of studies in the current sample adopted correlational designs, the zero-order correlation coefficient was selected as the effect size metric for analysis. In studies where zero-order correlations among constructs of interest were not reported, we computed effect sizes from other data, where available, such as differences in means, tests of difference (e.g., *t*-tests, *F*-ratios), or *p*-values, using appropriate conversion formulas (Borenstein et al., 2009; Digby, 1983; see online supplemental materials for details). Where insufficient data were reported to compute effect sizes, or where studies reported correlations corrected for measurement error (e.g., latent variable analyses), we requested the required data or zero-order correlations from study authors.

Construct Classification

An important step in the extraction process was to ensure equivalence of measures of the habit and intention constructs and behavior across studies. Data on measures at the item level were therefore extracted and evaluated for consistency in measures across studies.

Habit measures. Consistent with inclusion criteria, studies included at least one of the three measures of habit: the behavioral frequency x context stability measure (Ouellette & Wood, 1998; Wood et al., 2005); the response frequency measure (Verplanken et al., 1994); and the self-reported habit index (Verplanken & Orbell, 2003) and derivative self-report measures (e.g., LaRose & Eastin, 2004; Limayem et al., 2007).

Studies using behavioral frequency x context stability measures of habit (*k* = 15) generally used self-reports of the frequency and context stability components with similar procedures. Such measures typically prompt respondents to indicate the frequency with which they performed the target behavior over a given

[5]Two studies (Chatzisarantis & Hagger, 2007; Thurn et al., 2014) included data for two separate behaviors, one of which included a follow-up of behavior, while the other did not and only included a concurrent or past behavior measure, so these studies are represented in both groups.

period, and rate how typical or unchanging the contextual circumstances (e.g., time, location, situation, people present, environmental conditions) were on the occasion the behavior was performed (e.g., Galla & Duckworth, 2015; Sheeran & Conner, 2019). The frequency and stability ratings are then multiplied together to produce a composite habit score. Studies also used other measures of stability, such as the variability in the date and time in which a device measuring the target behavior was used (e.g., nebulizer use in cystic fibrosis patients, Hoo et al., 2019).

Of the studies using response frequency measures (k = 19), all were in the domain of transport use with the exception of one study which targeted technology use (computer, smartphone, and television use; Naab & Schnauber, 2016b). The measure prompted respondents to report, under time pressure, the typical transport mode or technology used in a set of typical given situations, with the first response assumed to be the most accessible and, therefore, the habitual response. Responses are then coded for whether or not the responses are consistent with the target behavior.

Of the 243 studies that used a self-report habit measure, the majority used Verplanken and Orbell's (2003) self-reported habit index or equivalent versions (k = 232). Of these, most (k = 121) adopted full, extended, or truncated versions of Verplanken and Orbell's original scale, which included combinations of automaticity (e.g., "Behavior X is something I do automatically"), self-identity (e.g., "Behavior X is something that's typically 'me'"), and behavioral frequency (e.g., "Behavior X is something I do frequently") items. A substantive number of studies (k = 111), however, used adapted versions of the original scale that omitted behavioral frequency items, or smaller subsets of the items that tapped only the automaticity component of the scale, including Gardner et al.'s (2012) four-item self-reported behavioral automaticity index. A small minority of the studies (k = 7) used alternative measures comprising items closely corresponding to those of the self-reported habit index. This included studies that adopted Limayem and Hirt's (2003) independently-developed habit scale, published in the same year as Verplanken and Orbell's self-reported habit index, and studies that adopted a similar scale developed by Larose and Eastin (2004). Item content of these self-reported habit scales have been explicitly linked to those from Verplanken and Orbell's scale. Finally, studies also used bespoke measures of habit closely aligned with the Orbell and Verplanken's measure (k = 5; Boiché et al., 2016, Study 3 and Study 5; Tappe & Glanz, 2013; Tokunaga, 2016, Studies 1 and 2). Of these alternative self-report habit measures, the majority included behavioral frequency items (k = 9).

Some studies included more than one measure of habit (k = 10), most using a version of the self-reported habit index with a measure of either the behavioral frequency x context stability (k = 5; Galla & Duckworth, 2015, Studies 1 and 5; McCloskey & Johnson, 2019; Norman & Cooper, 2011; Schnauber-Stockmann & Naab, 2019) or the response frequency (k = 4; Klöckner & Blöbaum, 2010; Klöckner & Friedrichsmeier, 2011; Klöckner & Matthies, 2012; Naab & Schnauber, 2016a, b) measure. Only one study reported relations between the behavioral frequency x context stability and response frequency measures (Friedrichsmeier et al., 2013).

Intention measures. The vast majority of studies adopted standardized scaled measures of intention consistent with rational decision theory guidelines (Ajzen, 1991). We also extracted data for intention measures referred to by different terms (e.g., protection motivation), that have documented equivalence in the conceptualization and measurement based on previous classification systems (McMillan & Conner, 2003; Protogerou et al., 2018).

Behavior and past behavior measures. Of the 253 studies that included a measure of behavior or past behavior, the vast majority adopted a self-report measure of behavior (k = 238), with a small minority adopting non-self-report behavior measures (k = 19). A few studies included both self-report and non-self-report measures (k = 4; Conroy et al., 2013; Hyde et al., 2012; Maher & Conroy, 2016; Thurn et al., 2014)[6]. Some studies adopted previously developed self-report behavior measures with evidence of concurrent validity, but many adopted bespoke single-item self-report measures developed specifically for the study. Studies adopting non-self-report behavior measures typically used devices such as accelerometers or pedometers to measure physical activity, home monitors to measure electricity consumption, and electronic pill dispensers to measure medication adherence, while others used observation such as the observed amount of an alcoholic beverage poured. Measures of behavior taken concurrently with measures of the habit and intention constructs were treated as measures of past behavior, irrespective of how they were treated in the study itself.

Moderator and Covariate Coding

[6]The reported number of studies that included self-reported and non-self-reported behavior measures exceeds the total number of studies due to some studies adopting both types of measure.

We coded four conceptual moderator variables expected to influence habit-behavior and intention-behavior effects in our proposed model: type of habit measure, opportunity for the behavior to be formed as a habit, behavioral complexity, and behavior type. We also coded further methodological moderators: inclusion or exclusion of frequency items in self-report habit measures, type of behavior measure, and measurement lag. In addition, we also coded a series of study characteristics used as covariates in our analyses: age, sex, sample type (student vs. non-student; clinical vs. non-clinical), study design, and study quality. Moderator and covariate coding for each study is summarized in the study characteristics table (see Table S3, supplemental materials)[7].

Conceptual Moderator Variables

Habit measure type. We coded studies into categories according to the habit measure adopted: behavioral frequency x context stability measures (k = 15; Ouellette & Wood, 1998; Wood et al., 2005), response frequency measures (k = 19; Verplanken et al., 1994), and self-reported measures including the self-reported habit index (k = 243; Verplanken & Orbell, 2003) and variations thereof (e.g., LaRose & Eastin, 2004; Limayem & Hirt, 2003)[8].

Opportunity for habit formation and behavioral complexity. We classified studies according to the likelihood the target behavior would be developed as a habit. Accordingly, behaviors that individuals had both a greater chance of performing frequently and a high likelihood of being performed in stable conditions or contexts were classified as affording high opportunity to develop into habits (k = 185). By contrast, behaviors for which individuals had fewer chances to perform frequently, or had a high likelihood of being performed in disparate or variable contexts, were classified as having low opportunity to be formed as a habit (k = 82; Ouellette & Wood, 1998; Webb & Sheeran, 2006). In addition, we classified behaviors according to their relative complexity (McCloskey & Johnson, 2019; Wood et al., 2002). Behaviors that involved multiple sub-actions, or required considerable planning and cognitive processing to enact, were classified as higher in complexity (k = 129). By contrast, behaviors requiring fewer sub-actions, or less planning and processing, were

[7]A spreadsheet providing full details of study characteristics and moderator coding is available online: https://osf.io/zq7c8/
[8]The number of studies in each category of the habit measure type moderator variable exceeded the total number of studies due the presence of studies including multiple behavior measures.

classified as lower in complexity (*k* = 138). The coding was conducted by two independent coders with good agreement (opportunity for habit formation moderator, κ = .929; behavioral complexity moderator, κ = .780)[9]. In each case, areas of disagreement were resolved by consensus through discussion between the coders.

Behavior type. We classified studies according to the broad type of behavior targeted. We classified studies into those targeting dietary behaviors, physical activity, alcohol consumption, and transport use. We also identified studies targeting behaviors that confer a protective effect to health, consistent with previous research (McEachan et al., 2011). We were unable to estimate our model in groups of studies targeting other behaviors due to missing data in some cells or too few studies targeting that behavior. For example, groups of studies comprising studies targeting technology use, medication adherence, and conservation behaviors had empty cells in the pooled correlation matrix precluding model estimation.

Methodological Moderator Variables

Frequency items in self-report habit measures. We also coded a moderator variable that distinguished between studies adopting versions of self-report habit measures that included behavioral frequency items (*k* = 129) and those that excluded these items (*k* = 114).

Type of behavior measure. Studies were classified as those that adopted self-report and non-self-report measures of the target behavior. A substantive majority of the studies adopted self-report measures of behavior or past behavior while relatively few adopted non-self-report measures.

Measurement lag. We classified studies according to the lag in time between measures of habit and/or intention and follow-up behavior. Studies with a lag period of four weeks or fewer were assigned to a proximal moderator category (*k* = 102) and studies with a lag period of more than four weeks were assigned to the distal category (*k* = 38), based on meta-analyses of previous model tests (Hagger et al., 2018; McEachan et al., 2011). Where studies adopted designs with more than one behavioral follow up, we included data at each time point and these were treated as multiple dependent measures in our multi-level analysis, each of which was coded as proximal or distal, accordingly. Two studies adopted prospective designs in which habit/intention and follow-up behavior were measured in sequence at different time points (de Vries et al., 2014; van Bree et al., 2015). In

[9]A spreadsheet summarizing the coding for these moderators is available online along with the analysis scripts and output for the inter-rater agreement analysis: https://osf.io/zq7c8/

only one study did the measure of behavior precede the measure of habit in a two-wave design, in this case the measure of behavior was treated as a measure of past behavior (Fleig et al., 2014). Studies adopting single-wave designs without behavioral follow-up were excluded from moderator coding (k = 127).

Covariates

We also included several demographic and methodological variables as covariates in our analyses, derived from available data reported in the included studies: sample age, sample type, and study design. Specifically, studies were classified according to reported sample age (older, younger, and mixed age samples), type of participants in the sample (school or undergraduate student samples and non-student samples), and study design (cross-sectional and prospective or longitudinal designs). In addition, we assessed the quality of each included study using a 10-item study quality checklist based on the Quality of Survey Studies in Psychology (Q-SSP) appraisal checklist (Protogerou & Hagger, 2020). The application of the checklist yields a single quality score, which was included as an additional covariate in our analyses. Full descriptions of our covariate coding and study quality assessment procedures are provided in the supplemental materials.

Data Analysis

Meta-analytic structural equation models. We estimated relations among the habit, intention, and behavior/past behavior according to our proposed models using a multi-level implementation of Cheung's (2015) meta-analytic structural equation modeling procedure proposed by Wilson et al. (2016). In the analysis, a pooled matrix of correlations among model constructs was generated correcting for sampling error using a random effects method and accounting for dependency among variables using multivariate multi-level meta-analysis. The procedure also allowed the correlation coefficient in each cell of the pooled matrix to be adjusted for our covariates. Heterogeneity in the resulting pooled correlation matrix was estimated using the Q statistic, an overall test of heterogeneity, and the I^2 statistic, a relative estimate of the overall variability in the set of studies not attributable to the variance components corrected for in the analysis. A statistically significant Q value and an I^2 value exceeding 25% was considered indicative of substantive heterogeneity.

The proposed model was then fit to the pooled correlation matrix yielding point and variability estimates of the proposed relations among model constructs. Two models were estimated. The first model specified independent effects habit measures and intention on behavior (see Figure 1, panel a), and the second augmented this model to include direct effects and indirect effects, through habit measures and intention, of past behavior on behavior (see Figure 1, panel b). The analysis produces standardized parameter estimates for each model with accompanying Wald confidence intervals. Estimates were considered non-zero if the lower bound of the confidence interval did not encompass zero[10]. Missing data are imputed using full information maximum likelihood estimation. The analyses were implemented using the metafor (Viechtbauer, 2010) and metaSEM (Cheung, 2015) packages in R. Full details of the meta-analytic structural equation modeling procedures are provided in the supplemental materials.

Moderator analyses. Effects of candidate moderator variables on the proposed effects in our model excluding past behavior were tested by separately estimating the model in groups of studies at each level of the moderator. Differences in the standardized parameter estimates of the model effects across moderator groups were tested using a method based on the confidence interval about the parameter estimate difference (Schenker & Gentleman, 2001).

Correlations among habit measures and confirmatory factor analysis. We also estimated averaged correlations among the habit measures in studies that included multiple measures of habit. To do so, we applied Wilson et al.'s (2016) multi-level multivariate meta-analytic procedure to data from studies adopting at least two of the three habit measures. The analysis produced a corrected matrix of averaged correlations among the habit measures with accompanying standard error and 95% confidence interval estimates. As before, the analysis produced covariate-adjusted and unadjusted estimates, variability statistics for the level 2 and level 3 variance components, and heterogeneity estimates. We also tested the viability of a model in which each habit measure indicated an overall latent habit factor using a multi-level meta-analytic confirmatory factor analysis applied to the pooled matrix of correlations among the habit measures (Cheung, 2015; Wilson et al., 2016). The model provided standardized factor loadings and variability estimates for each habit measure on the latent factor, and the variance accounted for in each measure by the latent factor (R^2).

[10]As all models in the current analysis were 'saturated' and, therefore, could not be distinguished from the fully-free model, model fit was perfect in each case according to standard goodness-of-fit indices.

Bias assessment. Selective reporting bias, an indicator of publication bias, in the averaged correlations among the habit, intention, and behavior measures was evaluated using two sets of bias-correction methods: one set based on 'funnel' plots of study effect sizes against a precision estimate (e.g., the inverse standard error) and another based on selection models (Carter et al., 2019). Methods based on the funnel plot included Begg and Mazumdar's (1994) rank correlation test, Duval and Tweedie's (2000) 'trim and fill' analysis, and a regression based method (Egger et al., 1997; Sterne et al., 2001). A signal of potential bias was indicated by the following: a significant rank correlation test based on Kendall's tau (τ); a large number of imputed studies and the 'corrected' value for the correlation from the 'trim and fill' analysis; a significant intercept (*z*-test) from Egger et al.'s regression model; and 'corrected' correlation estimates from two modified forms of Egger et al.'s regression model: the precision effect test (PET) and the precision effect estimate with standard error (PEESE) (Stanley & Doucouliagos, 2014)[11]. Analyses based on the 'funnel' plot were implemented using the metafor package in R.

Methods based on selection models included a modified version of Hedges' (1984) original model (Vevea & Hedges, 1995), and two recent implementations: the *p*-curve (Simonsohn et al., 2014) and *p*-uniform* (van Aert & van Assen, 2018) procedures. The selection model yields a corrected estimate of the effect size and a likelihood ratio (χ^2) test of whether the selection model differs from the standard meta-analytic model, which should be non-significant in the absence of bias. The *p*-curve of a 'bias free' effect size should exhibit significant right-skewness and non-significant estimates of flatness. The *p*-uniform* provides corrected estimates of the averaged effect size and the between study variance (τ^2) and a likelihood-ratio test of publication bias. The selection model, *p*-curve, and *p*-uniform* analyses were implemented using the weightr (Coburn & Vevea, 2019), dmetar (Harrer et al., 2019), and puniform (van Aert, 2020) functions, respectively, in R.

As most bias detection techniques have not been implemented with multi-level models, we implemented the bias correction methods for each correlation after aggregating the effect sizes within studies

[11]Note that when the PET estimate is statistically significant, implying a non-zero effect, the PEESE estimate is taken, while in the absence of a statistically significant PET estimate, it is recommended that the PET estimate is used (Stanley & Doucouliagos, 2014).

using Hunter and Schmidt's (2015) formula using the MAc package (Del Re & Hoyt, 2018) in R. A full description of the bias detection analyses is provided in the supplemental materials.

Results

Multi-Level Meta-Analytic Structural Equation Models

Standardized parameter estimates and 95% confidence intervals for the effects of our proposed models excluding (Figure 1, panel a, solid arrowed lines) and including (Figure 1, panel b) past behavior are presented in Table 2. Consistent with hypotheses, we found non-zero direct effects of habit (H1) and intention (H2) on behavior in our first model with small effect sizes. In addition, we found a non-zero indirect effect of past behavior on behavior mediated by habit (H3a) in our second model. We also observed a large non-zero residual effect of past behavior on behavior independent of habit and intention (H3b). The mediation of past behavior by habit was, therefore, partial and accounted for approximately one quarter of the total effect of past behavior on behavior. Although habit accounted for a non-trivial proportion of the total effect of past behavior on behavior, a substantive proportion of the total effect is directed through intention and the direct effect. Overall, models excluding (R^2 = .178) and including (R^2 = .242) past behavior accounted for modest but non-trivial variance in behavior. It should also be noted that substantive heterogeneity was observed in each model, indicated by statistically significant Q-values and I^2 values greater than 50%. In addition, for all models, both the between (level 3) and within (level 2) variability components of the multi-level model contributed significantly to the overall variability in effect sizes across studies[12].

Moderator Analyses

We tested effects of our conceptual (opportunity for habit formation, behavioral complexity, habit measure type, opportunity for habit formation x habit measure type interaction, behavioral complexity x habit measure type interaction, behavior type) and methodological (inclusion or exclusion of frequency items, type of behavior measure, measurement lag) moderator variables on habit-behavior and intention-behavior effects in

[12]Zero-order correlations from the multivariate multi-level meta-analysis and heterogeneity statistics for all multi-level MASEM models are presented in Tables S4 and S5, respectively, in the supplemental materials.

our first model (Figure 1, panel 1, dashed arrowed lines)[13]. We did so by estimating our model separately in groups of studies at each level of the moderator. Results are summarized in Table 3.

A key hypothesis of the current study was that studies targeting behaviors with high opportunity to be formed as habits, classified as those likely to be performed frequently and in stable contexts, would have larger habit effects (H4a), and smaller intention effects (H4b), on behavior, than studies targeting behaviors with low opportunity for habit formation. Consistent with our hypothesis, we found larger habit-behavior effects in studies targeting behaviors classified as having high opportunity to be formed as habits. By contrast, the size of the intention-behavior effect did not differ.

We also tested whether habit (H5a) and intention (H5b) effects on behavior differed according to the type of habit measure adopted. While the pattern of effects was largely similar across measures, with small-sized effects of both habit and intention on behavior in each case, the effect size for habit was larger in studies adopting self-report habit measures compared to those adopting behavioral frequency x context stability measures. The effect size for intention on behavior was also larger in studies adopting the response frequency measure relative to those adopting self-report habit measures. There were no other differences.

In addition, we explored whether the habit measures differed in their sensitivity to identify the patterns of effects for habit (H6a) and intention (H6b) on behavior according to the opportunity for the target behavior to be formed as a habit. This amounted to testing the interactive effects of the opportunity to form habits and habit measure type moderator on the habit-behavior and intention-behavior effects. Consistent with our hypothesis (H6a), and corroborating our moderator analysis in the full sample of studies, we found larger habit-behavior effects in studies targeting behaviors with high opportunity to form habits relative to those targeting behaviors with low opportunity to form habits in studies using self-report habit measures. We also observed the same pattern of habit-behavior effects in studies adopting the other habit measures, but our formal test revealed that the differences were no different from zero. We also found larger intention-behavior effects for studies targeting behaviors with low opportunity to form habits relative to those targeting behaviors with high opportunity to form habits and adopted the response frequency habit measure, a pattern consistent with our

[13]Parameter estimates for multi-level meta-analytic structural equation models for each moderator unadjusted for covariates are presented in Table S6 in the supplemental materials.

hypothesis (H6b). However, a caveat to this finding is that the estimate in low opportunity group was based on a single study. In addition, this effect did not vary substantially across moderator groups in studies adopting other habit measures, and, unlike findings for the habit-behavior effects, there was no clear observed trend.

We further predicted that studies targeting behaviors classified as lower in complexity would be more likely to exhibit larger effects of habit on behavior (H7a), and smaller intention effects (H7b) compared to studies targeting behaviors classified as higher in complexity. Consistent with our hypothesis, we observed larger habit-behavior effects in studies targeting lower complexity behaviors relative to those targeting high complexity behaviors. However, we again found no differences in the intention-behavior effect across levels of complexity.

We also examined the interaction between the behavioral complexity and habit measure type moderators on the habit-behavior and intention-behavior effects. As predicted (H8a), we found larger habit-behavior effects in studies targeting behaviors low in complexity relative to those targeting behaviors high in complexity in studies using self-report habit measures. We also observed trends in the predicted direction across complexity moderator groups for the habit-behavior effect in studies adopting the behavioral frequency x context stability measure, but we did not find any non-zero differences. We could not make the comparison for the analysis of studies adopting the response frequency measure because we could not estimate our model in the higher complexity moderator group due to missing data. Finally, while we noted some differences in the intention-behavior effect across the high and low in behavioral complexity moderator groups in studies adopting different habit measure types in line with predictions (H8b), we found no differences in this effect size and no systematic trend.

We compared model effects across studies targeting specific types of behavior, and expected larger habit-behavior effects (H9a), and smaller intention-behavior effects (H9b), in behaviors likely to be more rewarding. We observed smaller habit-behavior effects in studies targeting physical activity behavior relative to the other behaviors, but only found a non-zero mean difference for the comparison with dietary behaviors. By contrast, and contrary to predictions, the intention-behavior effect was larger for studies targeting alcohol behavior relative studies targeting the other behaviors.

We also anticipated that studies adopting self-report measures of habit that included behavioral frequency items would likely share greater variance with behavior measures, and, therefore, exhibit larger habit-behavior effects than studies adopting measures that excluded frequency items (H10). Consistent with our prediction, we observed larger habit-behavior effects in studies adopting self-reported habit measures that included frequency items relative to those adopting measures that omitted these items.

Type of behavior measure, self-report or non-self-report, was also examined as a moderator with habit-behavior (H11a) and intention-behavior (H11b) effects expected to be larger in studies adopting self-report measures relative to those adopting non-self-report measures. The analysis revealed no differences for the habit-behavior effects, but we observed a larger intention-behavior effect in studies adopting self-report behavior measures relative to those targeting non-self-report measures.

Finally, we examined the effect of measurement lag between measures of habit and behavior on habit-behavior (H12a) and intention-behavior (H12b) effects. Our analysis revealed larger habit-behavior effects in studies adopting a shorter lag, but this pattern was not observed for the intention-behavior effect.

Correlations Among Habit Measures and Confirmatory Factor Analysis

We also expected non-zero intercorrelations among the three habit measures in studies that included more than one habit measure (H13a-c). Results are presented in Table 4[14]. Confirming our hypotheses, all correlations were non-zero with medium-to-large effect sizes, although we observed substantive heterogeneity in each correlation. Correlations of behavioral frequency x context stability and response frequency measures with the self-reported habit measure were larger than the intercorrelation between these two measures, with non-zero differences in the correlations. In addition, our confirmatory factor analytic model specifying the three habit measures as indicators of a latent habit factor revealed large, non-zero factor loadings of the habit measures on the latent factor with R^2 values approaching or exceeding .500 in each case (Table 4).

Bias Assessment

Results of the panel of bias assessment analyses applied to the correlations among study constructs are presented in Table 5. Results did not provide strong evidence for substantive bias in the correlations, and the

[14]Heterogeneity statistics for the multi-level meta-analysis of correlations and meta-analytic confirmatory factor analysis are presented in Table S6 in the supplemental materials.

adjusted estimates did not lead us to alter our conclusions regarding the size and pattern of the correlations. Our adoption of a 'profile' approach to bias analyses as recommended by Carter et al. (2019) aimed to provide converging evidence for the presence or absence of bias[15]. Caution, however, should be applied when interpreting these results – some of bias correction methods over- or under-estimate bias under certain conditions, such as when meta-analyzing small numbers of studies, or when heterogeneity is high, and researchers have suggested that no single method provides definitive evidence of bias (Carter et al., 2019).

Discussion

In the present review, we analysed the independent effects of habit measures and intention on behavior across multiple studies using meta-analytically synthesized data. We also tested the extent to which habit mediated past behavior-behavior effects, the effects of a series of key moderator variables on these effects consistent with habit theory, and convergence in correlations among the habit measures. Specifically, we estimated the averaged size and variability of the effects of habit and intention on behavior in the total sample of studies, and the indirect effect of past behavior on behavior mediated by habit. We also examined whether habit and intention effects varied according to the type of habit measure tested. Importantly, consistent with habit theory, we examined whether effects varied according to target behaviors with greater or less propensity to be formed as habits, or behaviors with greater or lesser complexity, and the interaction between these moderators and type of habit measure. In addition, we examined these effects in specific behaviors, and were interested in comparisons between highly rewarding and less rewarding behaviors, as the former were expected to be more likely formed as habits. We also tested effects of methodological moderators on these effects: whether or not self-reported habit measures adopted in studies included frequency items, the type of behavior measure (self-report or non-self-report), and the time lag between habit and behavior measures. Finally, we examined correlations among the habit measures and the extent to which they indicated a single latent habit factor.

Our analysis in the full sample of studies revealed non-zero small-to-medium sized averaged effects of both habit and intention on behavior, and that habit partially mediated the effect of past behavior on

[15]Data files and analysis code and output for the bias assessment analyses are available online: https://osf.io/zq7c8/

subsequent behavior, although we observed a large residual past behavior effect. Importantly, we observed larger effects of habit on behavior in studies with a high opportunity to be formed as habit and lower in complexity, but did not observe differences in intention-behavior effects. Habit-behavior effects were largely consistent across habit measure type, although the habit-behavior effect was smaller for the behavioral frequency x context stability measure relative to self-report measures. Examining the interaction of these moderators, the theory-driven pattern of effects held for self-report habit measures, but not for the other habit measures, but we did observe trends in the expected direction for each. In addition, we observed larger habit-behavior effects of in studies targeting dietary behavior, a highly rewarding behavior, relative to physical activity, but also observed larger intention-behavior effects for alcohol behavior, which we also considered highly rewarding. We also found larger habit-behavior effects in studies with a proximal measurement lag relative to those with a more distal lag, and larger intention-behavior effects in studies adopting self-report behavior measures relative to those adopting non-self-report behaviors, but no differences in habit-behavior effects. Finally, our analysis revealed large non-zero averaged correlations among the habit measures across studies, and large non-zero factor loadings and explained variance estimates for each habit measure on a latent habit factor.

Theory-Derived Effects of Habit and Intention on Behavior

The observation of non-zero independent effects of habit and intention on behavior in our model test in the overall sample of studies has value as it provides information on the typical habit-behavior and intention-behavior associations in correlational studies and, importantly, the robustness and extent of variability in these effects (Gardner et al., 2011). Our findings corroborate prior primary (e.g., Conroy et al., 2013; Friedrichsmeier et al., 2013; van Bree et al., 2015) and meta-analytic (Gardner et al., 2011) studies examining these patterns of effects. From the perspective of dual-process theories of action, however, it seems unfeasible that both habit and intention simultaneously affect behavior. Such theories predict that either habit, representing one form of automatic or non-conscious process, or intention, representing reasoned, deliberative processes, should be the pervading determinant of behavior (e.g., Hagger et al., 2017; Sheeran et al., 2013; Strack & Deutsch, 2004). It is important to recognize that the observed pattern represents an aggregated view derived from sets of studies that encompass target behaviors or contexts in which one or the other construct is the likely predominant behavioral determinant. The result is that the effect sizes for both habit and intention had sufficient strength to present in the overall analysis.

The simultaneous effects may also be due to the presence of within-sample variability in the extent to which study participants have formed the target behavior as a habit. This premise is consistent with research suggesting that habit development is a relatively drawn-out process indicated by gradual shifts from intentional to habitual control (Lally et al., 2010; Verplanken & Orbell, 2022; Wood & Neal, 2007). Furthermore, there is also evidence that the process of acquisition varies across individuals, with some developing given behaviors as habits more rapidly than others (e.g., Lally et al., 2010; Lin et al., 2016). In addition, variability in habit and intention effects on behavior within-samples may also be due to discontinuity patterns for existing habits (Verplanken & Orbell, 2022; Verplanken & Roy, 2016). For example, participants for whom the target behavior is habitual may have been experiencing disruptive conditions (e.g., moving house, chronic illness, the arrival of a child, changing jobs) at the time of the study leading to a suspension of habitual control over the behavior and a switch to intentional control before prior habits can be resumed or new ones formed. The observed independent effects of habit and intention on behavior in the overall sample of studies, therefore, may be due to the presence of individuals in the sample at different stages of habit formation, or those experiencing discontinuity patterns in their habits.

These interpretations of the observed simultaneous effects in our full sample analysis notwithstanding, these effects are not informative with respect to the conditions that determine when habit or intention is the prevailing behavioral determinant. We surmised that it should be possible to observe different patterns of habit and intention effects at the study level according to generalized conditions that, consistent with habit theory, make either habitual or intentional control over behavior more likely. Accordingly, we found larger habit-behavior effects in groups of studies classified as high in opportunity to be formed as habits and lower in complexity. These findings support primary research demonstrating these effects for habit measures (e.g., Danner et al., 2008; Verplanken, 2006), as well as meta-analytic research on past behavior as a proxy for habit (Ouellette & Wood, 1998). They also provide further cumulative data confirming this pattern of effects for habit, and illustrate that tests adopting these habit measures conform to the theory-derived prediction that habitual control over the behavior is more likely observed among behaviors where both frequency of performance and contextual cues coincide, and among behaviors that are higher in complexity.

A caveat to this finding is that we did not observe the analogous pattern of effects for the intention-behavior relationship. This is of concern given that we expected mutual change in habit-behavior and intention-behavior relations as a result of the effects of these moderators, consistent with theory, and meant that our data only provided partial verification of our hypotheses. The expected mutual changes are important if this type of analysis is to be considered analogous to habit as a moderator of the intention-behavior relationship, which has been verified in primary research (e.g., Ji & Wood, 2007) and in a systematic review (Gardner et al., 2011). A possible reason why we did not find this moderation effect may have been due to insufficient sensitivity in the coding of the moderator variable. While we applied coding procedures consistent with prior systematic reviews and meta-analyses in this area (Ouellette & Wood, 1998; Webb & Sheeran, 2006), such coding focuses on generalized tendencies for the target behavior to be formed as habits, or to be experienced as higher or lower in complexity. However, as noted previously, the presence of within-study variability in the extent to which individual participants had formed the behavior as a habit, or experienced it as complex, may have reduced the likelihood of finding differences across moderator groups at the study level. This also chimes with theory and research suggesting that formation is a gradual process with considerable inter-individual variability in speed of development (Lally et al., 2010; Lin et al., 2016), which further points to the possibility of within-study variance in the extent of habit formation, the generalized tendency for the behavior to be formed as a habit notwithstanding. This is a clear limitation of current and prior approaches to examining this pattern of effects at the study level (Ouellette & Wood, 1998; Webb & Sheeran, 2006).

We also examined whether the moderating effects of opportunity for habit formation, and behavioral complexity, on habit-behavior and intention-behavior effects varied according to habit measure type. This analysis was expected to enable an evaluation of the level of sensitivity of the habit measures in identifying the predicted effects across moderator groups. Our analysis indicated that the self-reported habit measures demonstrated the same pattern of habit-behavior effects observed for these moderators in the overall sample of studies. We also observed similar patterns of effects for the other habit measures, but none of the differences were non-zero. By contrast, although we also found the analogous effects for intention-behavior relationship in groups of studies adopting the response frequency measure, neither this effect nor any clear theory-consistent trends were observed for the other measures. Further, the finding for the response frequency measure should be considered unreliable given one moderator group relied on data from a single study. As before, the same caveat relating to within-sample variability in habit formation and experiences of the behavior as complex may have mitigated observation of study-level trends for the habit-behavior. Two further methodological caveats relating to these analyses should be noted. First, high variability in some of the estimates may have contributed to the lack of non-zero differences despite substantive observed differences in the averaged effect sizes. This was particularly the case for the habit-behavior relation in studies adopting the response frequency habit measure for the opportunity for habit formation moderator analysis, which exhibited particularly wide confidence intervals about the mean effect size. Second, comparisons for this analysis relied on effect sizes derived from small samples of studies in some of the moderator groups, which may have been a source of the relatively high variability estimates, and even precluded estimation of an effect size at one level of the complexity moderator for the response frequency measure. The current results should, therefore, be interpreted with these limitations in mind. Taken together, these findings provide signal but not unequivocal verification for the proposed patten of habit and intention effects on behavior according to habit theory.

What types of data would permit more definitive conclusions to be drawn with respect to the effects of moderators on habit-behavior and intention-behavior effects? It would be important to replicate these effects in large samples of individuals that have not yet formed a habit for the target behavior (e.g., those taking up the behavior for the first time) and those that have (e.g., those that have performed the behavior regularly and in stable contexts), and in behaviors that are formally assessed to be, or manipulated to be, higher or lower in complexity, as well as including all three habit measures alongside measures of intention and behavior. Assuming such replications were conducted in representative samples, they would provide important data on the capacity for each measure to account for variation in habit and intention effects on behavior for behaviors that have been formed as a habit and those that have not, and for behaviors higher and lower in complexity.

Another recommended approach would be to repeat the current synthesis after accumulation of more data from studies on behaviors at each level of these moderators and adopt different habit measures, particularly the behavioral frequency x context stability and response frequency measures, for which available data were particularly sparse. In addition, such future analyses would be facilitated if researchers examining effects of habit measures were to make their entire data sets available for reanalysis. Doing so would, over time, increase the available data for each cell of the correlation matrix used in the analysis. In addition, making full data available would facilitate meta-analysis of interactive effects of habit measures and intention on behavior. A prior systematic review reported trends in research for this interaction effect for dietary and physical activity behaviors (Gardner et al., 2011), but was not able to estimate the effect meta-analytically. Recent research has demonstrated that interaction effects can be meta-analyzed provided full data sets are available (e.g., Hagger et al., 2022). We therefore envisage future meta-analytic tests of the effect of the habit x intention interaction on behavior in groups of studies adopting different habit measures, which would extend and embellish current findings. As research in this area proliferates, we anticipate a time when such an analysis would be feasible.

Mediation of Past Behavior

Our analysis indicated that habit partially mediated effects of past behavior on future behavior. To the extent that current habit measures adequately capture the habit construct, this finding provides further confirmation that the effect of past behavior on future behavior can, in part, be attributed to habit, corroborating observations in prior studies (e.g., de Vries et al., 2014; Hagger et al., 2018; Phipps et al., 2020; van Bree et al., 2015). These data are informative in light of criticisms of prior research relying on past behavior as a proxy habit measure given that the former is not a psychological construct and reflects only one component of the habit construct, behavioral frequency (Ouellette & Wood, 1998; Verplanken, 2006). However, a substantive non-zero residual effect of past behavior remained. How should this effect be interpreted? To speculate, one possibility is that current habit measures do not sufficiently capture the habit construct. While the included measures encompassed multiple habit components including the contingency between performance frequency and context stability, accessibility, and experiences of automaticity, lack of thought, and awareness, they excluded other components such as reward contingency, cue salience, and goal independence. These components may be difficult to capture with these types of measure, and their lack of representation in these measures may reduce their capacity to fully account for past behavior effects.

Another interpretation is that the residual effect of past behavior is mediated by unmeasured constructs that reflect other forms of automaticity, such as implicit attitudes or beliefs. Such constructs reflect cognitive and emotional evaluations of target behavior that come to be represented alongside the behavioral response in memory through repeated co-occurrence of behavior and the evaluation such that subsequent activation of the belief, implicitly or explicitly, will lead to the concomitant activation of the behavioral response (e.g., Gawronski et al., 2016). Implicit attitudes and beliefs have been shown to predict behavior independent of explicit attitude and intention (e.g., Greenwald et al., 2009). Mediation of residual past behavior effects by implicit attitudes and beliefs may model these alternative automatic effects. However, it should be noted that although implicit beliefs for a target behavior may share variance with habits, activation of the belief is not necessary for habit enactment. It would therefore be expected that habit effects on behavior are independent of effects of implicit beliefs, as shown in research examining the independent effects of each on behavior (e.g., Conner et al., 2007).

Moderator Effects

Turning to our other moderator analyses, although we predicted larger habit-behavior effects and smaller intention-behavior effects in studies targeting behaviors that were highly rewarding and, therefore, more prone to habit formation compared to studies targeting less-rewarding behaviors, our analysis did not provide strong evidence to support this hypothesis. Sure enough, the habit-behavior effect was larger in studies targeting dietary behaviors than those targeting physical activity behaviors, which supports the prediction, but we did not find the same pattern for alcohol behaviors. Furthermore, the intention-behavior effect was larger in studies targeting alcohol, while this effect was smaller in all other behavior groups, a finding counter to hypotheses and prior studies comparing habit effects across rewarding and less rewarding behaviors. However, we should acknowledge that the current moderator classification may not have been sufficiently sensitive to capture the effect due to within-study variability the extent to which the target behavior was rewarding. For example, some behaviors within the dietary category such as snacking or eating candy are likely to be more appetitive and rewarding, and, therefore, prone to habit formation than others such as eating fruit and vegetables. However, study numbers in each separate category were insufficient to conduct a more fine-grained moderator analysis, and this should be considered a priority for future research.

A salient methodological moderator of the habit-behavior effect was whether or not studies adopting versions of self-reported habit measures included (e.g., Verplanken & Orbell, 2003) or excluded (e.g., LaRose & Eastin, 2004; Limayem & Hirt, 2003) behavioral frequency items. The conceptual basis of this moderator analysis was that habit-behavior effects estimated in studies adopting habit measures that include frequency items may be inflated due to shared method variance with measures of behavior that also tend to use frequency reports. That we found no differences in habit effects suggests that inclusion or exclusion of frequency items is relatively inconsequential to habit effects on behavior for self-reported habit measures. This is likely because there is still close alignment between self-report measures that include frequency items and those that do not but encompass other habit characteristics such as experienced automaticity and lack of awareness (Labrecque & Wood, 2015).

We also hypothesized larger habit and intention effects on behavior in studies reporting a closer lag between taking measures of habit and intention and subsequent measures behavior relative to those reporting a distal lag. Our findings supported our predictions for the habit-behavior effect, but not for the intention-behavior effect. Although this finding may seem contrary to the theoretical premise that effects of habit should be consistent over time given they tend to be stable and play an important role in behavioral persistence (e.g., Friedrichsmeier et al., 2013; Hamilton et al., 2020), it is consistent with a common method effect. The current habit measures relied on self-report behavior measures, with few exceptions (e.g., Hoo et al., 2019), and the vast majority adopted self-report measures of behavior. This measurement artifact is likely to bias effect sizes involving these variables upwards, particularly when they are administered in close proximity. More effective means to test persistence in habit effects over time would be to adopt non-self-report measures of habit and behavior (e.g., Hoo et al., 2019; Thurn et al., 2014) and study designs that track habits at multiple points in time rather than on a single occasion (Hamilton et al., 2020). Studies adopting panel designs, for example, would assist in establishing consistent habit effects on behavior over time while controlling for covariance stability, and also provide a means establish the degree of entropy in effects over time. Such data would be more effective in informing the sustainability of habit effects over time, consistent with habit theory.

Finally, intention-behavior effects were larger in studies adopting self-report measures of behavior relative to those adopting non-self-report measures, consistent with predictions, but this pattern was not observed for the habit-behavior effect. Again, a likely reason for this observed effect may be due to common method variance. Use of scaled self-report measures of behavior have been consistently shown to inflate relations with other self-report measures of psychological constructs, such as intention, although this seemed not to be the case for habit measures in the current analysis. As before, a solution would be to adopt non-self-report behavior measures to minimize this method factor and provide greater precision in effect estimates. The widespread use of self-report behavior measures in psychological research and the need alternatives has been noted elsewhere (Baumeister et al., 2007), and the onus lies on researchers to identify options for adopting non-self-report behavior measures in future habit research.

Convergence of Habit Measures

As predicted, intercorrelations among the three types of habit measure in the current study were large, indicating substantive shared variance among them. Similarly, our confirmatory factor analytic model suggested that the measures indicated a latent habit factor. This is unsurprising given the measures aim to capture the same underlying habit construct, albeit focusing on different components and adopting different approaches. These findings suggest convergence in these habit measures across the extant research and that they may be subsumed by a global habit construct. In addition, these findings also fit well with the results of our habit measure type moderator analyses, and analyses involving the interaction of this moderator with the opportunity for habit formation and behavioral complexity moderator variables. Although we only found non-zero differences in habit-behavior relations in studies adopting self-report measures, overall trends seemed to suggest general consistency in the pattern of effects for all measures. Taken together, these findings seem to signal a level of convergence in the predictive validity of these measures, and it would not be unreasonable for researchers examining habit effects to expect similar habit-behavior relations regardless of the type of habit measure used. However, drawing definitive conclusions based on these observations should be tempered in light of a few limiting caveats. Current data were derived from a small subset of studies and a narrow range of behaviors. This was particularly the case for the response frequency measure, which was represented by a small pool of studies drawn almost exclusively from studies on transport choice and, for some of the moderator groups, a single study. Similarly, no study reported data examining correlations and behavioral effects of all three habit measures in the same study. As a consequence, future studies should seek measure all these habit measures concurrently, and across multiple contexts and behaviors, and use these data to verify the patterns of effects observed here. In addition, research examining the predictive validity of a single habit factor, indicated by each habit measure, including examining its predictions under conditions of high or low likelihood of habit formation and behavioral complexity, would make a valuable addition to current knowledge.

Contribution, Limitations, and Recommendations for Future Research

The current analysis makes a number of contributions that corroborate and extend current research on habit and its measurement. Specifically, our analysis supports primary research findings identifying the unique effects of habit and intention on behavior (e.g., Gardner et al., 2011), this time in a synthesis of research across available studies. Importantly, we demonstrated patterns of habit-behavior effects consistent with theory – habitual control over behavior is more likely under conditions where the behavior is likely to form as a habit, such as when there is high opportunity for it to be performed regularly and in stable contexts, and when the behavior is lower in complexity. Uniquely, we revealed similar patterns of effects for these moderators across the different types of habit measure, although we only observed non-zero differences across moderator groups for self-reported habit measures. Our analysis also enabled us to corroborate previous findings such as the partial mediation of past behavior effects by habit (e.g., van Bree et al., 2015; Verplanken, 2006), and to also test effects of candidate moderators on habit-behavior and intention-behavior effects such as behavior type, inclusion of frequency items in self-report habit measures, behavior measure type, and measurement lag. Finally, it also allowed us to estimate the degree of shared variance among the habit measures, and the extent to which they indicate a single habit factor. However, it is also important to flag some of the limitations of the current analysis that should be considered when interpreting its findings.

A prominent limitation of our analysis is that the included data were exclusively correlational. Few of the included studies adopted experimental or randomized controlled designs, and, of those that did, none included manipulations or interventions aimed at changing habit and examining their effects on behavior. While correlational designs have value in providing evidence for relations among model constructs and proposed mechanisms, they do not permit causal inferences, or the modeling of change or dynamic associations in constructs over time. There are also documented limitations in testing mediation effects using correlational data (e.g., Fiedler et al., 2018). Causal relations among constructs in research adopting correlational designs, such as those in the current analysis, therefore, are inferred from theory alone, not the data.

Resolution lies in accumulating evidence from experimental and intervention studies in which techniques expected to promote habit development are applied, and their subsequent effects on habit and behavior observed. For example, techniques prompting context-dependent behavioral repetition (Lally et al., 2008), or pairing behavior with a salient environmental cue (Lally et al., 2010), have been shown to promote habit and behavior change. Similarly, implementation intentions, in which individuals are promoted to form plans linking a target behavior with a situational cue (Gollwitzer, 1999; Hagger et al., 2012), is another technique shown to be effective in promoting habit formation and behavior change (Adriaanse et al., 2011), and may share a similar mechanism to that by which habits are formed (Verplanken & Orbell, 2022). A synthesis of studies adopting these designs and techniques would provide the type of evidence necessary to draw more robust conclusions on causal habit-behavior effects, particularly if mediation of effects of the manipulation or intervention on behavior by habit measures can be shown. Such a synthesis will likely become feasible as the research evidence accumulates. A further means for studies to examine change in habit-behavior and intention-behavior effects would be to adopt panel designs. Research adopting such designs would enable tests of reciprocal effects among model constructs, and provide a means to model dynamic change in these effects over time. Few of the included studies in the current analysis adopted panel designs, or reported more than one follow-up behavior measure, so future studies should prioritize such design features to allow an evaluation of the long-term predictive validity of these effects.

The studies in the current analysis also relied heavily on self-report behavior measures. Our moderator analysis of behavior measure type indicated that the use of self-report and non-self-report behavior measures did not alter habit-behavior effects, but it did affect the intention-behavior relationship. Furthermore, the habit measures that were the focus of the current analysis predominantly adopted self-report methods, a practice which has attracted considerable criticism (e.g., Danner et al., 2008; Hagger et al., 2015; Labrecque & Wood, 2015; Sniehotta & Presseau, 2012). It is feasible to adopt non-self-report methods for some habit measures. For example, Hoo et al. (2019) used a version of the behavioral frequency x context stability measure that used devices and observation to generate a habit score. However, studies adopting non-self-report habit measures are rare. Researchers should be encouraged to study the theory-derived habit effects tested in the current study when adopting non-self-report measures of behavior and habit.

Conclusion

We set out to examine the unique effects of the habit construct and intention on behavior, and identify the conditions and variables that moderate these effects, through a meta-analytic synthesis of the extant research. Beyond corroborating prior research demonstrating independent effects of habit measures and intention on behavior, and partially mediating effects of past behavior on subsequent behavior, our work is informative of the conditions that determine the relative size of the habit-behavior and intention-behavior effects according to habit theory. Of particular note is the observation of larger habit-behavior effects in studies targeting behaviors with high opportunity to be formed as habits, and behaviors higher in complexity, and that this effect pattern was supported in studies adopting self-report measures with observed trends in the predicted direction for the other measures. We also observed convergence in habit measures based on intercorrelations and their indication of a higher-order habit factor. Taken together our findings lend support to theory-consistent patterns for the effect of these habit measures, and some evidence for the consistency in these effects across measures albeit with caveats relating to study methods and limitations in the available data. Our research is expected to serve as a stimulus for future studies that may further elucidate the mechanisms underpinning habit effects, such as systematic comparisons of habit effects in specific behaviors, comparisons of effects of different habit measures, and developing a broader body of research that will enable synthesis of effects of other key moderators of habit-behavior effects, such as the moderating effect of habit on the intention-behavior relationship. Current findings, therefore, make an incremental contribution to knowledge through its support of the patterns of habit effects on behavior observed in prior primary research and meta-analyses, but also extend them by exploring the conditions likely to magnify or diminish the habit-behavior and intention-behavior effects according to habit theory. We encourage future researchers to use these data as a catalyst for future studies aiming to advance habit theory and measurement.

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Table 1

Hypothesized Effects Among Habit Measures, Intentions, Past Behavior, and Behavior

Hypothesis	Effect	Moderator	Expected moderator effect
Direct and indirect effects			
H1	Habit→Behavior	–	–
H2	Intention→Behavior	–	–
H3a	PB→Habit→Behavior	–	–
H3b	PB→Behavior[a]	–	–
Moderation effects			
H4a	Habit→Behavior	Opportunity for behavior to be formed as a habit[b]	Upwards[c]
H4b	Intention→Behavior		Downwards[c]
H5a	Habit→Behavior	Habit measure type: BFCS, RF, and SRH[d]	Equivalent[e]
H5b	Intention→Behavior		Equivalent[e]
H6a	Habit→Behavior	Habit measure type x opportunity[f]	Consistent pattern[g]
H6b	Intention→Behavior		Consistent pattern[g]
H7a	Habit→Behavior	Behavioral complexity[h]	Downwards[i]
H7b	Intention→Behavior		Upwards[i]
H8a	Habit→Behavior	Habit measure type x complexity[j]	Consistent pattern[k]
H8b	Intention→Behavior		Consistent pattern[k]
H9a	Habit→Behavior	Behavior type: Rewarding vs. non-rewarding[l]	Upwards[m]
H9b	Intention→Behavior		Downwards[m]
H10	Habit→Behavior	SRH: Inclusion vs exclusion of frequency items[n]	Upwards[o]
H11a	Habit→Behavior	Type of behavior measure[p]	Upwards[q]
H11b	Intention→Behavior		Upwards[q]
H12a	Habit→Behavior	Measurement lag[r]	Downwards[s]
H12b	Intention→Behavior		Downwards[s]
Habit measure correlations			
H13a	BFCS↔RF	–	–
H13b	BFCS↔SRH	–	–
H13c	RF↔SRH	–	–

Note. [a]Residual effect of past behavior on future behavior independent of indirect effects through habit and intention. [b]Opportunity for the behavior to be formed as a habit moderator variable – habit and intention effects on behavior are compared across groups of studies targeting behaviors likely to be performed frequently and in stable contexts with groups of studies targeting behavior unlikely to be performed frequently or in stable contexts, or both. [c]The habit-behavior effect is predicted to be larger (moderated upwards) in studies targeting behaviors likely to be performed frequently and in stable contexts while the intention-behavior effect is predicted to be smaller (moderated downwards), with the opposite pattern predicted in studies targeting behaviors unlikely to be performed frequently or in stable contexts, or both. [d]Habit measure type moderator – habit and intention effects are compared across groups of studies adopting behavioral frequency x context stability (BFCS), response frequency measures of habit (RFM), and self-report measures of habit (SRH) habit measures. [e]Habit-behavior and intention-behavior effects are predicted not to vary across habit measures assuming the measures tap the same underlying habit construct. [f]Interaction of the habit measure type and opportunity for the behavior to be formed as a habit moderator variables – habit and intention effects on behavior are compared in groups of studies defined by the interaction of the two moderator variables. [g]Habit-behavior and intention-behavior effects in studies adopting behavioral frequency x context stability (BFCS), response frequency measures of habit (RFM), and self-report measures of habit (SRH) habit are expected to be consistent with the patterns observed for the opportunity for behavior to be formed as a habit moderator analysis (H4a and H4b). [h]Behavioral complexity moderator variable – habit and intention effects on behavior are compared across groups of studies targeting behaviors classified as high in complexity and groups of studies targeting behaviors classified as lower in complexity. [i]The habit-behavior effect is predicted to be smaller (moderated downwards) in studies targeting behaviors high in complexity while the intention-behavior effect is predicted to be larger (moderated downwards), with the opposite pattern predicted in studies targeting behaviors lower in complexity. [j]Interaction of the habit measure type and behavioral complexity moderator variables – habit and intention effects on behavior are compared in groups of studies defined by the interaction of the two moderator variables. [k]Habit-behavior and intention-behavior effects among studies adopting behavioral frequency x context stability (BFCS), response frequency measures of habit (RFM), and self-report measures of habit (SRH) habit are expected to be consistent with the patterns observed for the behavioral complexity moderator analysis (H7a and H7b). [l]Behavior type moderator variable – habit and intention effects on behavior are compared across groups of studies targeting behaviors classified as more likely to be rewarding (e.g., dietary behaviors, alcohol consumption) and groups of studies targeting behaviors less likely to be rewarding (e.g., physical activity, transport use). [m]The habit-behavior effect is predicted to be larger (moderated upwards) in studies targeting behaviors likely to be rewarding while the intention-behavior effect is predicted to be smaller (moderated downwards), with the opposite pattern predicted for studies targeting behaviors less likely to be rewarding. [n]Type of self-reported habit measure moderator – habit effects on behavior are compared across groups of studies adopting self-reported habit measures that include and exclude behavioral frequency items. [o]The habit-behavior effect is predicted to be larger (moderated upwards) in studies adopting habit measures adopting self-reported habit measures that include behavioral frequency items. [p]Behavior measure type moderator – habit and intention effects on behavior are compared across groups of studies adopting self-report behavior measures and groups of studies targeting non-self-report behavior measures. [q]The habit-behavior and intention-behavior effects are predicted to be larger (moderated upwards) in studies adopting self-report behavior measures behaviors while both effects are predicted to be smaller (moderated downwards) in studies adopting non-self-report behavior measures. [r]Measurement lag moderator – habit and intention effects on behavior are compared across groups of studies reporting a shorter (proximal) and longer (distal) lag between measures of habit and intention and measures of behavior. [s]The habit-behavior and intention-behavior effects are predicted to be larger (moderated upwards) in studies reporting a proximal measurement lag while both effects are predicted to be smaller (moderated downwards) in studies adopting a distal measurement lag. PB = Past behavior; BFCS = Behavioral frequency x context stability habit measure; RFM = Response frequency habit measure; SRH = Self-report habit measure.

Table 2
Standardized Parameter Estimates from the Multi-Level Meta-Analytic Structural Equation Model for the Full Sample Analyses Including and Excluding Past Behavior

Effect	Model including past behavior			Model excluding past behavior		
	β	95% CI		β	95% CI	
		LL	UL		LL	UL
Direct effects						
Past behavior→Intention	.452	.420	.484	–	–	–
Intention→Behavior	.215	.173	.258	.317	.285	.349
Habit→Behavior	.124	.082	.166	.246	.217	.276
Past behavior→Behavior	.330	.274	.387	–	–	–
Past behavior→Habit	.485	.459	.512	–	–	–
Indirect effects						
Past behavior→Habit→Behavior	.060	.040	.080	–	–	–
Past behavior→Intention→Behavior	.097	.078	.117	–	–	–
Sums of indirect effects						
Past behavior→Behavior[a]	.157	.131	.184	–	–	–
Total effect						
Past behavior→Behavior[b]	.488	.446	.529	–	–	–
Correlation						
Habit↔Intention	.184	.158	.209	.434	.407	.461

Note. All parameter estimates are non-zero with confidence intervals that do not encompass zero ($p < .001$). Model parameters are adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. [a]Sum of indirect effects of past behavior on behavior through the habit and intention constructs; [b]Total effect of past behavior on behavior. β = Standardized path coefficient; 95% CI = 95% confidence interval of parameter estimate; LL = Lower limit of 95% CI.

Table 3

Standardized Parameter Estimates for Effects of Habit and Intention on Behavior from Multi-Level Meta-Analytic Structural Equation Modeling Analysis at Each Level of Key Moderator Variables

Moderator	Effect								
	Hab→Beh			Int→Beh			Hab↔Int		
	β	95% CI		β	95% CI		β	95% CI	
		LL	UL		LL	UL		LL	UL
Opportunity to develop behavior as a habit									
Low opportunity	.180[a]	.137	.223	.308	.259	.356	.397	.358	.437
High opportunity	.257[a]	.222	.292	.298	.260	.336	.414	.381	.446
Behavioral complexity									
Low complexity	.291[a]	.249	.333	.308	.263	.354	.429	.389	.469
High complexity	.178[a]	.145	.212	.276	.240	.313	.365	.333	.396
Habit measure									
SRH	.226[a]	.197	.255	.254[a]	.222	.285	.366[a]	.338	.394
BFCS	.124[a]	.060	.189	.276	.215	.336	.257[a,b]	.215	.299
RFM	.169	.086	.252	.354[a]	.277	.432	.370[b]	.323	.417
Habit measure x opportunity[†Δ]									
High opportunity x SRH	.286[a,b]	.248	.324	.284[a,b,c]	.243	.325	.434	.398	.471
High opportunity x BFCS	.205	.107	.302	.419[a,d]	.323	.514	.450	.374	.525
High opportunity x RFM	.304	.197	.412	.226[d,e,f]	.106	.345	.395	.299	.491
Low opportunity x SRH	.198[a]	.148	.247	.317[g,h]	.260	.373	.435	.389	.480
Low opportunity x BFCS	.182[b]	.112	.252	.428[b,e,g]	.336	.519	.426	.323	.530
Low opportunity x RFM	.203	.076	.330	.505[c,f,h]	.385	.624	.470	.386	.554
Habit measure x Complexity[††‡]									
High complexity x SRH	.214[a]	.173	.256	.319[a,b]	.273	.364	.436	.399	.472
High complexity x BFCS	.187[b]	.106	.269	.364	.280	.447	.451	.364	.538
Low complexity x SRH	.314[a,b]	.270	.359	.272[c,d]	.225	.318	.437	.392	.482
Low complexity x BFCS	.205	.081	.329	.524[a,c]	.385	.663	.436	.322	.551
Low complexity x RFM	.203	.076	.330	.505[b,d]	.385	.624	.470	.386	.554
Inclusion vs. exclusion of frequency items									
SRHF	.298[a]	.250	.346	.279	.226	.333	.463[a]	.422	.503
SRHE	.224[a]	.185	.263	.288	.246	.330	.392[a]	.355	.430
Behavior type									
Dietary behaviors	.285[a]	.232	.339	.293[a]	.235	.350	.394[a]	.350	.437

Physical activity	.187[a]	.146	.228	.308[b]	.262	.354	.408[b]	.367	.449
Alcohol behaviors	.256	.184	.328	.460[a,b,c,d]	.387	.533	.601[a,b,c,d]	.546	.656
Protection behaviors	.264	.181	.347	.220[c]	.137	.304	.399[c]	.334	.464
Transport behaviors	.238	.173	.304	.290[d]	.222	.358	.356[d]	.297	.415
Behavior measure									
Self-reported behavior	.224	.195	.253	.287[a]	.256	.318	.384[a]	.357	.412
Non-self-reported behavior	.229	.164	.293	.182[a]	.097	.267	.294[a]	.224	.365
Measurement lag									
Proximal	.301[a]	.265	.336	.337	.299	.375	.526[a]	.490	.562
Distal	.170[a]	.115	.225	.323	.260	.387	.350[a]	.290	.409

Note. All parameter estimates are non-zero with confidence intervals that do not encompass zero ($p < .01$). Model parameters are adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. Parameter estimates with matching superscripted letters within moderators and columns are statistically significantly different ($p < .05$) using Schenker and Gentleman's (2001) 'standard method' based on confidence intervals about the mean difference. 95% CI = 95% confidence interval of parameter estimate; Beh = Behavior; BFCS = Behavioral frequency x context stability habit measure; Hab = Habit; Int = Intention; LL = Lower limit of 95% CI; RFM = Response frequency habit measure; SRH = Self-report habit measure; SRHF = Self-reported habit measures including behavioral frequency items; SRHE = Self-reported habit measures excluding behavioral frequency items; SRHF = Self-reported habit measures including behavioral frequency items; SRHE = Self-reported habit measures excluding behavioral frequency items; UL = Upper limit of 95% CI; β = Standardized path coefficient.

[†]Interaction effects of the opportunity to develop behavior as a habit and the habit measure type moderator variables on model effect sizes. These models are not adjusted for covariates due to small numbers of studies in a majority of the moderator groups.

[††]Interaction effects of the behavioral complexity and the habit measure type moderator variables on model effect size. These models are not adjusted for covariates due to small numbers of studies in a majority of the moderator groups.

[∆]Only one study was available the model in the low opportunity x RFM moderator group so the parameter estimates are from a single study and are not meta-analytic estimates;

[‡]Only one study was available the model in the low opportunity x RFM moderator group so the parameter estimates are from a single study and are not meta-analytic estimates, and the model in the high behavioral complexity x RFM moderator group could not be estimated due to a lack of available studies resulting in empty cells in the input correlation matrix.

Table 4

Results of Meta-Analytic Multi-Level Confirmatory Factor Analysis of Habit Measures and Multi-Level Multivariate Meta-Analysis of Correlations Among Habit Measures

Habit measure	Confirmatory factor analysis[a]			Correlations[c,d]		
	Factor loading	*SE*	R^{2b}	SRH	BFCS	RFM
SRH	.682	.136	.466	–	.676	.695
	.983	.094	.966		[.640; .713]	[.625; .765]
BFCS	.576	.115	.332	.393	–	.487
	.688	.066	.473	[.285; 501]		[.312; .661]
RFM	.677	.135	.458	.462	.390	–
	.707	.068	.500	[.339; .585]	[.124; .656]	

Note. All coefficients are non-zero with confidence intervals that do not encompass zero ($p < .001$). [a]Coefficients printed on the upper line are unadjusted for covariates, coefficients printed on the lower line are adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. [b]Variance (R^2) in habit measure accounted for by the latent habit factor. [c]Coefficients printed on upper line are zero-order correlation coefficients corrected for sampling error (r^+) and coefficients printed on lower line are 95% confidence intervals of r^+. [d]Coefficients printed below the principal diagonal are unadjusted for covariates, coefficients printed above the principal diagonal are adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. SRH = Self-report habit measure; BFCS = Behavioral frequency x context stability habit measure; RFM = Response frequency habit measure.

Table 5

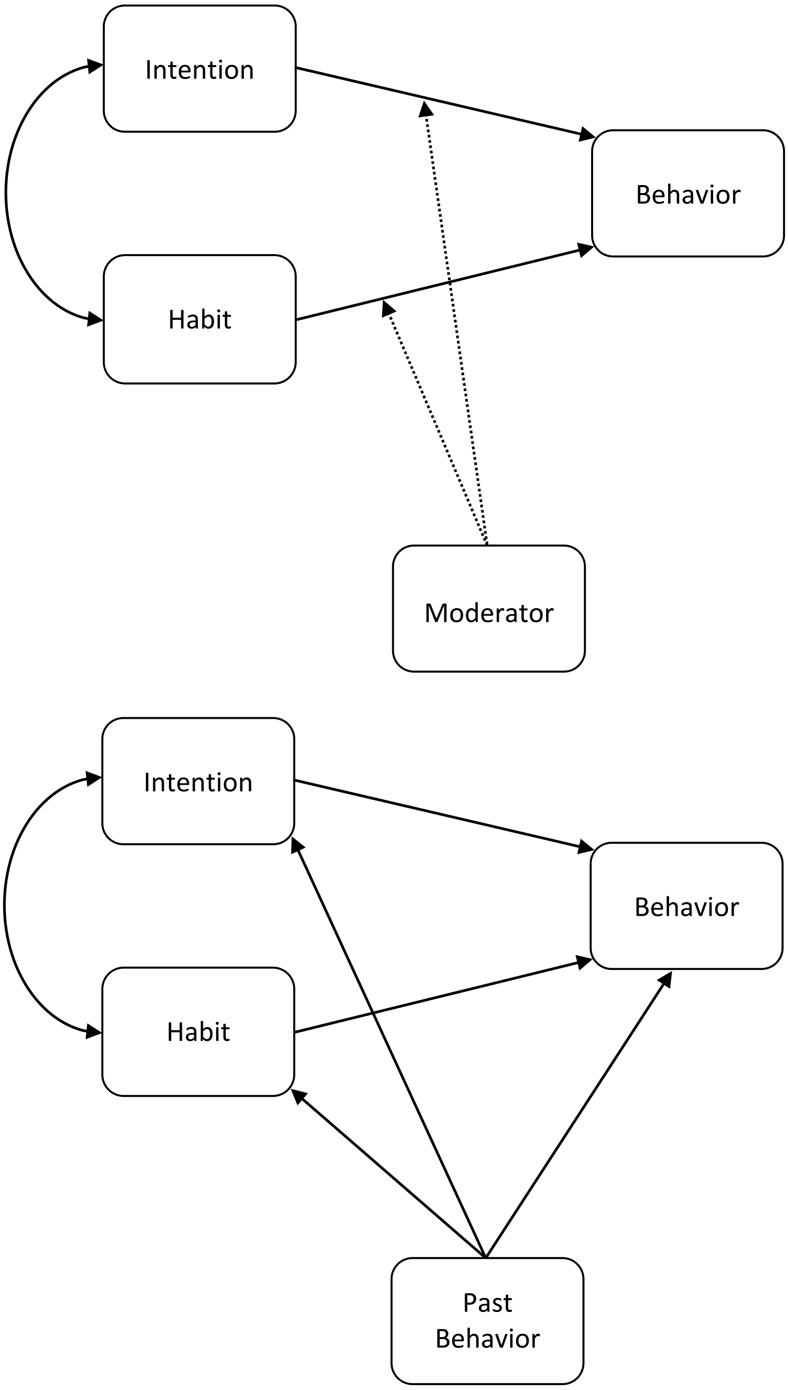
Publication Bias Statistics for Meta-Analysis of Effect Sizes Between the Habit Construct, Intention, and Behavior

Bias test	Effect size					
	Int-Beh	Int-Hab	Int-PB	Beh-Hab	Beh-PB	Hab-PB
Rank correlation test						
τ^a	.049	-.073	.050	.017	-.037	.026
Trim and fill						
r^+	.461***	.462***	.494***	.340***	.474***	.428***
95% CI (LL)	.423	.430	.449	.305	.411	.394
95% CI (UL)	.500	.494	.540	.376	.538	.462
k0	0	0	0	31	13	28
Regression tests						
z	0.070	-0.029	0.465	0.564	0.758	1.920
r^+_{PET}	.458***	.463***	.473***	.392***	.506***	.425***
r^+_{PEESE}	.464***	.468***	.496***	.405***	.536***	.469***
p-curve[b]						
z (right skewness)	-59.846***	-79.714***	-66.504***	-57.682***	-48.463***	-83.641***
z^a (Flatness)[a]	56.219	76.982	64.430	51.215	46.764	81.574
p-uniform*						
r^+	.499***	.511***	.192	.424***	.365***	.484***
95% CI (LL)	.426	.451	-.008	.365	.089	.408
95% CI (UL)	.570	.572	.383	.481	.624	.559
τ^2	.082	.098	.399	.059	.456	.150
$\chi^2_{p\text{-uni.*}}$	1.095	0.909	16.428***	2.034	5.666	6.542*
Selection model						
r^+	.464***	.468***	.454***	.391***	.547***	.464***
95% CI (LL)	.421	.430	.379	.345	.495	.419
95% CI (UL)	.509	.505	.528	.439	.599	.509
χ^2_{SM}	0.552	0.332	4.559	3.112	1.391	5.387

Note. [a]Test statistic non-significant ($p > .05$) in all cases. [b]Statistical power estimate (1-β) is >99% in all cases. τ = Kendall's τ from Begg and Mazumdar's (1994) rank correlation test; Trim and fill = Duval and Tweedie's (2000) trim and fill analysis; r^+ = Corrected meta-analytic effect size estimate from publication bias test; 95% CI = 95% confidence interval of corrected effect size estimate; LL = Lower limit of 95% CI; UL = Upper limit of 95% CI; *k*0 = Estimated number of 'missing' studies on the right-hand/left-hand side of the funnel plot from trim and fill analysis; Regression tests = Publication bias tests based on regression of study effect size on precision estimate; *z* = Funnel plot asymmetry test statistic from Sterne et al.'s (2001) regression test; PET = Stanley and Doucouliagos' (2014) precision effect test; PEESE = Stanley and Doucouliagos' (2014) precision effect estimate with standard error; *p*-curve = Simonsohn et al.'s (2014) *p*-curve analysis; *z* (right skewness) = Test statistic for *p*-curve right skewness; *z* (flatness) = Test statistic for degree of *p*-curve 'flatness'; *p*-uniform* = van Aert and van Assen's (2018) *p*-uniform* analysis; τ^2 = Estimate of 'true' variance in population from *p*-uniform* analysis; $\chi^2_{p\text{-uni.*}}$ = Likelihood ratio test of publication bias from *p*-uniform* analysis; SM = Vevea and Hedges' (2005) selection model analysis including 0.025, 0.050, 0.500, and 1.000 as *p*-value cut-points; χ^2_{SM} = Likelihood ratio test of publication bias from selection model analysis; Int = Intention; Beh = Behavior; Hab = Habit; PB = Past behavior.

*** $p < .001$ ** $p < .01$ * $p < .05$.

Figure 1. Proposed models illustrating effects of intention and habit on behavior (solid arrowed lines) with effect of a candidate moderator variable (dashed arrowed lines) on the habit-behavior and intention-behavior relations (panel a), and effects of intention, habit, and past behavior on behavior, with indirect effects of past behavior on behavior mediated by habit (panel b).



(a)

(b)

Supplemental Materials for the Article: "Effects of the Habit and Intention on Behavior: Meta-Analysis and Test of Key Moderators"

Contents

Electronic Database Search Strings

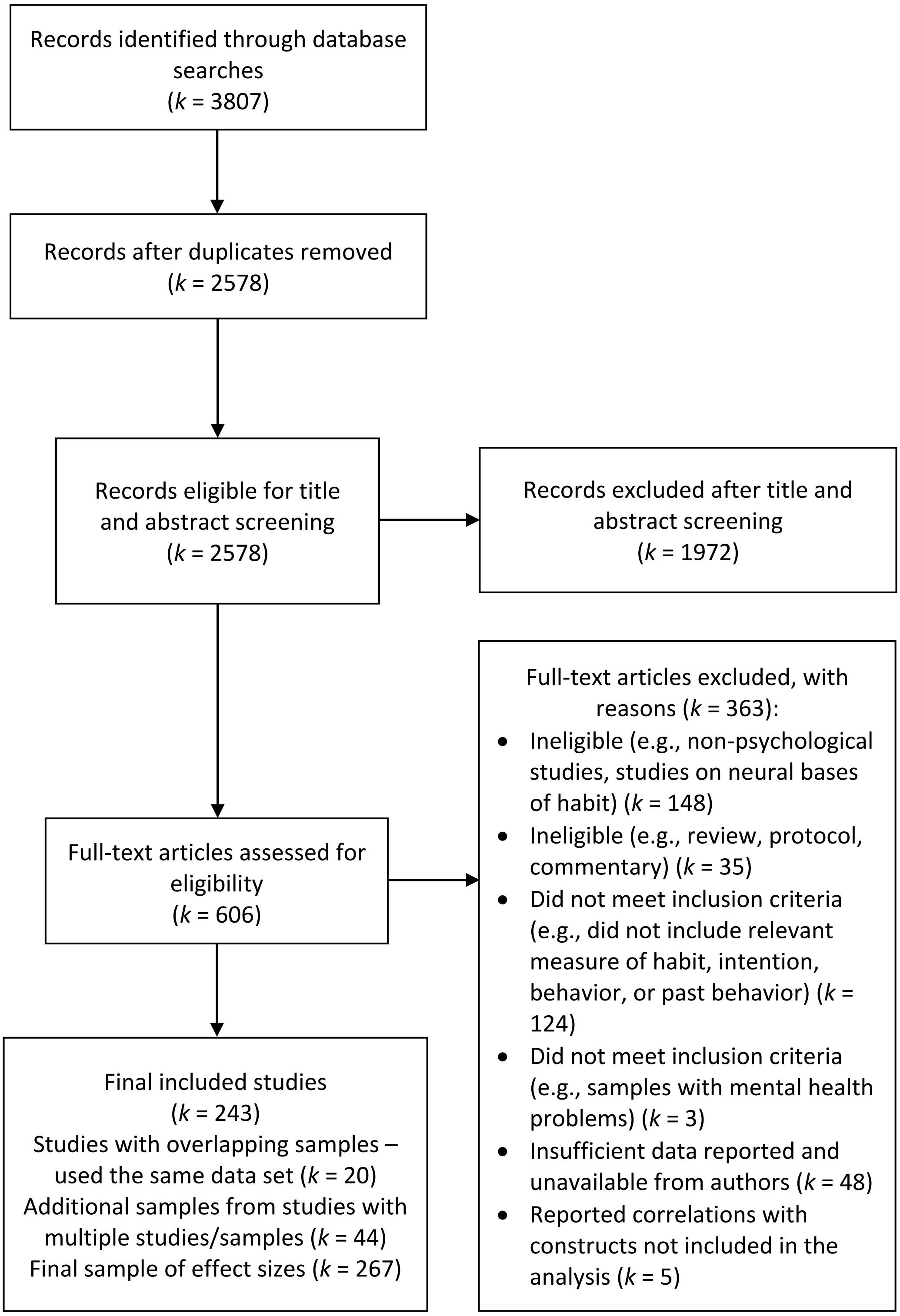
Self-report habit measures: “habit index” OR “automaticity index” AND “habit” AND “automatic*” AND “behav*”

Behavioral frequency x context stability measures: "response frequency" AND "habit" AND "behav*" AND "automatic*"

Response frequency measures: "behav*" AND "frequency" AND "context stability" AND "habit" AND "automatic*"

Figure S1

PRISMA Flow Diagram for Study Search and Inclusion Strategy



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Studies with Multiple Studies/Samples and Overlapping Samples

Table S1
Studies Included in Meta-Analysis with Multiple Studies/Samples

Reference	Number of studies/samples
Adriaanse, M. A., de Ridder, D. T. D., & Evers, C. (2011). Emotional eating: Eating when emotional or emotional about eating? *Psychology & Health, 26*, 23-39. https://doi.org/10.1080/08870440903207627	2 studies
Boiché, J., Marchant, G., Nicaise, V., & Bison, A. (2016). Development of the generic multifaceted automaticity scale (GMAS) and preliminary validation for physical activity. *Psychology of Sport and Exercise, 25*, 60-67. https://doi.org/10.1016/j.psychsport.2016.03.003	2 studies
Brown, D. J., Hagger, M. S., & Hamilton, K. (2020). The mediating role of constructs representing reasoned-action and automatic processes on the past behavior-future behavior relationship. *Social Science & Medicine, 258*, 113085. https://doi.org/10.1016/j.socscimed.2020.113085	3 samples
Brown, D. J., Charlesworth, J., Hagger, M. S., & Hamilton, K. (2020). *The role of intentional and automatic processes in two health-promoting nutrition behaviours: A test across a middle-school and university sample*. Griffith University, Brisbane, Australia. Retrieved from https://doi.org/10.31234/osf.io/zkfrc	2 samples
Chatzisarantis, N. L. D., & Hagger, M. S. (2007). Mindfulness and the intention-behavior relationship within the theory of planned behavior. *Personality and Social Psychology Bulletin, 33*, 663-676. https://doi.org/10.1177/0146167206297401	2 studies
Conner, M. T., Perugini, M., O'Gorman, R., Ayres, K., & Prestwich, A. (2007). Relations between implicit and explicit measures of attitudes and measures of behavior: Evidence of moderation by individual difference variables. *Personality and Social Psychology Bulletin, 33*(12), 1727-1740. https://doi.org/10.1177/0146167207309194	2 studies
Danner, U. N., Aarts, H., & de Vries, N. K. (2008). Habit vs. intention in the prediction of future behaviour: The role of frequency, context stability and mental accessibility of past behaviour. *British Journal of Social Psychology, 47*(2), 245-265. https://doi.org/10.1348/014466607X230876	2 studies
Diefenbacher, S., Pfattheicher, S., & Keller, J. (2020). On the role of habit in self-reported and observed hand hygiene behavior. *Applied Psychology: Health and Well-Being, 12*(1), 125-143. https://doi.org/10.1111/aphw.12176	2 studies
Elavsky, S., Doerksen, S. E., & Conroy, D. E. (2012). Identifying priorities among goals and plans: A critical psychometric reexamination of the exercise goal-setting and planning/scheduling scales. *Sport, Exercise and Performance Psychology, 1*, 158-172. https://doi.org/10.1037/a0028156	2 samples

Evans, R., Norman, P., & Webb, T. L. (2017). Using temporal self-regulation theory to understand healthy and unhealthy eating intentions and behaviour. *Appetite, 116*, 357-364. https://doi.org/10.1016/j.appet.2017.05.022	2 samples
Galla, B., M., & Duckworth, A. L. (2015). More than resisting temptation: Beneficial habits mediate the relationship between self-control and positive life outcomes. *Journal of Personality and Social Psychology, 109*, 508-525. https://doi.org/10.1037/pspp0000026	3 studies
Gardner, B. (2009). Modelling motivation and habit in stable travel mode contexts. *Transportation Research Part F: Traffic Psychology and Behaviour, 12*, 68-76. https://doi.org/10.1016/j.trf.2008.08.001	2 studies
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*, 102. https://doi.org/10.1186/1479-5868-9-102	2 samples
Garvill, J., Marell, A., & Nordlund, A. (2003). Effects of increased awareness on choice of travel mode. *Transportation, 30*(1), 63-79. https://doi.org/10.1023/a:1021286608889	2 samples
Hamilton, K., Ng, H. T. H., Zhang, C.-Q., Phipps, D. J., & Zhang, R. (2021). Social psychological predictors of sleep hygiene behaviors in Australian and Hong Kong university students. *International Journal of Behavioral Medicine, 28*(2), 214-226. https://doi.org/10.1007/s12529-020-09859-8	2 samples
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	2 studies
Kremers, S. P. J., & Brug, J. (2008). Habit strength of physical activity and sedentary behavior among children and adolescents. *Pediatric Exercise Science, 20*, 5-17. https://doi.org/10.1123/pes.20.1.5	2 studies
Lo, S. H., van Breukelen, G. J. P., Peters, G.-J. Y., & Kok, g. (2016). Commuting travel mode choice among office workers: Comparing an Extended Theory of Planned Behavior model between regions and organizational sectors. *Travel Behaviour and Society, 4*, 1-10. https://doi.org/10.1016/j.tbs.2015.11.002	2 samples
Matei, R., Thuné-Boyle, I., Hamer, M., Iliffe, S., Fox, K. R., Jefferis, B. J., & Gardner, B. (2015). Acceptability of a theory-based sedentary behaviour reduction intervention for older adults ('On Your Feet to Earn Your Seat'). *BMC Public Health, 15*, 606. https://doi.org/10.1186/s12889-015-1921-0	2 samples
Meier, A., Reinecke, L., & Meltzer, C. E. (2016). "Facebocrastination"? Predictors of using Facebook for procrastination and its effects on students' well-being. *Computers in Human Behavior, 64*, 65-76.	2 studies

https://doi.org/10.1016/j.chb.2016.06.011	
Menozzi, D., Halawany-Darson, R., Mora, C., & Giraud, G. (2015). Motives towards traceable food choice: A comparison between French and Italian consumers. *Food Control, 49*, 40-48. https://doi.org/10.1016/j.foodcont.2013.09.006	4 samples
Morean, M. E., DeMartini, K. S., Foster, D., Patock-Peckham, J., Garrison, K. A., Corlett, P. R., Krystal, J. H., Krishan-Sarin, S., & O'Malley, S. S. (2018). The self-report habit index: Assessing habitual marijuana, alcohol, e-cigarette, and cigarette use. *Drug and Alcohol Dependence, 186*, 207-214. https://doi.org/10.1016/j.drugalcdep.2018.01.014	4 studies, 7 samples
Olsen, S. O., Tudoran, A. A., Brunsø, K., & Verbeke, W. (2013). Extending the prevalent consumer loyalty modelling: The role of habit strength. *European Journal of Marketing, 47*, 303-323. https://doi.org/10.1108/03090561311285565	2 samples
Orbell, S., & Verplanken, B. (2010). The automatic component of habit in health behavior: Habit as cue-contingent automaticity. *Health Psychology, 29*, 374-383. https://doi.org/10.1037/a0019596	3 studies
Phillips, L. A., Chamberland, P. E., Hekler, E. B., Abrams, J., & Eisenberg, M. H. (2016). Intrinsic rewards predict exercise via behavioral intentions for initiators but via habit strength for maintainers. *Sport Exercise and Performance Psychology, 5*(4), 352-364. https://doi.org/10.1037/spy0000071	2 studies
Rhodes, R. E., & de Bruijn, G.-J. (2010). Automatic and motivational correlates of physical activity: Does intensity moderate the relationship? *Behavioral Medicine, 36*(2), 44-52. https://doi.org/10.1080/08964281003774901	2 samples
Sczesny, S., Moser, F., & Wood, W. (2015). Beyond sexist beliefs: How do people decide to use gender-inclusive language? Personality and *Social Psychology Bulletin, 41*(7), 943-954. https://doi.org/10.1177/0146167215585727	2 studies
Sheeran, P., & Conner, M. T. (2019). Degree of reasoned action predicts increased intentional control and reduced habitual control over health behaviors. *Social Science & Medicine, 228*, 68-74. https://doi.org/10.1016/j.socscimed.2019.03.015	2 studies
Thurn, J., Finne, E., Brandes, M., & Bucksch, J. (2014). Validation of physical activity habit strength with subjective and objective criterion measures. *Psychology of Sport and Exercise, 15*, 65-71. https://doi.org/10.1016/j.psychsport.2013.09.009	2 studies
Tokunaga, R. S. (2016). An examination of functional difficulties from internet use: Media habit and displacement theory explanations. *Human Communication Research, 42*(3), 339-370. https://doi.org/10.1111/hcre.12081	2 studies

van Bree, R. J. H., Mudde, A. N., Bolman, C., van Stralen, M. M., Peels, D. A., de Vries, H., & Lechner, L. (2016). Are action planning and physical activity mediators of the intention-habit relationship? *Psychology of Sport and Exercise, 27*, 243-251. https://doi.org/10.1016/j.psychsport.2016.09.004	2 studies
van Keulen, H. M., Otten, W., Ruiter, R. A., Fekkes, M., van Steenbergen, J., Dusseldorp, E., & Paulussen, T. W. (2013). Determinants of HPV vaccination intentions among Dutch girls and their mothers: A cross-sectional study. *BMC Public Health, 13*, 111. https://doi.org/10.1186/1471-2458-13-111	2 samples
Verplanken, B., Aarts, H., & van Knippenberg, A. (1997). Habit, information acquisition, and the process of making travel mode choices. *European Journal of Social Psychology, 27*(5), 539-560. https://doi.org/https://doi.org/10.1002/(SICI)1099-0992(199709/10)27:5<539::AID-EJSP831>3.0.CO;2-A	2 studies
Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology, 45*(3), 639-656. https://doi.org/10.1348/014466605X49122	2 studies

Table S2
Studies Included in Meta-Analysis with Overlapping Samples

Studies	Group name[a]
1. Baranowski, T., Beltran, A., Chen, T.-A., Thompson, D., O'Connor, T., Hughes, S., . . . Baranowski, J. C. (2014). Predicting use of ineffective vegetable parenting practices with the Model of Goal Directed Behavior. *Public Health Nutrition, 18*, 1028-1035. https://doi.org/10.1017/S1368980014001220 2. Diep, C. S., Beltran, A., Chen, T.-A., Thompson, D., O'Connor, T., Hughes, S., . . . Baranowski, T. (2015). Predicting use of effective vegetable parenting practices with the Model of Goal Directed Behavior. *Public Health Nutrition, 18*, 1389-1396. https://doi.org/10.1017/S1368980014002079	Baranowski et al. (2015); Diep et al. (2015)
3. de Bruijn, G.-J., & Gardner, B. (2011). Active commuting and habit strength: An interactive and discriminant analyses approach. American Journal of Health Promotion, 25, e27-e35. https://doi.org/10.4278/ajhp.090521-QUAN-170 4. de Bruijn, G.-J., & Rhodes, R. E. (2011). Exploring exercise behavior, intention and habit strength relationships. *Scandinavian Journal of Medicine & Science in Sports, 21*, 482-491. https://doi.org/10.1111/j.1600-0838.2009.01064.x 5. de Bruijn, G.-J. (2010). Understanding college students' fruit consumption. Integrating habit strength in the theory of planned behaviour. *Appetite, 54*, 16-22. https://doi.org/10.1016/j.appet.2009.08.007	de Bruijn & Gardner (2011); de Bruijn & Rhodes (2011); de Bruijn (2010)
6. de Bruijn, G.-J., Wiedemann, A. U., & Rhodes, R. E. (2014). An investigation into the relevance of action planning, theory of planned behaviour concepts, and automaticity for fruit intake action control. *British Journal of Health Psychology, 19*, 652-669. https://doi.org/10.1111/bjhp.12067 7. de Bruijn, G.-J., Rhodes, R. E., & van Osch, L. (2012). Does action planning moderate the intention-habit interaction in the exercise domain? A three-way interaction analysis investigation. *Journal of Behavioral Medicine, 35*, 509-519. https://doi.org/10.1007/s10865-011-9380-2	de Bruijn, Wiedemann et al. (2014); de Bruijn et al. (2012b)
8. De Vet, E., De Ridder, D. T. D., Stok, M., Brunso, K., Baban, A., & Gaspar, T. (2014). Assessing self-regulation strategies: development and validation of the tempest self-regulation questionnaire for eating (TESQ-E) in adolescents. *International Journal of Behavioral Nutrition and Physical Activity, 11*, 106. https://doi.org/10.1186/s12966-014-0106-z 9. De Vet, E., Stok, F. M., De Wit, J. B. F., & De Ridder, D. T. D. (2015). The habitual nature of unhealthy snacking: How powerful are habits in adolescence? *Appetite, 95*, 182-187. https://doi.org/10.1016/j.appet.2015.07.010	de Vet et al. (2014, 2015)
10. Kaushal, N., Rhodes, R. E., Meldrum, J. T., & Spence, J. C. (2017). The role of habit in different phases of exercise. *British Journal of Health Psychology, 22*(3), 429-448. https://doi.org/10.1111/bjhp.12237	Kaushal, Rhodes, Meldrum, & Spence (2017,

11. Kaushal, N., Rhodes, R. E., Meldrum, J. T., & Spence, J. C. (2018). Mediating mechanisms in a physical activity intervention: A test of habit formation. *Journal of Sport and Exercise Psychology, 40*(2), 101. https://doi.org/10.1123/jsep.2017-0307	2018)
12. Klöckner, C. A., & Friedrichsmeier, T. (2011). A multi-level approach to travel mode choice – How person characteristics and situation specific aspects determine car use in a student sample. *Transportation Research Part F: Traffic Psychology and Behaviour, 14*(4), 261-277. https://doi.org/10.1016/j.trf.2011.01.006 13. Klöckner, C. A., & Matthies, E. (2012). Two pieces of the same puzzle? Script-based car choice habits between the influence of socialization and past behavior. *Journal of Applied Social Psychology, 42*(4), 793-821. https://doi.org/10.1111/j.1559-1816.2011.00817.x[b]	Klöckner & Friedrichsmeier (2011); Klöckner & Matthies (2012) Study 1
14. Klöckner, C. A., Matthies, E., & Hunecke, M. (2003). Problems of operationalizing habits and integrating habits in normative decision-making models. *Journal of Applied Social Psychology, 33*(2), 396-417. https://doi.org/10.1111/j.1559-1816.2003.tb01902.x 15. Klöckner, C. A., & Matthies, E. (2004). How habits interfere with norm-directed behaviour: A normative decision-making model for travel mode choice. *Journal of Environmental Psychology, 24*(3), 319-327. https://doi.org/10.1016/j.jenvp.2004.08.004	Klöckner et al. (2003); Klöckner & Matthies (2004)
16. Klöckner, C. A., & Matthies, E. (2009). Structural modeling of car use on the way to the university in different settings: Interplay of norms, habits, situational restraints, and perceived behavioral control. *Journal of Applied Social Psychology, 39*(8), 1807-1834. https://doi.org/10.1111/j.1559-1816.2009.00505.x 17. Klöckner, C. A., & Matthies, E. (2012). Two pieces of the same puzzle? Script-based car choice habits between the influence of socialization and past behavior. *Journal of Applied Social Psychology, 42*(4), 793-821. https://doi.org/10.1111/j.1559-1816.2011.00817.x[b]	Klöckner & Matthies (2009); Klöckner & Matthies (2012) Study 2
18. Kovač, V. B., Rise, J., & Moan, I. S. (2010). From intentions to quit to the actual quitting process: The case of smoking behavior in light of the TPB. *Journal of Applied Biobehavioral Research, 14*, 181-197. https://doi.org/10.1111/j.1751-9861.2010.00048.x 19. Kovač, V. B., & Rise, J. (2008). The role of explicit cognition in addiction: Development of the mental representations scale. Addiction Research & Theory, 16, 595-606. https://doi.org/10.1080/16066350801896263	Kovač et al. (2010); Kovač & Rise (2008)
20. Kremers, S. P. J., & Brug, J. (2008). Habit strength of physical activity and sedentary behavior among children and adolescents. *Pediatric Exercise Science, 20*, 5-17. https://doi.org/10.1123/pes.20.1.5 21. Kremers, S. P. J., Dijkman, M. A. M., de Meij, J. S. B., Jurg, M. E., & Brug, J. (2008). Awareness and habit: important factors in physical activity in children. *Health Education, 108*, 475-488. https://doi.org/10.1108/09654280810910881	Kremers & Brug (2008) Study 1; Kremers et al. (2008)

22. Menozzi, D., & Mora, C. (2012). Fruit consumption determinants among young adults in Italy: A case study. *LWT - Food Science and Technology, 49*, 298-304. https://doi.org/10.1016/j.lwt.2012.03.028 23. Menozzi, D., & Mora, C. (2012). Fruit consumption determinants among young adults in Italy. In V. L. Rush (Ed.), *Planned behavior: Theory, applications and perspectives* (pp. 55-72). New York, NY: Novascience.	Menozzi & Mora (2012, 2014)
24. Panter, J. R., Griffin, S., Jones, A., Mackett, R., & Ogilvie, D. (2011). Correlates of time spent walking and cycling to and from work: Baseline results from the Commuting and Health in Cambridge study. *International Journal of Behavioral Nutrition and Physical Activity, 8*, 124. https://doi.org/10.1186/1479-5868-8-124 25. Panter, J. R., Desousa, C., & Ogilvie, D. (2013). Incorporating walking or cycling into car journeys to and from work: The role of individual, workplace and environmental characteristics. *Preventive Medicine, 56*, 211-217. https://doi.org/10.1016/j.ypmed.2013.01.014 26. Panter, J. R., Griffin, S., Dalton, A. M., & Ogilvie, D. (2013). Patterns and predictors of changes in active commuting over 12months. *Preventive Medicine, 57*, 776-784. https://doi.org/10.1016/j.ypmed.2013.07.020	Panter at al. (2011b); Panter et al. (2013a); Panter et al. (2013b)
27. Presseau, J., Johnston, M., Heponiemi, T., Elovainio, M., Francis, J. J., Eccles, M. P., . . . Sniehotta, F. F. (2014a). Reflective and automatic processes in health care professional behaviour: A dual process model tested across multiple behaviours. *Annals of Behavioral Medicine, 48*, 347-358. https://doi.org/10.1007/s12160-014-9609-8 28. Presseau, J., Johnston, M., Francis, J. J., Hrisos, S., Stamp, E., Steen, N., . . . Eccles, M. P. (2014b). Theory-based predictors of multiple clinician behaviors in the management of diabetes. *Journal of Behavioral Medicine, 37*, 607-620. https://doi.org/10.1007/s10865-013-9513-x 29. Eccles, M. P., Hrisos, S., Francis, J. J., Stamp, E., Johnston, M., Hawthorne, G., . . . Hunter, M. (2011). Instrument development, data collection, and characteristics of practices, staff, and measures in the Improving Quality of Care in Diabetes (iQuaD) Study. *Implementation Science, 6*, 61. https://doi.org/10.1186/1748-5908-6-61	Presseau et al. (2014a); Presseau et al. (2014b); Eccles et al. (2011)
30. Şimşekoğlu, Ö., Nordfjærn, T., & Rundmo, T. (2015). The role of attitudes, transport priorities, and car use habit for travel mode use and intentions to use public transportation in an urban Norwegian public. *Transport Policy, 42*, 113-120. https://doi.org/10.1016/j.tranpol.2015.05.019 31. Nordfjærn, T., Lind, H. B., Şimşekoğlu, Ö., Jørgensen, S. H., Lund, I. O., & Rundmo, T. (2015). Habitual, safety and security factors related to mode use on two types of travels among urban Norwegians. *Safety Science, 76*, 151-159. https://doi.org/10.1016/j.ssci.2015.03.001 32. Nordfjærn, T., Şimşekoğlu, Ö., & Rundmo, T. (2014). The role of deliberate planning, car habit and resistance to change in public transportation mode use. *Transportation Research Part F: Traffic Psychology and Behaviour, 27*, Part A, 90-98. https://doi.org/10.1016/j.trf.2014.09.010	Şimşekoğlu et al. (2015); Nordfjærn et al. (2015); Nordfjærn et al. (2014)

33. Thomas, E. L., & Upton, D. (2014a). Psychometric properties of the physical activity questionnaire for older children (PAQ-C) in the UK. *Psychology of Sport and Exercise, 15*, 280-287. https://doi.org/10.1016/j.psychsport.2014.02.002 34. Thomas, E., & Upton, D. (2014b). Automatic and motivational predictors of children's physical activity: Integrating habit, the environment, and the theory of planned behavior. *Journal of Physical Activity & Health, 11*, 999-1005. https://doi.org/10.1123/jpah.2012-0095	Thomas & Upton (2014a, 2014b)
35. van Bree, R. J. H., van Stralen, M. M., Bolman, C., Mudde, A. N., de Vries, H., & Lechner, L. (2013). Habit as moderator of the intention–physical activity relationship in older adults: a longitudinal study. *Psychology & Health, 28*, 514-532. https://doi.org/10.1080/08870446.2012.749476 36. 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	van Bree et al. (2015); van Bree et al. (2013)

Note. [a]Summary name used to refer to the group of overlapping studies in the study characteristics table presented in Section D of these supplemental materials; [b]Study repeated in two groups.

Table S3

Summary Characteristics and Covariate and Moderator Coding of Studies Included in the Meta-Analysis

Study	*N*	Sample age *M* (SD), range[a]	Sex[b]	W-S meas.[c]	Covariates						Moderator variables						
					Age[d]	Sex[e]	Sample type		Study design[h]	Study quality[i]	Habit meas. type[j]		Behav. type[m]	Behav. meas.[n]	Oppr. for habit[o]	Behav. complex.[p]	Meas. lag[q]
							Student status[f]	Clin. status[g]			Cand. meas.[k]	Incl. or excl. freq.[l]					
Aarts (1996) - Matrix A	30	NA	NA	MB	M	NA	NS	NC	CS	6	RFM	NA	TR	SR	HIGH	LC	NA
Aarts (1996) - Matrix B	30	NA	NA	MB	M	NA	NS	NC	CS	6	RFM	NA	TR	SR	LOW	LC	NA
Adriaanse et al. (2010) Study 1	51	20.76 (2.18), 17-27	100	NA	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Adriaanse, de Ridder, & Evers (2011) Study 1	151	20.53 (2.06)	100	NA	Y	F	ST	NC	PR	4	SRH	SRHF	DB	SR	HIGH	LC	PRX
Adriaanse, de Ridder, & Evers (2011) Study 2	235	21.22 (2.54)	100	NA	Y	F	ST	NC	PR	4	SRH	SRHF	DB	SR	HIGH	LC	PRX
Adriaanse, van Oosten et al. (2011) Study 4	61	21.00 (1.88)	100	NA	Y	F	ST	NC	PR	3	SRH	SRHF	DB	SR	HIGH	LC	PRX
Adriaanse et al. (2014) - Sample 1 - Matrix A	87	22.11 (3.31)	92	MB	Y	F	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Adriaanse et al. (2014) - Sample 1 - Matrix B	87	22.11 (3.31)	92	MB	Y	F	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Adriaanse et al. (2016)	1292	51.23 (16.78), 16-89	65	NA	M	B	NS	NC	PR	2	SRH	SRHF	DB	SR	HIGH	LC	PRX
Albery et al. (2015)	46	24.7 (7.9), 18-53	82.61	NA	Y	F	ST	NC	CS	4	SRH	SRHF	AL	NSR	LOW	LC	PRX
Albani et al. (2018) - Matrix A	335	9-15	49	MB	Y	B	NS	NC	CS	9	SRH	SRHF	DB	SR	HIGH	LC	NA
Albani et al. (2018) - Matrix B	335	9-15	49	MB	Y	B	NS	NC	CS	9	SRH	SRHF	DB	SR	HIGH	LC	NA
Allom & Mullan (2012)	209	20.06 (4.39)	75.1	NA	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Allom et al. (2013) Study 2	178	19.41 (4.00), 17-44	74	NA	Y	B	ST	NC	PR	7	SRH	SRHF	PR	SR	HIGH	HC	PRX
Allom et al. (2016)	101	19.60 (4.88), 17-54	81.4	NA	Y	F	ST	NC	PR	7	SRH	SRHF	PA	SR	LOW	HC	PRX
Allom et al. (2018)	594	31.06 (10.66) 18-73	62	NA	Y	B	ST	NC	CS	6	SRH	SRHE	MISC	SR	LOW	LC	NA
Arnautovska, Fleig, O'Callaghan, & Hamilton (2017)	165	73.80 (SD =7.0), 65-95	66.7	NA	O	B	NS	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	PRX
Aunger et al. (2010) – Matrix A	802	≤ 18 = 1%, 18-24 = 30%, 25-30 = 29%, 41-35 = 23%, 36-40 = 8%, >41 = 6%, no response = 2%	100	MB	M	F	NS	NC	CS	9	SRH	SRHF	PR	NSR	HIGH	LC	NA

Aunger et al. (2010) – Matrix B	802	≤ 18 = 1%, 18-24 = 30%, 25-30 = 29%, 41-35 = 23%, 36-40 = 8%, >41 = 6%, no response = 2%	100	MB	M	F	NS	NC	CS	9	SRH	SRHF	PR	NSR	HIGH	LC	NA
Bai et al. (2014)	901	18-35 = 21.80%, 36-55 = 54.50%, >55 = 23.70%	54.7	NA	M	B	NS	NC	CS	7	SRH	SRHF	PR	SR	HIGH	LC	NA
Baranowski et al. (2015); Diep et al. (2015)	307	NA	89.3	NA	M	F	NS	NC	CS	8	SRH	SRHF	DB	SR	HIGH	HC	NA
Bartle, Mullan, Novoradovskaya, Allom, & Hasking (2019)	166	NA	71	NA	Y	B	NA	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Bayer & Campbell (2012)	441	18.43 (2.49)	62	NA	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	HC	NA
Bayer et al. (2016) Study 1	925	28.84 (12.38)	57.3	NA	Y	B	NA	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Black, Mullen, & Sharpe (2017) - Matrix A	149	25.89 (9.99)	65.8	MT, MB	Y	B	ST	NC	PR	3	SRH	SRHF	AL	SR	HIGH	LC	PRX
Black, Mullen, & Sharpe (2017) - Matrix B	149	25.89 (9.99)	65.8	MT, MB	Y	B	ST	NC	PR	3	SRH	SRHF	AL	SR	HIGH	LC	PRX
Black, Mullen, & Sharpe (2017) - Matrix C	149	25.89 (9.99)	65.8	MT, MB	Y	B	ST	NC	PR	3	SRH	SRHF	AL	SR	HIGH	LC	PRX
Black, Mullen, & Sharpe (2017) - Matrix D	149	25.89 (9.99)	65.8	MT, MB	Y	B	ST	NC	PR	3	SRH	SRHF	AL	SR	HIGH	LC	PRX
Black, Mullen, & Sharpe (2017) - Matrix E	149	25.89 (9.99)	65.8	MT, MB	Y	B	ST	NC	PR	3	SRH	SRHF	AL	SR	HIGH	LC	PRX
Black, Mullen, & Sharpe (2017) - Matrix F	149	25.89 (9.99)	65.8	MT, MB	Y	B	ST	NC	PR	3	SRH	SRHF	AL	SR	HIGH	LC	PRX
Bolman et al. (2011)	139	31.5 (5.6)	70.5	NA	Y	B	NS	CL	CS	6	SRH	SRHF	MA	SR	HIGH	LC	NA
Bonne et al. (2007)	576	≤ 25 = 37.3%, 26-35 = 35.9%, 36-45 = 16.5%, 46-55 = 7.7%, >55 = 2.6%	46.9	NA	Y	B	NS	NC	CS	5	SRH	SRHE	DB	NA	LOW	HC	NA
Bordarie (2019)	391	21.79 (2.37), 18-30	78	NA	Y	F	ST	NC	CS	8	SRH	SRHE	MISC	NA	HIGH	LC	NA
Brijs et al. (2011)	210	21.21 (1.80)	44.29	NA	Y	B	ST	NC	CS	5	SRH	SRHE	PR	SR	HIGH	LC	NA
Boiché et al. (2016) Study 3 - Matrix A	117	30.9 (12.1)	53.24	MHM	Y	B	NA	NC	PR	4	SRH	SRHE	PA	SR	HIGH	HC	PRX
Boiché et al. (2016) Study 3 - Matrix B	117	30.9 (12.1)	53.24	MHM	Y	B	NA	NC	PR	4	SRH	SRHE	PA	SR	HIGH	HC	PRX
Boiché et al. (2016) Study 3 - Matrix C	117	30.9 (12.1)	53.24	MHM	Y	B	NA	NC	PR	4	SRH	SRHE	PA	SR	HIGH	HC	PRX
Boiché et al. (2016) Study 3 - Matrix D	117	30.9 (12.1)	53.24	MHM	Y	B	NA	NC	PR	4	SRH	SRHE	PA	SR	HIGH	HC	PRX

Boiché et al. (2016) Study 5	125	19.70 (SD=1.23), 18-24	22%	NA	Y	B	ST	NC	PR	4	SRH	SRHE	PA	SR	HIGH	HC	PRX
Briskin, Bogg, & Haddad (2018) - Matrix A	634	21.19 (4.77)	68.1	MB, MC	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Briskin, Bogg, & Haddad (2018) - Matrix B	634	21.19 (4.77)	68.1	MB, MC	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Briskin, Bogg, & Haddad (2018) - Matrix C	634	21.19 (4.77)	68.1	MB, MC	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Briskin, Bogg, & Haddad (2018) - Matrix D	634	21.19 (4.77)	68.1	MB, MC	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Briskin, Bogg, & Haddad (2018) - Matrix E	634	21.19 (4.77)	68.1	MB, MC	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Briskin, Bogg, & Haddad (2018) - Matrix F	634	21.19 (4.77)	68.1	MB, MC	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Brown, Hagger, & Hamilton (2020) - Sample 1, Binge Drinking	177	23.47 (7.87)	78.5	NA	Y	F	ST	NC	PR	9	SRH	SRHE	AL	SR	HIGH	LC	DSL
Brown, Hagger, & Hamilton (2020) - Sample 2, Flossing	177	32.50 (12.58)	79.7	NA	Y	F	NS	NC	PR	9	SRH	SRHE	PR	SR	HIGH	LC	DSL
Brown, Hagger, & Hamilton (2020) - Sample 3, Sun Safety	100	35.12 (5.07)	88	NA	Y	F	NS	NC	PR	9	SRH	SRHE	PR	SR	HIGH	HC	DSL
Brown, Charlesworth, Hagger, Hamilton (2020) Sample 1 - Matrix A	191	23.05 (7.52)	46	MBM	Y	B	NS	NC	PR	9	SRH	SRHE	DB	SR	HIGH	LC	PRX
Brown, Charlesworth, Hagger, Hamilton (2021) Sample 1 - Matrix B	191	23.05 (7.52)	46	MBM	Y	B	ST	NC	PR	9	SRH	SRHE	DB	SR	HIGH	HC	PRX
Brown, Charlesworth, Hagger, Hamilton (2021) Sample 2 - Matrix A	223	19.33 (1.96)	75	MBM	Y	F	NS	NC	PR	9	SRH	SRHE	DB	SR	HIGH	LC	PRX
Brown, Charlesworth, Hagger, Hamilton (2021) Sample 2 - Matrix B	223	19.33 (1.96)	75	MBM	Y	F	ST	NC	PR	9	SRH	SRHE	DB	SR	HIGH	HC	PRX
Brug et al. (2006)	644	37.5 (13.9), 15-78	50.9	NA	Y	B	NS	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Canova & Manganelli (2016)	162	19.85 (1.4), 18-27	73.3	NA	Y	B	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Carr et al. (2016)	325	45.81 (14.35), 18-80	66.5	NA	O	B	NS	NC	CS	4	SRH	SRHE	TU	NA	HIGH	LC	NA
Chang & Gibson (2015) - Matrix A	706	24 (7.28)	73	MBM	Y	B	ST	NC	CS	4	SRH	SRHE	MISC	SR	LOW	HC	NA
Chang & Gibson (2015) - Matrix B	706	24 (7.28)	73	MBM	Y	B	ST	NC	CS	4	SRH	SRHE	MISC	SR	LOW	HC	NA
Chatzisarantis & Hagger (2007) Study 1	226	19.23 (1.08)	51.33	NA	Y	B	ST	NC	PR	4	SRH	SRHF	PA	SR	LOW	HC	DSL

Chatzisarantis & Hagger (2007) Study 2 - Matrix A	292	19.48 (1.23)	51.37	MBM	Y	B	ST	NC	PR	4	SRH	SRHF	PA	SR	LOW	HC	DSL
Chatzisarantis & Hagger (2007) Study 2 - Matrix B	292	19.48 (1.23)	51.37	MBM	Y	B	ST	NC	PR	4	SRH	SRHF	AL	SR	HIGH	LC	NA
Chiu & Huang (2010)	657	<20 = 7.8%, 20-29 = 70.3%, 30-39 = 18.0%, >40 = 4.0%	44.7	NA	Y	B	NS	NC	CS	3	SRH	SRHE	TU	NA	HIGH	LC	NA
Chiu et al. (2012)	454	<20 = 6.2%, 20-24 = 32.6%, 25-29 = 27.7%, >30 = 33.5%	54.4	NA	Y	B	NS	NC	CS	6	SRH	SRHE	TU	NA	HIGH	LC	NA
Conner et al. (2007) Study 1	123	23.7 (5.8)	61.69	NA	Y	B	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Conner et al. (2007) Study 2 - Matrix A	104	23.2 (4.90)	81.	MBM	Y	F	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Conner et al. (2007) Study 2 - Matrix B	104	23.2 (4.90)	81	MBM	Y	F	ST	NC	PR	5	SRH	SRHF	DB	NSR	LOW	LC	PRX
Conroy et al. (2013) - Matrix A	128	21.3 (1.1)	58.59	MBM	Y	B	ST	NC	PR	5	SRH	SRHE	PA	NSR	LOW	LC	PRX
Conroy et al. (2013) - Matrix B	128	21.3 (1.1)	58.59	MBM	Y	B	ST	NC	PR	5	SRH	SRHE	PA	SR	LOW	HC	PRX
Cortoos et al. (2012)	195	31 (8.9), 25-64	37	NA	Y	B	NS	NC	CS	6	SRH	SRHF	MISC	SR	HIGH	HC	NA
Danner et al. (2008) Study 1 - Matrix A	139	20.23 (1.44), 19-28	79	MB	Y	F	ST	NC	PR	3	BFCS	NA	DB	SR	HIGH	LC	PRX
Danner et al. (2008) Study 1 - Matrix B	139	20.23 (1.44), 19-28	79	MB	Y	F	ST	NC	PR	3	BFCS	NA	DB	SR	HIGH	LC	PRX
Danner et al. (2008) Study 1 - Matrix C	139	20.23 (1.44), 19-28	79	MB	Y	F	ST	NC	PR	3	BFCS	NA	DB	SR	HIGH	LC	PRX
Danner et al. (2008) Study 2	80	NA	76	NA	Y	F	ST	NC	PR	3	BFCS	NA	TR	SR	HIGH	HC	DSL
de Bruijn & Gardner (2011); de Bruijn & Rhodes (2011); de Bruijn (2010)	538	21.19 (2.57)	71.56	NA	Y	B	ST	NC	CS	5	SRH	SRHF	TR	SR	HIGH	HC	NA
de Bruijn & van den Putte (2009) - Matrix A	312	14.62 (1.26)	65.3	MBM	Y	B	ST	NC	CS	4	SRH	SRHE	DB	SR	LOW	HC	NA
de Bruijn & van den Putte (2009) - Matrix B	312	14.62 (1.26)	65.3	MBM	Y	B	ST	NC	CS	4	SRH	SRHE	PA	SR	HIGH	LC	NA
de Bruijn (2011)	330	21.49 (3.04)	74.5	NA	Y	B	ST	NC	PR	5	SRH	SRHE	PA	SR	LOW	HC	PRX
de Bruijn et al. (2007)	521	34.5 (10.87)	53.7	NA	Y	B	NS	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	DSL
de Bruijn et al. (2008)	764	44.3 (10.20)	34.7	NA	O	B	NS	NC	CS	5	SRH	SRHF	DB	SR	HIGH	LC	NA
de Bruijn et al. (2009)	317	42.09 (0.87)	53.3	NA	O	B	NS	NC	CS	5	SRH	SRHF	TR	SR	HIGH	HC	NA
de Bruijn et al. (2012a)	52	23.21 (4.18)	55.8	NA	Y	B	ST	NC	CS	4	SRH	SRHF	DB	SR	HIGH	LC	NA
de Bruijn, Wiedemann et al. (2014); de Bruijn et al. (2012b)	413	21.4 (2.9)	70.8	NA	Y	B	ST	NC	PR	7	SRH	SRHE	DB	SR	HIGH	LC	PRX
de Bruijn, Gardner et al. (2014)	406	21.5 (2.59)	73.0	NA	Y	B	ST	NC	PR	6	SRH	SRHE	PA	SR	LOW	HC	PRX
de Vet et al. (2014, 2015)	11392	13.21 (2.00)	50.5	NA	Y	B	ST	NC	CS	6	SRH	SRHF	DB	SR	HIGH	LC	NA
de Vries et al. (2014)	434	47 (15.98)	46.7	NA	O	B	NS	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	DSL
Deliens et al. (2015) - Matrix A	425	21.2 (2.1)	59.8	MBM	Y	B	ST	NC	CS	6	SRH	SRHF	DB	SR	HIGH	LC	NA

Deliens et al. (2015) - Matrix B	425	21.2 (2.1)	59.8	MBM	Y	B	ST	NC	CS	6	SRH	SRHF	DB	SR	HIGH	LC	NA
Diefenbacher, Pfattheicher, & Keller (2019) Study 1	123	25.2 (5.2), 18-52	79	NA	Y	F	NS	NC	CS	8	SRH	SRHE	PR	SR	HIGH	LC	NA
Diefenbacher, Pfattheicher, & Keller (2019) Study 2	71	NA	72	NA	M	B	NS	NC	CS	8	SRH	SRHE	PR	NSR	LOW	LC	NA
Di Gangi & Wasko (2016)	408	18-27	49.26	NA	Y	B	ST	NC	CS	6	SRH	SRHF	TU	SR	HIGH	LC	NA
Dombrowski & Luszczynska (2009)	155	14.63 (0.76)	72	NA	Y	B	ST	NC	PR	6	SRH	SRHE	PA	SR	LOW	HC	PRX
Donald et al. (2014) - Matrix A	827	40.6, 17 to 78	49	NA	O	B	NS	NC	CS	5	RFM	NA	TR	SR	HIGH	LC	NA
Donald et al. (2014) - Matrix B	827	40.6, 17 to 78	49	NA	O	B	NS	NC	CS	5	RFM	NA	TR	SR	HIGH	HC	NA
Durand et al. (2018)	204	69.86 (10.69), 32-96	42.2	NA	O	B	NS	CL	CS	7	SRH	SRHE	MA	SR	HIGH	HC	NA
Elavsky et al. (2012) Sample 2	211	20.3 (1.4)	46.45	NA	Y	B	ST	NC	CS	6	SRH	SRHF	PA	SR	LOW	HC	NA
Elavsky et al. (2012) Sample 3	224	20.7 (1.9)	50	NA	Y	B	ST	NC	PR	6	SRH	SRHF	PA	SR	LOW	HC	PRX
Eriksson et al. (2008)	38	53	46	NA	O	B	NS	NC	PR	7	SRH	SRHF	TR	SR	LOW	HC	PRX
Evans, Norman, & Webb (2017) Sample 1	133	23.92 (7.4)	68.4	NA	Y	B	ST	NC	PR	9	SRH	SRHE	DB	SR	HIGH	LC	PRX
Evans, Norman, & Webb (2017) Sample 2	125	23.10 (5.18)	72.8	NA	Y	B	ST	NC	PR	9	SRH	SRHE	DB	SR	HIGH	LC	PRX
Fernández, Monge-Rojas, Lopez, & Cardemil (2019) - Sample 1 - Matrix A	555	17.52 (3.53)	54.6	MBM	Y	B	ST	NC	CS	7	SRH	SRHF	PA	SR	LOW	HC	NA
Fernández, Monge-Rojas, Lopez, & Cardemil (2019) - Sample 1 - Matrix B	555	17.52 (3.53)	54.6	MBM	Y	B	ST	NC	CS	7	SRH	SRHF	DB	SR	HIGH	LC	NA
Fleig et al. (2011)	342	48.65 (10.31), 19-76	57.4	NA	O	B	NS	CL	PR	7	SRH	SRHE	PA	SR	LOW	HC	DSL
Fleig et al. (2013a)	231	24.88 (6.4), 17-46	83.3	NA	Y	F	ST	NC	CS	5	SRH	SRHE	PA	SR	LOW	HC	NA
Fleig et al. (2013b)	435	49.5 (9.4), 19-76	54.1	NA	O	B	NS	CL	PR	7	SRH	SRHE	PA	SR	LOW	HC	DSL
Fleig et al. (2014)	470	50.46 (9.07), 19-77	59	NA	O	B	NS	CL	PR	6	SRH	SRHF	PA	SR	LOW	HC	NA
Forward (2014)	414	48 (14.48), 19-81	58	NA	O	B	NS	NC	CS	4	SRH	SRHE	TR	SR	LOW	HC	NA
Friedrichsmeier et al. (2013) - Matrix A	1048	< 21, n = 13.6%; 26 to 30, n = 21.0%; > 30, n = 5.8%, 21 to 25	53.4	MHM	Y	B	ST	NC	PR	5	BFCS	NA	TR	SR	HIGH	LC	DSL
Friedrichsmeier et al. (2013) - Matrix B	1048	< 21, n = 13.6%; 26 to 30, n = 21.0%; > 30, n = 5.8%, 21 to 25	53.4	MHM	Y	B	ST	NC	PR	5	RFM	NA	TR	SR	HIGH	LC	DSL
Fujii & Kitamura (2003) - Matrix	43	21.5, 1.57	6.98	MBM	Y	B	ST	NC	CS	4	RFM	NA	TR	SR	HIGH	HC	NA

A																	
Fujii & Kitamura (2003) - Matrix B	43	21.5, 1.57	6.98	MBM	Y	B	ST	NC	CS	4	RFM	NA	TR	SR	HIGH	LC	NA
Galla & Duckworth (2015) Study 1 - Matrix A	500	33.13 (12.3), 18-75	44	MBM, MHM	Y	B	NS	NC	CS	4	SRH	SRHE	PA	SR	LOW	HC	NA
Galla & Duckworth (2015) Study 1 - Matrix B	500	33.13 (12.3), 18-75	44	MBM, MHM	Y	B	NS	NC	CS	4	BFCS	NA	PA	SR	LOW	HC	NA
Galla & Duckworth (2015) Study 1 - Matrix C	500	33.13 (12.3), 18-75	44	MBM, MHM	Y	B	NS	NC	CS	4	BFCS	NA	PA	SR	HIGH	LC	NA
Galla & Duckworth (2015) Study 2 - Matrix A	142	20.91 (1.41), 18-26	50	MBM, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	MISC	SR	HIGH	HC	NA
Galla & Duckworth (2015) Study 2 - Matrix B	142	20.91 (1.41), 18-26	50	MBM, MHM	Y	B	ST	NC	CS	4	BFCS	NA	MISC	SR	HIGH	HC	NA
Galla & Duckworth (2015) Study 5 - Matrix A	109	16.76 (1.48), 13.75-20.25	62	MBM, MHM	Y	B	NS	NC	CS	4	SRH	SRHE	MISC	SR	HIGH	HC	NA
Galla & Duckworth (2015) Study 5 - Matrix B	109	16.76 (1.48), 13.75-20.25	62	MBM, MHM	Y	B	NS	NC	CS	4	BFCS	NA	MISC	SR	HIGH	HC	NA
Gardner & Lally (2013)	192	22.05 (3.59)	76.04	NA	Y	F	NA	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	PRX
Gardner (2009) Study 1	107	27.53 (9.69), 18-55	69.16	NA	Y	B	NA	NC	PR	5	SRH	SRHE	TR	SR	HIGH	LC	PRX
Gardner (2009) Study 2	102	21.58 (3.47)	75.49	NA	Y	F	NA	NC	PR	5	SRH	SRHE	TR	SR	HIGH	HC	PRX
Gardner et al. (2015)	239	41.8 (11.30)	77.8	NA	O	F	NS	NC	PR	6	SRH	SRHE	DB	SR	HIGH	HC	PRX
Gardner et al. (2012a) Dataset 3	188	31.29 (11.96), 18-76	NA	NA	Y	NA	ST	NC	PR	4	SRH	SRHE	DB	SR	HIGH	LC	PRX
Gardner et al. (2012a) Dataset 4	204	NA	73.53	NA	M	B	NS	NC	PR	4	SRH	SRHE	AL	SR	HIGH	LC	NA
Gardner et al. (2012b)	128	20.99 (2.59)	75	NA	Y	F	ST	NC	PR	6	SRH	SRHF	AL	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix A	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix B	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix C	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix D	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	PR	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix E	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	PR	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix F	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	PR	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix G	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix H	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Gardner, Phillips, & Judah (2016) - Sample 1 - Matrix I	229	20 (2), 18-36	84	MBM, MHM	Y	F	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Garvill et al. (2003) - Experimental group	66	NA	51	NA	M	B	NS	NC	CS	5	RFM	NA	TR	SR	HIGH	LC	PRX

Garvill et al. (2003) - Control group	54	NA	51	NA	M	B	NS	NC	CS	5	RFM	NA	TR	SR	HIGH	LC	PRX
Grove et al. (2014)	124	21.9 (4.8)	79.84	NA	Y	F	ST	NC	CS	4	SRH	SRHE	PA	SR	LOW	HC	NA
Guénette et al. (2016)	901	63.24 (9.12)	41.40	NA	O	B	NS	CL	CS	8	SRH	SRHE	MA	SR	HIGH	HC	NA
Haggar, Whitmarsh, & Skippon (2019)	250	18-21 years = 65.6%; 22-30 years = 29.6%	74	NA	Y	B	ST	NC	CS	6	SRH	SRHE	TR	SR	HIGH	HC	NA
Hagger et al. (2019) - Sample 5	235	13.67 (9.15), 12-16	54.7	NA	Y	B	ST	NC	PR	9	SRH	SRHE	PA	SR	LOW	HC	PRX
Hamilton et al. 2017	273	34.80 (5.21), 21-51	87.18	NA	Y	F	NS	NC	PR	8	SRH	SRHF	PR	SR	HIGH	HC	PRX
Hamilton, Cornish, Kirkpatrick, Kroon, & Schwarzer (2018)	281	37.05 (4.69)	70	NA	Y	B	NS	NC	PR	8	SRH	SRHE	PR	SR	HIGH	HC	PRX
Hamilton, Peden, Smith, & Hagger (2019) - Sample 1 - Matrix A	509	34.67 (8.76)	75	MBM	Y	F	NS	NC	CS	7	SRH	SRHE	MISC	SR	LOW	HC	NA
Hamilton, Peden, Smith, & Hagger (2019) - Sample 1 - Matrix B	509	34.67 (8.76)	75	MBM	Y	F	NS	NC	CS	7	SRH	SRHE	MISC	SR	LOW	HC	NA
Hamilton, Ng, Zhang, Phipps, & Zhang (2021) - Sample 1 - Australian Sample	201	22.82 (8.89)	82	NA	Y	F	ST	NC	PR	8	SRH	SRHE	MISC	SR	HIGH	HC	PRX
Hamilton, Ng, Zhang, Phipps, & Zhang (2021) - Sample 2 - Hong Kong Sample	161	20.47 (7.80)	52	NA	Y	B	ST	NC	PR	8	SRH	SRHE	MISC	SR	HIGH	HC	PRX
Hamilton, Phipps, Loxton, Modeki, & Hagger (2020, unpublished)	105	19.82 (2.36), 17-31	68	NA	Y	B	ST	NC	PR	8	SRH	SRHE	AL	SR	HIGH	LC	DSL
Hassandra et al. (2013)	40	45.6	70	NA	O	B	NS	CL	CS	6	SRH	SRHF	SM	SR	HIGH	LC	NA
Hinsz et al. (2007)	174	40.98, 17-85	37	NA	O	B	NS	NC	CS	4	SRH	SRHF	DB	SR	HIGH	HC	NA
Honkanen et al. (2005)	1579	48, 15-98	53	NA	O	B	NS	NC	CS	4	SRH	SRHF	DB	SR	LOW	LC	NA
Hoo, Wildman, Campbell, Walters, & Gardner (2019)	123	25	42.3	NA	Y	B	NS	CL	PR	8	BFCS	NA	MISC	NSR	HIGH	LC	DSL
Hyde et al. (2012) - Matrix A	33	22	57.58	MBM	Y	B	ST	NC	PR	5	SRH	SRHF	PA	NSR	LOW	HC	PRX
Hyde et al. (2012) - Matrix B	33	22	57.58	MBM	Y	B	ST	NC	PR	5	SRH	SRHF	PA	SR	LOW	HC	PRX
Jansson et al. (2010)	1832	51.77 (14.27)	33.6	NA	Y	B	NS	NC	CS	5	SRH	SRHF	TR	NA	HIGH	HC	NA
Jenkins & Tapper (2014)	45	20.67 (2.76)	71.0	NA	Y	B	ST	NC	PR	7	SRH	SRHF	DB	NSR	LOW	LC	PRX
Ji & Wood (2007) Study 1 - Matrix A	117	NA	51	MB	Y	B	ST	NC	CS	4	BFCS	NA	DB	SR	HIGH	LC	PRX
Ji & Wood (2007) Study 1 - Matrix B	117	NA	51	MB	Y	B	ST	NC	CS	4	BFCS	NA	MISC	SR	HIGH	LC	PRX
Ji & Wood (2007) Study 1 - Matrix C	117	NA	51	MB	Y	B	ST	NC	CS	4	BFCS	NA	TR	SR	HIGH	HC	PRX
Ji & Wood (2007) Study 2 - Matrix A	116	NA	49	MB	Y	B	ST	NC	CS	4	BFCS	NA	DB	SR	HIGH	LC	PRX
Ji & Wood (2007) Study 2 -	116	NA	49	MB	Y	B	ST	NC	CS	4	BFCS	NA	MISC	SR	HIGH	LC	PRX

Matrix B																	
Ji & Wood (2007) Study 2 - Matrix C	116	NA	49	MB	Y	B	ST	NC	CS	4	BFCS	NA	TR	SR	HIGH	HC	PRX
Judah et al. (2013)	50	TB group = 26.6 (7.06); After TB group = 28.1 (9.12)	68.0		Y	B	NA	NC	CS	6	SRH	SRHE	PR	SR	HIGH	LC	NA
Judah (2015) - Matrix A	118	35.7 (11.8)	55.08	MBM	Y	B	NS	NC	PR	9	SRH	SRHE	PR	SR	HIGH	LC	DSL
Judah (2015) - Matrix B	118	35.7 (11.8)	55.08	MBM	Y	B	NS	NC	PR	9	SRH	SRHE	PR	SR	HIGH	LC	DSL
Kassavou et al. (2014)	114	20-89	77.19	NA	M	F	NS	NC	PR	4	SRH	SRHF	PA	SR	HIGH	HC	DSL
Kaushal & Rhodes (2015)	111	47.7 (13.5)	70	NA	Y	B	NS	NC	PR	9	SRH	SRHE	PA	SR	LOW	HC	DSL
Kaushal (2016, unpublished)	147	37.85 (17.80), 18-80	59.2	NA	M	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Kaushal, Rhodes, Meldrum, & Spence (2017, 2018)	181	43.4 (15.3), 18-65	64	NA	O	B	NS	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	DSL
Khang et al. (2014)	603	48 (15.53)	48.2	NA	O	B	NS	NC	CS	5	SRH	SRHF	TU	SR	HIGH	LC	NA
Kliemann et al. (2016) - Matrix A	923	20-29 = 155 (17%), 30-39 = 167 (18%), 40-49 = 231 (25%), 50-59 = 238 (26%), 60-65 = 132 (14%)	58	MBM	M	B	NS	NC	CS	9	SRH	SRHF	DB	SR	HIGH	LC	NA
Kliemann et al. (2016) - Matrix B	923	20-29 = 155 (17%), 30-39 = 167 (18%), 40-49 = 231 (25%), 50-59 = 238 (26%), 60-65 = 132 (14%)	58	MBM	M	B	NS	NC	CS	9	SRH	SRHF	DB	SR	HIGH	LC	NA
Kliemann et al. (2016) - Matrix C	923	20-29 = 155 (17%), 30-39 = 167 (18%), 40-49 = 231 (25%), 50-59 = 238 (26%), 60-65 = 132 (14%)	58	MBM	M	B	NS	NC	CS	9	SRH	SRHF	DB	SR	HIGH	LC	NA
Klöckner & Blöbaum (2010) - Matrix A	389	24.7, 19-52	60.7	MHM	Y	B	ST	NC	PR	4	SRH	SRHE	TR	SR	HIGH	LC	PRX
Klöckner & Blöbaum (2010) - Matrix B	389	24.7, 19-52	60.7	MHM	Y	B	ST	NC	PR	4	RFM	NA	TR	SR	HIGH	LC	PRX
Klöckner & Friedrichsmeier (2011); Klöckner & Matthies (2012) Study 1 - Matrix A	3735	<21 = 497, 21-25 = 2323, 26-30 = 741, 31-35 = 103, 36-45 = 57, 46-65 = 13	55.15	MHM	Y	B	ST	NC	PR	4	SRH	SRHE	TR	SR	HIGH	HC	PRX

Klöckner & Friedrichsmeier (2011); Klöckner & Matthies (2012) Study 1 - Matrix B	3755	<21 = 497, 21-25 = 2323, 26-30 = 741, 31-35 = 103, 36-45 = 57, 46-65 = 13	55.1	MHM	Y	B	ST	NC	PR	5	RFM	NA	TR	SR	HIGH	LC	PRX
Klöckner & Oppedal (2011)	690	19-22 = 75%, 23-26 = 17%, >= 27 = 6.5%	43		Y	B	ST	NC	CS	4	SRH	SRHF	CO	SR	HIGH	HC	NA
Klöckner et al. (2003); Klöckner & Matthies (2004) - Matrix A	160	38.5, 19-78	36.9	MHM	M	B	NS	NC	PR	5	RFM	NA	TR	SR	HIGH	HC	PRX
Klöckner et al. (2003); Klöckner & Matthies (2004) - Matrix B	156	38.5, 19-78	36.9	MHM	M	B	NS	NC	PR	5	RFM	NA	TR	SR	HIGH	HC	PRX
Klöckner et al. (2003); Klöckner & Matthies (2004) - Matrix C	158	38.5, 19-78	36.91	MHM	M	B	NS	NC	PR	5	RFM	NA	TR	SR	HIGH	HC	PRX
Klöckner et al. (2003); Klöckner & Matthies (2004) - Matrix D	160	38.5, 19-78	36.9	MHM	M	B	NS	NC	PR	5	RFM	NA	TR	SR	HIGH	HC	PRX
Klöckner et al. (2003); Klöckner & Matthies (2004) - Matrix E	132	38.5, 19-78	36.9	MHM	M	B	NS	NC	PR	5	RFM	NA	TR	SR	HIGH	HC	PRX
Klöckner & Matthies (2009); Klöckner & Matthies (2012) Study 2	430	First-year students = 137; Older students = 177	61.63	NA	Y	B	ST	NC	CS	4	RFM	NA	TR	SR	HIGH	LC	PRX
Kothe et al. (2015)	228	45.2(14.3), 18-80	89.5	NA	O	F	NS	CL	CS	6	SRH	SRHF	DB	SR	HIGH	HC	NA
Kovač et al. (2010); Kovač & Rise (2008)	939	35.8 (11.7), 15-74	49	NA	Y	B	NS	NC	PR	5	SRH	SRHF	SM	SR	HIGH	HC	DSL
Köykka et al. (2019)	234	Intervention group = 46.4 (10.0), Control = 48.5 (9.7)	Intervention group: 79.2; Control group: 73.9	NA	O	F	NS	NC	CS	8	SRH	SRHE	PA	NA	HIGH	LC	NA
Kremers et al. (2007) - Matrix A	383	13.5 (0.6), 12-16	55.1	MBM	Y	B	NS	NC	CS	5	SRH	SRHF	MISC	SR	HIGH	LC	NA
Kremers et al. (2007) - Matrix B	383	13.5 (0.6), 12-16	55.1	MBM	Y	B	NS	NC	CS	5	SRH	SRHF	DB	SR	HIGH	LC	NA
Kremers & Brug (2008) Study 1; Kremers et al. (2008)	419	10.3 (1.0), 8-13	50.4	NA	Y	B	ST	NC	CS	4	SRH	SRHF	PA	SR	LOW	HC	NA
Kremers & Brug (2008) Study 2	383	13.5 (0.6), 12-17	55.4	NA	Y	B	NS	NC	CS	4	SRH	SRHF	TU	SR	HIGH	LC	NA
LaRose & Eastin (2004)	172	NA	41	NA	M	B	NS	NC	CS	5	SRH	SRHF	TU	SR	HIGH	LC	NA
Lawler et al. (2012)	234	23.2 (3.8)	59.1	NA	Y	B	NS	NC	CS	6	SRH	SRHF	PR	SR	HIGH	HC	NA
Lee et al. (2014)	165	< 19 = 86, 19-	48.48	NA	Y	B	ST	NC	PR	5	SRH	SRHE	TU	SR	HIGH	LC	DSL

		22 = 46, 22-24 = 22, >24 = 11															
Lemieux & Godin (2009)	130	24.0 (4.9)	71.54	NA	Y	B	ST	NC	PR	7	SRH	SRHF	TR	SR	HIGH	HC	PRX
Lheureux et al. (2016) - Matrix A	642	34.3 (14.2)	53	MBM	Y	B	NS	NC	CS	6	SRH	SRHF	PR	SR	HIGH	LC	NA
Lheureux et al. (2016) - Matrix B	642	34.3 (14.2)	53	MBM	Y	B	NS	NC	CS	6	SRH	SRHF	PR	SR	LOW	LC	NA
Lheureux & Auzoult (2016) - Matrix A	543	34.15 (14.07), 18-75	53	MBM	Y	B	NS	NC	CS	5	SRH	SRHF	PR	SR	LOW	LC	NA
Lheureux & Auzoult (2016) - Matrix B	543	34.15 (14.07), 18-75	53	MBM	Y	B	NS	NC	CS	5	SRH	SRHF	AL	SR	LOW	LC	NA
Lindgren et al. (2015)	506	18.57 (0.69)	56.92	NA	Y	B	ST	NC	CS	7	SRH	SRHE	AL	SR	HIGH	LC	NA
Limayem & Cheung (2011)	100	20	55	NA	Y	B	ST	NC	PR	7	SRH	SRHF	TU	SR	HIGH	HC	PRX
Limayem et al. (2007)	227	NA	56.83	NA	Y	B	ST	NC	PR	6	SRH	SRHF	TU	SR	HIGH	LC	PRX
Limayem & Hirt (2003)	60	NA	46	NA	Y	B	ST	NC	PR	7	SRH	SRHF	TU	SR	HIGH	HC	PRX
Lin (2016)	510	20-24 = 65.9%, 25-31 = 28%, 32-38 = 5.3%, 39-45 = 0.2%, >= 46 = 0.6%	60.8	NA	Y	B	ST	NC	PR	5	SRH	SRHF	TU	SR	HIGH	HC	PRX
Lo et al. (2016) Sample 1 - Matrix A	385	NA	54	MBM	M	B	NS	NC	CS	6	SRH	SRHE	TR	SR	HIGH	LC	NA
Lo et al. (2016) Sample 1 - Matrix B	385	NA	54	MBM	M	B	NS	NC	CS	6	SRH	SRHE	PA	SR	HIGH	HC	NA
Lo et al. (2016) Sample 1 - Matrix C	385	NA	54	MBM	M	B	NS	NC	CS	6	SRH	SRHE	TR	SR	HIGH	HC	NA
Lo et al. (2016) Sample 2 - Matrix A	453	NA	54	MBM	M	B	NS	NC	CS	6	SRH	SRHE	TR	SR	HIGH	LC	NA
Lo et al. (2016) Sample 2 - Matrix B	453	NA	54	MBM	M	B	NS	NC	CS	6	SRH	SRHE	PA	SR	HIGH	HC	NA
Lo et al. (2016) Sample 2 - Matrix C	453	NA	54	MBM	M	B	NS	NC	CS	6	SRH	SRHE	TR	SR	HIGH	HC	NA
Loibl et al. (2011)	128	38 (10.8), 19-77	87	NA	Y	F	NS	NC	CS	5	SRH	SRHF	MISC	SR	HIGH	HC	NA
Loy et al. (2016)	28	22.64 (5.68)	75	NA	Y	B	ST	NC	PR	6	SRH	SRHF	DB	SR	HIGH	LC	PRX
Maher & Conroy (2015) - Matrix A	195	20.4	45.64	MBM	Y	B	ST	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	PRX
Maher & Conroy (2015) - Matrix B	195	20.4	45.64	MBM	Y	B	ST	NC	PR	7	SRH	SRHE	PA	SR	HIGH	LC	PRX
Maher & Conroy (2016) - Matrix A	100	74.2 (8.2)	67.0	MBM	O	B	NS	NC	PR	9	SRH	SRHE	PA	NSR	HIGH	LC	PRX
Maher & Conroy (2016) - Matrix B	100	74.2 (8.2)	67.0	MBM	O	B	NS	NC	PR	9	SRH	SRHE	PA	SR	HIGH	LC	PRX
Matei et al. (2015) Sample 1 - Matrix A	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 1 - Matrix B	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 1 -	16	66.91 (4.18)	12.5	MT,	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL

Matrix C				MB													
Matei et al. (2015) Sample 1 - Matrix D	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 1 - Matrix E	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 1 - Matrix F	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 1 - Matrix G	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	HIGH	LC	DSL
Matei et al. (2015) Sample 1 - Matrix H	16	66.91 (4.18)	12.5	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	HIGH	LC	DSL
Matei et al. (2015) Sample 2 - Matrix A	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 2 - Matrix B	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 2 - Matrix C	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 2 - Matrix D	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	LOW	HC	DSL
Matei et al. (2015) Sample 2 - Matrix E	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	HIGH	HC	DSL
Matei et al. (2015) Sample 2 - Matrix F	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	HIGH	HC	DSL
Matei et al. (2015) Sample 2 - Matrix G	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	HIGH	LC	DSL
Matei et al. (2015) Sample 2 - Matrix H	23	66.42 (4.81)	66.6	MT, MB	O	B	NS	NC	PR	8	SRH	SRHE	PA	SR	HIGH	LC	DSL
Matthies et al. (2006)	295	NA	NA	NA	M	NA	NS	NC	CS	4	RFM	NA	TR	SR	HIGH	HC	DSL
McCloskey & Johnson (2019) - Matrix A	374	NA	42.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PA	SR	LOW	HC	NA
McCloskey & Johnson (2019) - Matrix B	453	NA	43.4	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PR	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix C	143	NA	45.5	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	SM	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix D	257	NA	48.6	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	MA	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix E	153	NA	39.9	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix F	139	NA	41.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix G	97	NA	46.4	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	AL	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix H	153	NA	39.9	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix I	119	NA	42.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	LC	NA

McCloskey & Johnson (2019) - Matrix J	149	NA	40.3	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix K	125	NA	36.8	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix L	109	NA	51.4	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PA	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix M	152	NA	50.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix N	113	NA	54.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PR	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix O	152	NA	50.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PA	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix P	122	NA	53.3	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PR	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix Q	133	NA	52.6	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	CO	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix R	94	NA	53.2	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	MISC	SR	LOW	LC	NA
McCloskey & Johnson (2019) - Matrix S	136	NA	38.2	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	TR	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix T	118	NA	39.0	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	MISC	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix U	78	NA	33.3	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	PR	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix V	119	NA	39.5	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	MISC	SR	LOW	LC	NA
McCloskey & Johnson (2019) - Matrix W	110	NA	37.3	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix X	147	NA	38.8	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix Y	45	NA	37.8	MBM, MHM	M	B	NS	NC	CS	6	SRH	SRHE	TU	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix Z	374	NA	42.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PA	SR	LOW	HC	NA
McCloskey & Johnson (2019) - Matrix AA	453	NA	43.4	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PR	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix BB	143	NA	45.5	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	SM	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix CC	257	NA	48.6	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	MA	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix DD	153	NA	39.9	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix EE	139	NA	41.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix FF	97	NA	46.4	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	AL	SR	HIGH	LC	NA

McCloskey & Johnson (2019) - Matrix GG	153	NA	39.9	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix HH	119	NA	42.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix II	149	NA	40.3	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	DB	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix JJ	125	NA	36.8	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix KK	109	NA	51.4	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PA	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix LL	152	NA	50.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix MM	113	NA	54.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PR	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix NN	152	NA	50.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PA	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix OO	122	NA	53.3	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PR	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix PP	133	NA	52.6	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	CO	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix QQ	94	NA	53.2	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	MISC	SR	LOW	LC	NA
McCloskey & Johnson (2019) - Matrix RR	136	NA	38.2	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	TR	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix SS	118	NA	39.0	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	MISC	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix TT	78	NA	33.3	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	PR	SR	HIGH	HC	NA
McCloskey & Johnson (2019) - Matrix UU	119	NA	39.5	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	MISC	SR	LOW	LC	NA
McCloskey & Johnson (2019) - Matrix VV	110	NA	37.3	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	DB	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix WW	147	NA	38.8	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	TU	SR	HIGH	LC	NA
McCloskey & Johnson (2019) - Matrix XX	45	NA	37.8	MBM, MHM	M	B	NS	NC	CS	6	BFCS	NA	TU	SR	HIGH	HC	NA
Meier, Reinecke, & Meltzer (2016) Study 1	354	22.89 (2.51)	71.2	NA	Y	B	ST	NC	CS	6	SRH	SRHE	TU	SR	HIGH	LC	NA
Meier, Reinecke, & Meltzer (2016) Study 2	345	21.17 (1.98)	62.3	NA	Y	B	ST	NC	CS	6	SRH	SRHE	TU	SR	LOW	LC	NA
Menozzi et al. (2015) French sample (honey)	250	18-30 = 34.0%; 21-40 = 12.8%; 41-50 = 16.8%; 51-60 = 16.4%; >60 = 20.0%	65.2	NA	M	B	NS	NC	CS	7	SRH	SRHF	DB	NA	LOW	HC	NA
Menozzi et al. (2015) French	251	18-30 = 35.1%;	59.4	NA	M	B	NS	NC	CS	7	SRH	SRHF	DB	NA	LOW	HC	NA

sample (chicken)		21-40 = 12.4%; 41-50 = 13.9%; 51-60 = 16.3%; >60 = 22.3%														
Menozzi et al. (2015) Italian sample (honey)	258	18-30 = 26.5%; 21-40 = 14.3%; 41-50 = 21.6%; 51-60 = 20.0%; >60 = 17.6%	75.1	NA	M	F	NS	NC	CS	7	SRH	SRHF	DB	NA	LOW	HC	NA
Menozzi et al. (2015) Italian sample (chicken)	245	18-30 = 29.8%; 21-40 = 15.9%; 41-50 = 28.3%; 51-60 = 13.2%; >60 = 12.8%	72.5	NA	M	B	NS	NC	CS	7	SRH	SRHF	DB	NA	LOW	HC	NA
Menozzi & Mora (2012, 2014)	692	22 (3)	59	NA	Y	B	ST	NC	CS	6	SRH	SRHF	DB	SR	HIGH	LC	NA
Moody & Siponen (2013)	238	NA	NA	NA	M	NA	NS	NC	CS	4	SRH	SRHF	TU	SR	HIGH	LC	NA
Moore & Brown (2019) - Matrix A	170	28.11 (12.04), 18-66	71.2	MBM	Y	B	NA	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Moore & Brown (2019) - Matrix B	170	28.11 (12.04), 18-66	71.2	MBM	Y	B	NA	NC	CS	4	SRH	SRHE	TU	SR	HIGH	HC	NA
Morean et al. (2018) Study 1A	189	19.12 (1.80)	40.2		Y	B	NS	NC	CS	7	SRH	SRHF	SM	SR	LOW	LC	NA
Morean et al. (2018) Study 1B	170	19.78 (2.42)	30.1		Y	B	NS	NC	CS	7	SRH	SRHF	SM	SR	LOW	LC	NA
Morean et al. (2018) Study 2 - Sample 1 - Matrix A	100	25.04 (1.69)	25	MBM	Y	B	NS	NC	CS	7	SRH	SRHF	AL	SR	HIGH	LC	NA
Morean et al. (2018) Study 2 - Sample 1 - Matrix B	100	25.04 (1.69)	25	MBM	Y	B	NS	NC	CS	7	SRH	SRHF	AL	SR	HIGH	LC	NA
Morean et al. (2018) Study 2 - Sample 2	58	25.00 (1.77)	46.6		Y	B	NS	NC	CS	7	SRH	SRHF	SM	SR	HIGH	LC	NA
Morean et al. (2018) Study 3 - Matrix A	133	27.80 (8.09)	48	MBM	Y	B	NS	NC	CS	7	SRH	SRHF	AL	SR	HIGH	LC	NA
Morean et al. (2018) Study 3 - Matrix B	133	27.80 (8.09)	48	MBM	Y	B	NS	NC	CS	7	SRH	SRHF	AL	SR	HIGH	LC	NA
Morean et al. (2018) Study 4 - Sample 1	239	37.45 (13.39)	52.3		Y	B	NS	NC	CS	7	SRH	SRHF	SM	SR	HIGH	LC	NA
Morean et al. (2018) Study 4 - Sample 2 - Matrix A	371	37.88 (13.01)	50.7	MBM	Y	B	NS	NC	CS	7	SRH	SRHF	SM	SR	HIGH	LC	NA
Morean et al. (2018) Study 4 - Sample 2 - Matrix B	371	37.88 (13.01)	50.7	MBM	Y	B	NS	NC	CS	7	SRH	SRHF	SM	SR	HIGH	LC	NA
Mullan et al. (2014)	13	22.15 (6.58)	92.3		Y	F	ST	NC	PR	7	SRH	SRHE	PR	SR	HIGH	LC	DSL
Mullan et al. (2015) - Matrix A	188	19.8 (4.39)	77.1	MBM	Y	F	ST	NC	PR	9	SRH	SRHE	PR	SR	HIGH	HC	PRX
Mullan et al. (2015) - Matrix B	188	19.8 (4.39)	77.1	MBM	Y	F	ST	NC	PR	9	SRH	SRHE	PR	SR	HIGH	HC	PRX
Mullan et al. (2015) - Matrix C	188	19.8 (4.39)	77.1	MBM	Y	F	ST	NC	PR	9	SRH	SRHE	PR	SR	HIGH	HC	PRX
Mullan et al. (2015) - Matrix D	188	19.8 (4.39)	77.1	MBM	Y	F	ST	NC	PR	9	SRH	SRHE	PR	SR	HIGH	HC	PRX
Mullan et al. (2016) - Matrix A	195	30.17 (4.46)	100	MBM	Y	F	NS	CL	PR	7	SRH	SRHF	DB	SR	HIGH	LC	PRX
Mullan et al. (2016) - Matrix B	195	30.17 (4.46)	100	MBM	Y	F	NS	CL	PR	7	SRH	SRHF	PA	SR	LOW	HC	PRX
Murphy, Eustace, Sarma, &	245	22.41 (4.78),	100%		Y	F	ST	NC	CS	8	SRH	SRHE	MA	SR	HIGH	LC	NA

Molloy (2018)		18-52														
Murray & Mullan (2019) - Matrix A	386	24.50 (7.72), 18-62	76.8	MBM	Y	F	ST	NC	PR	6	SRH	SRHF	AL	SR	HIGH	LC	PRX
Murray & Mullan (2019) - Matrix B	386	24.50 (7.72), 18-62	76.8	MBM	Y	F	ST	NC	PR	6	SRH	SRHF	AL	SR	HIGH	LC	PRX
Murtagh et al. (2012)	126	8.66 (0.49)	41		Y	B	NS	NC	PR	7	SRH	SRHF	PA	NSR	HIGH	HC	PRX
Naab & Schnauber (2016) - Matrix A	247	23.8 (3.35)	64	MBM, MHM	Y	B	ST	NC	CS	7	SRH	SRHF	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016) - Matrix B	247	23.8 (3.35)	64	MBM, MHM	Y	B	ST	NC	CS	7	SRH	SRHF	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016) - Matrix C	247	23.8 (3.35)	64	MBM, MHM	Y	B	ST	NC	CS	7	RFM	SRHF	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016) - Matrix D	247	23.8 (3.35)	64	MBM, MHM	Y	B	ST	NC	CS	7	RFM	SRHF	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix A	740	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix B	324	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix C	770	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix D	340	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix E	618	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix F	259	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix G	740	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	RFM	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix H	324	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	RFM	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix I	770	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	RFM	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix J	340	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	RFM	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished) - Matrix K	618	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	RFM	SRHE	TU	SR	HIGH	LC	NA
Naab & Schnauber (2016, unpublished)- Matrix L	259	43.41 (13.18), 18-69	49	MBM, MHM	O	B	NS	NC	CS	5	RFM	SRHE	TU	SR	HIGH	LC	NA
Naughton et al. (2015)	477	18-24 = 13.0%; 25-34 = 25.4%; 35-44 = 17.6%; 45-54 = 20.1%; 55-64 = 14.5%; ≥65 = 9.4%	49.9	NA	M	B	NS	NC	CS	6	SRH	SRHF	DB	SR	LOW	LC	NA
Neal et al. (2013) - Study 1 - Matrix A	65	NA	55	MB	Y	B	ST	NC	PR	3	BFCS	NA	MISC	SR	HIGH	LC	DSL

Neal et al. (2013) - Study 1 - Matrix B	65	NA	55	MB	Y	B	ST	NC	PR	3	BFCS	NA	MISC	SR	HIGH	LC	DSL
Niermann et al. (2016)	89	female: 45.2 (8.1); male: 43.8 (10.8)	66.29	NA	O	B	NS	NC	PR	5	SRH	SRHF	PA	NSR	LOW	HC	PRX
Norman & Cooper (2011) - Matrix A	77	19.01 (1.14)	100	MHM	Y	F	ST	NC	PR	6	SRH	SRHF	PR	SR	LOW	HC	PRX
Norman & Cooper (2011) - Matrix B	66	19.01 (1.14)	100	MHM	Y	F	ST	NC	PR	6	BFCS	NA	PR	SR	LOW	HC	PRX
Norman (2011)	137	19.12 (1.85)	81.75	NA	Y	F	ST	NC	PR	6	SRH	SRHF	AL	SR	HIGH	LC	PRX
Norris & Myers (2013)	268	<17 = 7 (2.6%), 18–20 = 31 (11.6%), 21–29 = 69 (25.7%), 30–39 = 44 (16.4%), 40–49 = 71 (26.5%), 50–59 = 34 (12.7%), >60 = 12 (4.5%)	86.57	NA	M	F	NS	NC	CS	9	SRH	SRHF	PR	SR	HIGH	HC	NA
Oh & LaRose (2014)	148	21.1 (2.22), 18-29	64.9	NA	Y	B	ST	NC	PR	8	SRH	SRHF	DB	SR	HIGH	LC	PRX
Ohtomo (2013) - Matrix A	286	18.97 (1.09)	100	MBM	Y	F	ST	NC	PR	4	SRH	SRHF	DB	SR	HIGH	LC	PRX
Ohtomo (2013) - Matrix B	286	18.97 (1.09)	100	MBM	Y	F	ST	NC	PR	4	SRH	SRHF	DB	SR	HIGH	LC	PRX
Olsen et al. (2013) Danish sample	1110	NA	77	NA	M	F	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	LC	NA
Olsen et al. (2013) Spanish sample	953	NA	77	NA	M	F	NS	NC	CS	6	SRH	SRHE	DB	SR	HIGH	LC	NA
Onwezen et al. (2016) Study 2	1497	45.76 (15.20)	50.09	NA	O	B	NS	NC	CS	2	SRH	SRHF	DB	SR	HIGH	LC	NA
Orbell & Verplanken (2010) Study 1 - Matrix A	47	24.55 (9.16)	61.70	MBM	Y	B	NS	NC	CS	8	SRH	SRHF	SM	SR	HIGH	LC	NA
Orbell & Verplanken (2010) Study 1 - Matrix B	47	24.55 (9.16)	61.70	MBM	Y	B	NS	NC	CS	8	SRH	SRHF	SM	NSR	HIGH	LC	NA
Orbell & Verplanken (2010) Study 2	65	41.74, 18-69	36.92	NA	M	B	NS	NC	PR	8	SRH	SRHF	SM	SR	HIGH	LC	DSL
Orbell & Verplanken (2010) Study 3	144	21.15 (1.56), 18-26	53.28	NA	Y	B	ST	NC	PR	8	SRH	SRHF	PR	NSR	HIGH	LC	PRX
Ouellette (1996) - Matrix A	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	CO	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix B	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	MISC	SR	HIGH	LC	PRX
Ouellette (1996) - Matrix C	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	PA	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix D	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	AL	SR	HIGH	LC	PRX
Ouellette (1996) - Matrix E	141	18-19	NA	MBM,	Y	B	ST	NC	PR	8	SRH	SRHE	PR	SR	HIGH	HC	PRX

				MHM													
Ouellette (1996) - Matrix F	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	CO	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix G	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	MISC	SR	HIGH	LC	PRX
Ouellette (1996) - Matrix H	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	PA	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix I	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	AL	SR	HIGH	LC	PRX
Ouellette (1996) - Matrix J	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	PR	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix K	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	CO	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix L	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	MISC	SR	HIGH	LC	PRX
Ouellette (1996) - Matrix M	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	PA	SR	HIGH	HC	PRX
Ouellette (1996) - Matrix N	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	AL	SR	HIGH	LC	PRX
Ouellette (1996) - Matrix O	141	18-19	NA	MBM, MHM	Y	B	ST	NC	PR	8	SRH	SRHE	PR	SR	HIGH	HC	PRX
Pahnila & Siponen (2010)	57	<22 = 14 (24.6%), 22-31 = 30 (52.6%), 32-41 = 6 (10.5%), >41 = 6 (10.5%), missing = 1 (1.8%)	24.6	NA	Y	B	ST	NC	PR	4	SRH	SRHF	TU	SR	HIGH	LC	PRX
Panter at al. (2011a)	1297	60.4 (5.4)	61.1	NA	O	B	NS	NC	CS	8	SRH	SRHF	PA	SR	HIGH	HC	NA
Panter at al. (2011b); Panter et al. (2013a); Panter et al. (2013b)	419	43.7 (11.9)	76.6	NA	O	F	NS	NC	CS	8	SRH	SRHE	PA	SR	HIGH	HC	NA
Pfeffer & Strobach (2018)	124	23.59 (2.76), 19-35	64.5	NA	Y	B	ST	NC	PR	6	SRH	SRHE	PA	SR	LOW	HC	PRX
Phipps, Hagger, & Hamilton (2020)	205	22.20 (7.92)	78	NA	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	LOW	HC	PRX
Phillips & Gardner (2016) - Matrix A	118	19.48 (2.08), 18-33	75.42	MBM	Y	F	NA	NC	PR	10	SRH	SRHE	PA	SR	LOW	HC	PRX
Phillips & Gardner (2016) - Matrix B	118	19.48 (2.08), 18-33	75.42	MBM	Y	F	NA	NC	PR	10	SRH	SRHE	PA	SR	LOW	HC	PRX
Phillips et al. (2013)	71	67.90 (12.28), 30-90	63	NA	O	B	NS	CL	PR	8	SRH	SRHF	MA	NSR	HIGH	HC	PRX
Phillips et al. (2016a) - Matrix A	133	56.96 (12.04)	62	MB, MBM	O	B	NS	CL	PR	9	SRH	SRHE	MA	SR	HIGH	HC	PRX
Phillips et al. (2016a) - Matrix B	133	56.96 (12.04)	62	MB, MBM	O	B	NS	CL	PR	9	SRH	SRHE	MA	NSR	HIGH	HC	PRX

Phillips et al. (2016a) - Matrix C	133	56.96 (12.04)	63	MB, MBM	O	B	NS	CL	PR	9	SRH	SRHE	PA	SR	LOW	HC	PRX
Phillips et al. (2016a) - Matrix D	133	56.96 (12.04)	64	MB, MBM	O	B	NS	CL	PR	9	SRH	SRHE	PA	NSR	LOW	HC	PRX
Phillips et al. (2016b) Study 1	463	19.40 (1.99)	70	NA	Y	B	ST	NC	CS	8	SRH	SRHE	PA	SR	LOW	HC	NA
Phillips et al. (2016b) Study 2	114	24.84 (11.33)	7	NA	Y	B	NA	NC	PR	8	SRH	SRHE	PA	NSR	LOW	HC	PRX
Phillips, Johnson, & More (2019) - Matrix A	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix B	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix C	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix D	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix E	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix F	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix G	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phillips, Johnson, & More (2019) - Matrix H	28	18.68 (1.06)	89.3	MT, MB	Y	F	ST	NC	PR	8	SRH	SRHE	DB	SR	HIGH	HC	PRX
Phipps & Hamilton (2019, unpublished)	109	21.88 (7.04)	58	NA	Y	B	ST	NC	PR	8	SRH	SRHF	PA	SR	LOW	HC	PRX
Pimm et al. (2016)	1244	55 (15)	50.5	NA	O	B	NS	NC	CS	8	SRH	SRHE	PA	SR	LOW	HC	NA
Presseau et al. (2014a); Presseau et al. (2014b); Eccles et al. (2011)	335	NA	NA	NA	M	NA	NS	NC	PR	7	SRH	SRHE	MA	SR	HIGH	HC	DSL
Rebar et al. (2014)	128	21	59.38	NA	Y	B	ST	NC	PR	7	SRH	SRHE	PA	NSR	LOW	HC	PRX
Rhodes & de Bruijn (2010) Sample 1	158	21.98 (5.47)	63.7	NA	Y	B	ST	NC	PR	9	SRH	SRHE	PA	SR	LOW	HC	PRX
Rhodes & de Bruijn (2010) Sample 2	179	21.98 (5.47)	63.7	NA	Y	B	ST	NC	PR	9	SRH	SRHE	PA	SR	LOW	HC	PRX
Rhodes & Lim (2016)	227	43.11 (12.37)	88.4	NA	O	F	NS	NC	CS	7	SRH	SRHE	PA	NA	HIGH	HC	NA
Rhodes et al. (2012)	216	24.02 (8.81)	69.4	NA	Y	B	ST	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	PRX
Rhodes et al. (2010)	153	22.17 (6.51)	74	NA	Y	B	ST	NC	PR	7	SRH	SRHF	PA	SR	LOW	HC	PRX
Rompotis et al. (2014)	44	19.34 (2.73)	77.27	NA	Y	F	ST	NC	PR	4	SRH	SRHE	DB	SR	HIGH	LC	PRX
Sainsbury, Halmos, Knowles, Mullan, & Tye-Din (2018)	5573	50.2 (SD =15.9), 16-94	83.2	NA	O	F	NS	CL	CS	9	SRH	SRHE	DB	SR	HIGH	HC	NA
Schmidt (2016)	87	Full sample: ≤25 = 99 (45.6%); 25-40 = 81 (37.3%); 40-60 = 33 (15.2%); 60-65 = 1 (0.5%); > 65	89.9	NA	Y	F	NS	NC	PR	5	SRH	SRHF	CO	SR	HIGH	HC	PRX

		= 3 (1.4%)															
Schmidt & Retelsdorf (2016)	1418	17.24 (0.67)	54.0	NA	Y	B	ST	NC	CS	3	SRH	SRHF	MISC	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix A	38	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix B	45	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix C	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix D	44	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix E	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix F	45	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix G	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix H	38	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix I	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix J	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix K	40	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix L	39	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix M	44	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix N	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix O	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix P	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix Q	35	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix R	33	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix S	39	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix T	39	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix U	41	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix V	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA

Schnauber-Stockmann & Naab (2019) - Matrix W	39	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix X	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix Y	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix Z	42	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix AA	41	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix BB	28	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix CC	29	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix DD	35	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	SRH	SRHE	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix EE	38	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix FF	45	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix GG	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix HH	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix II	42	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix JJ	45	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix KK	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix LL	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix MM	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix NN	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix OO	40	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix PP	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix QQ	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix RR	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix SS	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA

Schnauber-Stockmann & Naab (2019) - Matrix TT	43	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix UU	34	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix VV	33	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix WW	38	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix XX	39	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix YY	41	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix ZZ	42	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix AAA	38	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix BBB	37	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix CCC	36	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix DDD	42	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix EEE	40	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix FFF	26	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix GGG	29	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Schnauber-Stockmann & Naab (2019) - Matrix HHH	34	21.18 (2.06)	49.0	MT, MHM	Y	B	ST	NC	CS	4	BFCS	NA	TU	SR	HIGH	LC	NA
Sczesny et al. (2015) - Study 1	278	29.99 (9.59), 15-60	74.10	NA	Y	B	NA	NC	PR	6	SRH	SRHE	MISC	SR	LOW	HC	PRX
Sczesny et al. (2015) - Study 2	203	25.00 (6.91), 18-54	69.46	NA	Y	B	NA	NC	PR	6	SRH	SRHE	MISC	SR	LOW	HC	PRX
Shah et al. (2014) - Matrix A	570	NA	NA	MBM	M	NA	NS	NC	CS	1	SRH	SRHF	MISC	SR	LOW	HC	NA
Shah et al. (2014) - Matrix B	570	NA	NA	MBM	M	NA	NS	NC	CS	1	SRH	SRHF	MISC	SR	HIGH	LC	NA
Shah et al. (2014) - Matrix C	570	NA	NA	MBM	M	NA	NS	NC	CS	1	SRH	SRHF	MISC	SR	HIGH	LC	NA
Shah et al. (2014) - Matrix D	570	NA	NA	MBM	M	NA	NS	NC	CS	1	SRH	SRHF	MISC	SR	HIGH	LC	NA
Sheeran & Conner (2019) Study 1 - Matrix A	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	DB	SR	HIGH	LC	PRX
Sheeran & Conner (2019) Study 1 - Matrix B	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	PA	SR	LOW	HC	PRX
Sheeran & Conner (2019) Study 1 - Matrix C	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	MISC	SR	HIGH	LC	PRX
Sheeran & Conner (2019) Study 1 - Matrix D	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	AL	SR	HIGH	HC	PRX

Sheeran & Conner (2019) Study 1 - Matrix E	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	PA	SR	HIGH	HC	PRX
Sheeran & Conner (2019) Study 1 - Matrix F	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	DB	SR	HIGH	HC	PRX
Sheeran & Conner (2019) Study 1 - Matrix G	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	DB	SR	HIGH	HC	PRX
Sheeran & Conner (2019) Study 1 - Matrix H	633	33.8 (9.37)	63.5	MB	Y	B	NS	NC	PR	7	BFCS	NA	DB	SR	HIGH	HC	PRX
Sheeran & Conner (2019) Study 2 - Matrix A	1014	31.9 (11.3)	50.7	MB	Y	B	NS	NC	PR	7	BFCS	NA	DB	SR	HIGH	LC	DSL
Sheeran & Conner (2019) Study 2 - Matrix B	1014	31.9 (11.3)	50.7	MB	Y	B	NS	NC	PR	7	BFCS	NA	PA	SR	LOW	HC	DSL
Sheeran & Conner (2019) Study 2 - Matrix C	1014	31.9 (11.3)	50.7	MB	Y	B	NS	NC	PR	7	BFCS	NA	MISC	SR	HIGH	LC	DSL
Sheeran & Conner (2019) Study 2 - Matrix D	1014	31.9 (11.3)	50.7	MB	Y	B	NS	NC	PR	7	BFCS	NA	AL	SR	HIGH	HC	DSL
Sheeran & Conner (2019) Study 2 - Matrix E	1014	31.9 (11.3)	50.7	MB	Y	B	NS	NC	PR	7	BFCS	NA	PA	SR	HIGH	HC	DSL
Sheeran & Conner (2019) Study 2 - Matrix F	1014	31.9 (11.3)	50.7	MB	Y	B	NS	NC	PR	7	BFCS	NA	DB	SR	HIGH	HC	DSL
Şimşekoğlu et al. (2015); Nordfjærn et al. (2015); Nordfjærn et al. (2014)	546	41.43 (12.06)	46.6	NA	O	B	NS	NC	CS	8	SRH	SRHF	TR	SR	HIGH	HC	NA
Skagerström et al. (2013)	1291	≤24 = 139 (10.61%); 25-29 = 427 (32.60%); 30-34 = 474 (36.18%); 35-39 = 226 (17.25%); ≥40 = 44 (3.36%)	100	NA	Y	F	NS	CL	CS	8	SRH	SRHE	AL	SR	LOW	LC	NA
Soror et al. (2015)	300	29.30 (8.57)	49	NA	Y	B	NS	NC	CS	5	SRH	SRHE	TU	SR	HIGH	LC	NA
Tak et al. (2011)	1005	14.1 (1.2)	46	NA	Y	B	ST	NC	CS	6	SRH	SRHF	DB	SR	HIGH	LC	NA
Tak et al. (2013)	333	58.3 (13.7), 15-74	54.1	NA	O	B	NS	NC	CS	5	SRH	SRHE	DB	SR	HIGH	LC	NA
Tam et al. (2010)	591	22.8 (3.36)	52.12	NA	Y	B	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Tappe & Glanz (2013) - Matrix A	156	35.0 (12.6)	69	MHM	Y	B	NS	NC	CS	9	SRH	SRHE	PA	SR	LOW	HC	NA
Tappe & Glanz (2013) - Matrix B	156	35.0 (12.6)	69	MHM	Y	B	NS	NC	CS	9	SRH	SRHF	PA	SR	LOW	HC	NA
Tappe et al. (2013)	174	27.5	56	NA	Y	B	NS	NC	CS	6	SRH	SRHF	PA	SR	LOW	HC	NA
Tetlow et al. (2015)	81	NA	NA	NA	M	NA	NS	NC	CS	6	SRH	SRHF	CO	NSR	HIGH	HC	NA
Thøgersen (2009)	1015	43.55 19-75	48.7	NA	O	B	NS	NC	CS	6	SRH	SRHE	TR	SR	HIGH	HC	NA
Thøgersen & Møller (2008)	709	43.86, 10.51. 19-72	48.9	NA	O	B	NS	NC	CS	6	RFM	NA	TR	SR	HIGH	HC	NA
Thomas & Upton (2014a, 2014b)	336	9.93 (0.80)	50	NA	Y	B	ST	NC	PR	9	SRH	SRHE	PA	SR	LOW	HC	PRX

Thomas (2014, unpublished)	1682	30.19 (13.00), 17-68	57	NA	Y	B	NA	NC	CS	9	SRH	SRHF	TR	SR	HIGH	HC	NA
Thomas & Walker (2015)	1609	31.86 (13.31)	55.6	NA	Y	B	NA	NC	CS	6	SRH	SRHF	TR	SR	HIGH	HC	NA
Thurn et al. (2014) Study 1 - Matrix A	259	<25 = 30, 25-45 = 197, >45 = 33	21.15	MBM	M	B	NS	NC	CS	5	SRH	SRHF	PA	NSR	LOW	HC	NA
Thurn et al. (2014) Study 1 - Matrix B	35	NA	34	MBM	M	B	NS	NC	PR	5	SRH	SRHF	PA	NSR	LOW	HC	PRX
Thurn et al. (2014) Study 2	74	<25 = 38, 25-45 = 20, >45 = 16	58.11	NA	M	B	NS	NC	PR	5	SRH	SRHF	PA	NSR	LOW	HC	PRX
Tokunaga (2016) Study 1	179	28.6 (13.6), 18-86	64.80	NA	Y	B	NA	NC	CS	3	SRH	SRHF	TU	SR	HIGH	LC	NA
Tokunaga (2016) Study 2	292	18.1 (0.38), 18-20	68.84	NA	Y	B	ST	NC	PR	3	SRH	SRHF	TU	SR	HIGH	LC	DSL
Tsafou et al. (2016)	398	41.28 (13.27)	50.3	NA	O	B	ST	NC	CS	4	SRH	SRHF	PA	SR	LOW	HC	NA
Tseng et al. (2013)	544	< 40, n = 381; >40, n = 163	1.5	NA	Y	B	NS	NC	PR	6	RFM	NA	TR	SR	LOW	LC	DSL
Turel & Serenko (2012)	194	23, 19-40	48	NA	Y	B	ST	NC	CS	5	SRH	SRHF	TU	SR	HIGH	LC	NA
van Bree et al. (2015); van Bree et al. (2013)	1836	62.95 (8.17)	57	NA	O	B	NS	NC	PR	7	SRH	SRHF	PA	SR	LOW	HC	DSL
van Bree et al. (2016) Study 1	469	63.07 (7.61), 51-87	53	NA	O	B	NS	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	DSL
van Bree et al. (2016) Study 2	322	64.31 (9.39), 50-92	48.76	NA	O	B	NS	NC	PR	7	SRH	SRHE	PA	SR	LOW	HC	DSL
van der Horst et al. (2007)	383	13.5 (0.62)	55.1	NA	Y	B	ST	NC	CS	6	SRH	SRHF	DB	SR	HIGH	LC	NA
van Empelen & Kok (2006) - Matrix A	140	15 (0.86)	33.65	MBM	Y	B	ST	NC	PR	5	SRH	SRHE	PR	SR	HIGH	HC	DSL
van Empelen & Kok (2006) - Matrix B	140	15 (0.86)	33.65	MBM	Y	B	ST	NC	PR	5	SRH	SRHE	PR	SR	HIGH	HC	DSL
van Empelen & Kok (2008) - Matrix A	146	15 (0.88)	46.4	MBM	Y	B	ST	NC	CS	8	SRH	SRHF	PR	NA	HIGH	HC	NA
van Empelen & Kok (2008) - Matrix B	146	15 (0.88)	46.4	MBM	Y	B	ST	NC	CS	8	SRH	SRHF	PR	NA	HIGH	HC	NA
van Empelen & Kok (2008) - Matrix C	146	15 (0.88)	46.4	MBM	Y	B	ST	NC	CS	8	SRH	SRHF	PR	NA	HIGH	HC	NA
van Empelen & Kok (2008) - Matrix D	146	15 (0.88)	46.4	MBM	Y	B	ST	NC	CS	8	SRH	SRHF	PR	NA	LOW	HC	NA
van Keulen et al. (2013) Mothers	732	43.51 (4.54), 26-60	100	NA	O	F	NS	NC	CS	8	SRH	SRHE	PR	SR	LOW	HC	NA
van Keulen et al. (2013) Daughters	482	13.51 (0.51), 12-14	100	NA	Y	F	NS	NC	CS	8	SRH	SRHE	PR	SR	LOW	HC	NA
Vance et al. (2012)	210	NA	78	NA	M	F	NS	NC	CS	6	SRH	SRHE	TU	NA	LOW	HC	NA
Verhoeven et al. (2012)	1103	48.74 (14.10)	55.67	NA	O	B	NS	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Verhoeven et al. (2013) Study 1 - Matrix A	22	21.45 (1.71)	100	MBM	Y	F	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Verhoeven et al. (2013) Study 1 - Matrix B	22	21.45 (1.71)	100	MBM	Y	F	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX

Verhoeven et al. (2014)	161	20.86 (2.93) 17-33	62	NA	Y	B	ST	NC	PR	4	SRH	SRHF	DB	SR	HIGH	LC	PRX
Verplanken et al. (1994)	199	39.9, 19-65	53.77		M	B	NS	NC	CS	3	RFM	NA	TR	SR	HIGH	LC	NA
Verplanken et al. (1997) - Study 2	42	NA	NA	NA	Y	NA	ST	NC	CS	6	RFM	NA	TR	SR	HIGH	LC	NA
Verplanken et al. (1997) - Study 3	135	37.5, 13.7, 18-78	NA	NA	Y	NA	NS	NC	CS	6	RFM	NA	TR	SR	HIGH	LC	NA
Verplanken et al. (1998)	200	43.1, 20-70	52	NA	O	B	NS	NC	PR	6	RFM	NA	TR	SR	HIGH	LC	PRX
Verplanken (2006) Study 1	143	NA	57.34	NA	Y	B	ST	NC	PR	4	SRH	SRHF	DB	SR	HIGH	LC	PRX
Verplanken (2006) Study 2	194	NA	63	NA	Y	B	ST	NC	CS	4	SRH	SRHF	MISC	SR	LOW	LC	NA
Verplanken & Melkevik (2008)	111	NA	61.26	NA	Y	B	ST	NC	PR	4	SRH	SRHF	PA	SR	LOW	HC	PRX
Verplanken & Orbell (2003) Study 3 - Matrix A	143	NA	69.93	MBM	Y	B	ST	NC	PR	5	SRH	SRHF	MISC	SR	HIGH	LC	PRX
Verplanken & Orbell (2003) Study 3 - Matrix B	143	NA	69.93	MBM	Y	B	ST	NC	PR	5	SRH	SRHF	DB	SR	HIGH	LC	PRX
Verplanken & Orbell (2003) Study 3 - Matrix C	143	NA	69.93	MBM	Y	B	ST	NC	PR	5	SRH	SRHF	MISC	SR	HIGH	LC	PRX
Verplanken & Roy (2016)	521	41	63.34	NA	O	B	NS	NC	PR	7	SRH	SRHF	CO	SR	HIGH	HC	DSL
Walker et al. (2015)	70	38.8	58.6	NA	Y	B	NS	NC	PR	4	SRH	SRHE	TR	SR	HIGH	HC	DSL
Walton-Pattison, Dombrowski, & Presseau (2018)	86	30 (12)	67	NA	Y	B	NS	NC	CS	6	SRH	SRHE	MISC	SR	HIGH	LC	NA
Webb et al. (2014)	34	NA	NA	NA	Y	NA	NA	NC	PR	3	SRH	SRHF	CO	NSR	HIGH	HC	DSL
Wiedemann et al. (2014)	127	31.7 (10.1)	74	NA	Y	B	NS	NC	PR	6	SRH	SRHE	DB	SR	HIGH	LC	PRX
Wood et al. (2005) - Matrix A	115	NA	50	MB	Y	B	ST	NC	PR	7	BFCS	NA	PA	SR	LOW	HC	DSL
Wood et al. (2005) - Matrix B	115	NA	50	MB	Y	B	ST	NC	PR	7	BFCS	NA	MISC	SR	HIGH	LC	DSL
Wood et al. (2005) - Matrix C	115	NA	50	MB	Y	B	ST	NC	PR	7	BFCS	NA	MISC	SR	HIGH	LC	DSL
Zomer et al. (2013)	350	30, 19-57	99.9	NA	M	F	NS	NC	CS	3	SRH	SRHE	PR	SR	HIGH	LC	NA

Note. [a]In cases where mean, standard deviation, or range for age were not reported, proportion of sample in age groups is provided when available. [b]Proportion of females in sample (%). [c]Samples including multiple within-study (W-S) measures (meas.) of behavior, habit, or other outcome variables, or included multiple measures of an effect across time points. [d]Age covariate – studies classified as older, younger, or mixed age samples. [e]Sex covariate – studies classified as having predominantly female, predominantly male, or balanced sex samples. [f]Sample type (student status) covariate – studies classified as having student or non-student sample. [g]Sample type (clinical status) covariate – studies classified as having clinical or non-clinical samples. [h]Study design covariate – studies classified as cross-sectional or prospective/longitudinal in design . [i]Study quality covariate – total score on Study Quality Assessment Checklist (see Section F of these supplemental materials). [j]Habit measure (meas.) type moderator variable – type of habit measure adopted. [k]Candidate measure (meas.) – use of one or more of the three candidate habit measures in the current study: behavioral frequency x context stability measures, response frequency measures, and self-report habit measures. [l]Incl. (included) or excl. (excluded) freq. (frequency) – studies using a self-report habit measures that either included or excluded behavioral frequency items. [m]Behavior (behave.) type moderator variable. [n]Behavior (behav.) measure (meas.) moderator variable – studies classified as adopting (a) self-report measure(s) or (a) non-self-report measure(s) of behavior. [o]Opportunity (oppr.) for the behavior to be formed (form.) as a habit moderator variable – studies targeting behaviors that individuals had both a greater chance of performing frequently and a high likelihood of being performed in stable conditions or contexts were classified as affording high opportunity to develop into habits and studies targeting behaviors that individuals had fewer chances to perform frequently, or had a high likelihood of being performed in disparate or variable contexts, were classified as having low opportunity to become be formed as a habit. [p]Behavioral (behave.) complexity (complex.) moderator variable –

studies with target behaviors involving multiple sub-actions and considerable planning/cognitive processing assigned to the "complex" category and studies with target behaviors comprising relatively few sub-actions and less planning/cognitive processing assigned to the "simple" category.

[q]Measurement (meas.) lag moderator variable – time lag between measures of social cognition variables, habit, and/or past behavior and measures of behavior. MB = Study included multiple behaviors; MT = Study included multiple time points; MHM = Study included multiple measures of habit; MC = Study included multiple behavioral contexts; MBM = Studies included multiple measures of the same behavior; O = Samples classified as older samples for the age covariate (*M* age >= 40, SD ~ 15, or > 70% of the sample older than 40, or an age range with a lower limit >=40); Y = Samples classified as younger samples for the age covariate (*M* age < 40, SD ~ 15, or > 70% of the sample younger than 40, or an age range with upper limit <40); M = Samples comprising a mix of age groups for the age covariate; B = Balanced sex samples for sex covariate; F = Predominantly female samples (>=75% female) for sex covariate; M = Predominately male samples (<=25% female) for sex covariate; NS = Studies with samples comprising non-student participants for sample type (student status) covariate; ST = Studies with samples comprised exclusively of student participants for sample type (student status) covariate; CL = Studies with samples from clinical populations for sample type (clinical status) covariate; NC = Studies with samples from non-clinical populations for sample type (clinical status) covariate; CS = Studies with cross-sectional designs for study design covariate; PR = Studies with prospective designs for study design covariate; SRH = Studies adopting self-report habit measures consistent with Verplanken and Orbell's (2003) self-report habit index and derivatives; BFCS = Studies adopting behavioral frequency x context stability habit measures consistent with Wood et al.'s (2005) measure; RFM = Studies adopting response frequency habit measures consistent with Verplanken and Aarts' (1999) measure; SRHF = Self-report habit measures including behavioral frequency items for the habit measure type moderator; SRHE = Self-report habit measures excluding behavioral frequency items for the habit measure type moderator; SR = Studies adopting (a) self-report measure(s) of behavior for behavior type moderator; NSR = Studies adopting (a) non-self-report measure(s) of behavior for behavior type moderator; HIGH = Studies targeting behaviors classified as having high opportunity to be formed as a habit; LOW = Studies targeting behaviors classified as having low opportunity to be formed as a habit; LC = Studies targeting behaviors classified as low complexity for the behavioral complexity moderator; HC = Studies targeting behaviors classified as high complexity for the behavioral complexity moderator; DSL = Studies with a distal lag (> 4 weeks) for the measurement lag moderator; PRX = Studies with a proximal lag (≤ 4 weeks) for the measurement lag moderator; NA = Study could not be classified into a moderator category or data were unavailable.

Effect Size Conversion Formulas

Formulas Used to Convert Effect Sizes to r Prior to Meta-Analysis

Calculating *r* from standardized mean difference (*d*), assuming approximately equal sample sizes:

$$r = \frac{d}{\sqrt[2]{d^2 + 4}} \tag{1}$$

Calculating *r* from standardized mean difference (*d*), assuming unequal sample sizes:

$$r = \frac{d}{\sqrt[2]{d^2 + \frac{(N^2 - 2N)}{n_1 n_2}}} \tag{2}$$

Calculating *r* from *t*-ratios from *t*-tests:

$$r = \frac{t}{\sqrt[2]{t^2 + (N - 2)}} \tag{3}$$

Calculating *d* from *F*-ratio from univariate (one-way) ANOVA (equal sample sizes assumed):

$$d = \frac{(\sqrt[2]{F} \times 2)}{\sqrt[2]{N}} \tag{4}$$

Calculate *r* using the *d*-to-*r* conversion formula (1).

Calculating *r* from 2 x 2 chi-square tests (*df* = 1):

$$r = \frac{\chi^2}{N} \tag{5}$$

Reference for formulas (1) through (5): Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Sage.

Approximating *r* from odds, risk, or hazard ratio (*OR*)

$$r = \frac{(OR^{0.75} - 1)}{(OR^{0.75} + 1)} \tag{6}$$

Reference for formula (6): Digby, P. G. N. (1983). Approximating the tetrachoric correlation coefficient. *Biometrics, 39*(3), 753-757. https://doi.org/10.2307/2531104

Calculating *d* from two-group experimental/intervention/comparison studies using means (*M*), standard deviation (*SD*) and sample sizes (*n*) for both groups where post-test data are available only:

$$d = \frac{(M_1 - M_2)}{\sqrt[2]{\frac{((n_1 - 1) \times SD_1^2) + ((n_2 - 1) \times SD_2^2)}{(n_1 - 1) + (n_2 - 1)}}} \tag{7}$$

Calculate *r* using the *d*-to-*r* conversion formula (1).

Calculating *d* from two-group experimental/intervention/comparison studies using means (*M*), standard deviation (*SD*) and group sample sizes (*n*) where pre-test and post-test data are available for both groups with an assumed correlation between pre-test and post-test scores ($r_{\text{pre,post}}$):

$$d = \frac{(M_{1,pre} - M_{1,post}) - (M_{2,pre} - M_{2,post})}{\sqrt[2]{\frac{((n_1 - 1) \times \Delta SD_1^2) + ((n_2 - 1) \times \Delta SD_2^2)}{(n + n_2) - 2)}}} \tag{8.1}$$

Where change in *SD* (Δ*SD*) for the each group (*x*) is given by:

$$\Delta SD_x = \sqrt[2]{(SD_{x,pre}^2 + SD_{x,post}^2 - 2) \times r_{pre,post} \times SD_{x,pre} \times SD_{x,post}} \tag{8.2}$$

Calculate *r* using the *d*-to-*r* conversion formula (1).

Calculating *d* from experimental/intervention/comparison studies using *p*-value and group sample sizes (*n*):

$$d = \pm t^{-1}(p) \sqrt[2]{\frac{n_1 + n_2}{n_1 n_2}} \tag{9}$$

Where $t^{-1}(p)$ is the inverse of the cumulative function taken from the Student's *t* distribution with $n_1 + n_2 - 2$ degrees of freedom. The above formula is for *p*-values taken from one-tailed tests, the *p*-value is halved for values taken from two-tailed tests.

Calculate *r* using the *d*-to-*r* conversion formula (1).

Reference for formulas (7) through (9): Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Wiley. https://doi.org/10.1002/9780470743386

Detailed Description of Covariate Coding and Study Quality Assessment

Demographic Variables.

We included sample age and sex as demographic covariates in the meta-analytic tests of our proposed model. Study samples were classified as older samples (*k* = 46) if the reported average age of the sample was 40 years or older with a standard deviation below 15, or, in instances where average age was not reported, the majority of the sample were aged 40 years or older, or had an age range with lower limit greater than 40 years. By contrast, samples were classified as younger (*k* = 185) if the average sample age was younger than 40 years with a standard deviation below 15, the majority of the sample was younger than 40 years, or had an age range with an upper limit less than 40 years. Studies that deviated from these criteria were classified as 'mixed' age samples (*k* = 36). Relatively few studies we conducted exclusively on male or female samples. Based on recommendations from previous meta-analyses (Hamilton, van Dongen, et al., 2020), we categorized samples into majority female (>=75% female; *k* = 59), majority male (<=25% female; *k* = 7), or balanced sex profile (>25% female and < 75% female; *k* = 201) samples [16]. The three-category age and sex moderator variables were included as covariates in tests of our proposed model, with mixed age samples and balanced sex profile, respectively, designated as the reference group.

Sample Type

Given that a substantive proportion of the studies included in the current analysis reported data from school and undergraduate student samples, we aimed to include student status as a covariate when testing our proposed model in the current meta-analysis. This is consistent with general concerns over the generalizability of findings in research conducted on student samples with very narrow demographic and socio-structural characteristics (Henrich et al., 2010). We therefore coded studies according to whether they were conducted on school or university student samples, or on a combination of students and non-student samples (*k* = 136), and studies conducted on non-student samples (*k* = 131). We also coded studies according to whether they were conducted in samples in a clinical context such as a hospital or rehabilitation clinic (*k* = 14) or in a non-clinical context (*k* = 253). These dichotomous coded variables were included as covariates in our model tests.

Study Design

Although several experimental studies were included in the current analysis, none included a manipulation relevant to the proposed model (e.g., testing the effect of experimentally-manipulated habit on a measure of behavior). All studies were, therefore, treated as correlational in design, which precluded assessment of study design as moderator of model effects. In cases where studies included an experimental manipulation that was deemed to influence effect sizes among constructs of our proposed process model, we used data from the control group. However, we did make the distinction between studies using cross-sectional data in which all constructs including behavior were measured on a single occasion (*k* = 132), and studies using prospective or longitudinal data in which study constructs were measured on multiple occasions, such as studies that collected measures of social cognition and habit constructs on an initial occasion with a follow up measure of behavior collected on a subsequent occasion (*k* = 135). This dichotomous coded variable was included as a covariate in our model tests.

Study Quality Assessment

We assessed the quality of the included studies using a developmental version on the Quality of Survey Studies in Psychology (Q-SSP) appraisal checklist (Protogerou & Hagger, 2020), which was based on a content analysis of existing study quality appraisal tools (e.g., Crombie, 1996; Glynn, 2006). The checklist included 10

[16]Some studies (*k* = 10) did not report the sex profile of their sample. These studies were coded in the balanced sex sample category for analysis purposes.

quality appraisal criteria. Checklist item descriptions and required quality standards are presented annex below. Studies meeting quality standards were assigned a score of 1 for each criterion and those not meeting the quality standard or provided insufficient information to evaluate the criterion were assigned a score of zero. Scores for each criterion were summed to provide a total quality score out of 10. Each study was scored using the checklist by three researchers with training in the assessment of study quality using the checklist[17]. A subset of the sample of studies (k = 20) was independently scored by all three researchers. Intra-class correlation (R) and inter-rater agreement (Cohen's κ) analyses indicated good consistency in raters' scores across item (average intra-class correlation, R = .823) and total scores (R = .903) on the checklist, with high inter-rater agreement on total score classification (average κ = .823). Inconsistencies were resolved through discussion and attributed to minor interpretation errors of the quality criteria[18].Criteria were refined on the basis of the discussion and applied to the coding of the entire sample. Total quality score derived from the scale was used as a continuous covariate in our model tests.

Annex: Study Quality Checklist with Scoring Procedure and Item Descriptions

Domain	Criterion	Yes	No	Not stated clearly	N/A
Participants (Sampling)	1. Are participant selection criteria explicitly stated?	☐	☐	☐	☐
Participants (Recruitment)	2.Were participants recruited by an acceptable recruitment strategy?	☐	☐	☐	☐
Participants (Sampling)	3. Is the sample size acceptable?	☐	☐	☐	☐
Participants (Sampling)	4. Is the response rate acceptable?	☐	☐	☐	☐
Design (Method)	5. Was the study approved by a relevant institutional review board or research ethics committee?	☐	☐	☐	☐
Design (Method)	6. Did participants provide informed consent?	☐	☐	☐	☐
Design (Method)	7. Did the study include a formative research phase?	☐	☐	☐	☐
Data (Measures)	8. Are the measures/ questionnaires provided in the report (or in a supplement), in full?	☐	☐	☐	☐
Data (Measures)	9. Were the measures valid/ validated?	☐	☐	☐	☐
Data (Analysis)	10. Were all necessary data analyses conducted?	☐	☐	☐	☐

Scoring

For each of the 10 criteria, studies are assigned 1 for 'Yes' responses and 0 for No / Not stated clearly/Not applicable responses.

[17]A spreadsheet of methodological quality scores for each study is available online: https://osf.io/zq7c8/
[18]Data files and analysis code and output for the intra-class correlation and inter-rater agreement analyses are available online: https://osf.io/zq7c8/

Overall Study Quality Score

Simple sum of scores for each criterion to provide score out of 10.

Criteria

Definitions of terms and summaries of each criterion are provided below. Statements on the necessary information required to gain a "yes" score for each criterion are provided.

1. Are participant selection criteria explicitly stated?
Definition. Selection criteria: Inclusion and exclusion rules for participation in the study. Studies need to have clearly declared what criteria were used to assess selection of participants and what data were available to evaluate inclusion or exclusion.

2. Were participants recruited by an acceptable recruitment strategy?
Definitions. Recruitment: the process of enlisting people for participation in a research study. Examples of acceptable recruitment strategies include advertisements, flyers, information sheets, notices, postings on internet bulletin boards, web pages, and social media sites; direct contact with potential study participants (e.g., through a presentation); letters and emails (e.g., from an agency, hospital, school); pre-existing participant pools (e.g., past research participants who have given permission for future contact). Studies need to have clearly reported all recruitment strategies.

3. Is the sample size acceptable?
Definition. Sample size: the number of participants in a study. The appropriateness of the sample size depends on the research questions of interest, the statistical model used, the assumptions specified in the sample size planning procedure, and the goal(s) of the study. An appropriate sample size is often estimated through formal statistical power analyses, although 'rules of thumb' (e.g., reporting a ratio of at least 10 participants per independent variable in regression analyses) are also utilized. Studies need to have reported at least a 'rule of thumb' judgment on sample size or statistical power analysis. Sample sizes that exceeded the 10:1 ratio were also judged as acceptable.

4. Is the response rate acceptable?
Definitions. Response/recruitment rate: the proportion of all potentially eligible sample cases that agreed to participate. Response/recruitment rate is usually expressed as a percentage and is considered 'acceptable' when ≥ 75% (Evans, 1991). Studies needed to have reported a responses rate ≥ 75%.

5. Was the study approved by a relevant institutional review board or research ethics committee?
Definition. Institutional review board/research ethics committee: a board/committee that is responsible for reviewing research protocols for potential ethical issues. Studies need to have reported that the study was approved by the relevant committee.

6. Did participants provide informed consent?
Definitions. Informed consent: voluntary agreement by people to participate in a research study, subsequent to their being informed about study aims, procedures, potential risks and benefits of participation, including rights to withdraw. Assent: agreement to participate in research by people who are by definition too young to give informed consent (typically < 18 or 16 years of age, depending on country or state legislation), but are old enough to understand the aims of the research, their experience as participants, and rights to withdraw, without punishment or consequence. Assent may be requested from the ages of six or seven. In addition to assent, parental or guardian consent may also be required, although this may be waived under certain

circumstances (e.g., neglected, abused, emancipated, self-sufficient minors; non-FDA-regulated research; research that could not be practically carried out without the waiver; research that poses no harm to participants). Studies need to have reported informed consent in the case of adult participants, and assent and informed consent from parents/legal guardians for research on children below the age of 18.

7. Did the study include a formative research or pilot phase?
Definitions. Formative research: research conducted before (and sometimes during) the study in order to clarify, refine, and focus procedures and methods. Formative research takes various forms (e.g., focus groups and interviews with the target population; patient and public involvement - PPI; validity and reliability analyses of measures). Studies need to have reported conducting one form of formative research.

8. Were the measures provided the report (or in a supplement) in full?
Definitions. Measures: the items (typically in questionnaire format) of a research study to which the participant responds. Studies need to have provided all items and response scales for questionnaires and clear details of other measures used (e.g., studies using accelerometers for measure physical activity should provide the type, brand, method of utilization, administration instructions, period of use, data storage and treatment, and participant tolerance/acceptability of the device).

9. Were the measures valid/ validated?
Definitions. Validation: a procedure undertaken to ensure that measures accurately measure what they intended to, regardless of respondent characteristics. Validation refers to the psychometric properties of the instrument and is the result of some type of statistical and pilot testing (e.g., factor analysis, principal component analysis, internal consistency, pretesting). Studies need to have reported basic validity data of the measure or scale used in the study and in the study sample or a relevant sub-sample).

10. Were all necessary data analyses conducted?
Studies need to have conducted the necessary data analyses to answer research questions/hypotheses/objectives (e.g., descriptive and inferential stats, thematic analyses if there was a qualitative phase).

Detailed Description of Data Analysis Procedures

Meta-Analytic Structural Equation Models

Our goal in the current meta-analysis was to estimate relations among the habit, behavior, and past behavior according to our proposed models (see Figure 1, panels a and b) using the synthesized data from the samples identified in our search. To do so, we used meta-analytic structural equation modeling (MASEM; Cheung, 2015a, b) to pool the matrix of correlations among model constructs extracted from the samples included in our analysis, and provide standardized point and variability estimates of the model-stipulated relations among the constructs. A two-stage approach is proposed. In the first stage, correlation matrices among model constructs from each study included in the analysis are transformed to account for study-specific random effects, enabling them to be analyzed as covariance matrices in a structural equation model. In the second stage, the proposed model is fit to the pooled covariance matrix produced in the first stage, yielding point and variability estimates of the proposed relations among model constructs.

Many of the included studies reported multiple effect sizes within studies (e.g., multiple habit, behavior, or social cognition construct measures, or multiple time points). We accounted for this dependency by following the recommendations of Wilson et al. (2016), who proposed an analytic approach that combines MASEM and multi-level meta-analysis. The first stage produces a pooled correlation matrix with its sampling covariance matrix among the constructs in the proposed model using multivariate multi-level meta-analysis to handle within-study dependency in effect sizes. Consistent with Cheung's MASEM approach, this procedure also allows for the synthesis of studies that only contribute one or two effect sizes to the correlation matrix, and yields precise pooled point and variability estimates for each effect size based on data sets with these kinds of missing data patterns. In the second stage the proposed model is fit to the pooled matrices from the first stage using Cheung's MASEM approach. The procedure also allowed us to adjust the pooled correlation matrices for our proposed covariates (sample age, sex, sample type, study design, study quality) prior to model estimation using MASEM. We adjusted the correlation matrices for the covariates and then estimated our proposed model using MASEM, which allowed us to make comparisons between the parameter estimates of this model with the one estimated using the matrices unadjusted for covariates.

The first stage of Wilson et al.'s multi-level MASEM approach produces a matrix of zero-order bias-corrected correlations among constructs across studies with standard errors and 95% confidence intervals. Two matrices are produced, the unadjusted matrix and the matrix adjusted for covariates. The analysis also provides estimates of variance attributable to the level 2 (between-study) and level 3 (multiple effects within-studies) variance components. In addition, the percentage each variance component contributes to the overall variance is also estimated using the formula proposed by Cheung (2014). Cochran's (1952) Q statistic provides an overall test of the homogeneity of model estimates, with a statistically significant value indicative of substantive heterogeneity. The I^2 statistic provides an estimate of the overall variability in the set of studies not attributable to the variance components corrected for in the analysis, with I^2 values exceeding 25% typically considered a relative indicator of substantive heterogeneity.

In the second stage of the analysis, models representing proposed relations among study variables were fitted to the averaged correlation matrices and the accompanying sampling covariance matrix derived from the first stage. Our first model (Figure 1, panel a) specified effects among habit measures, intention, and behavior and our second model also tested these specified effects but included effects of past behavior (Figure 1, panel b). Fit of the proposed models with the data from the first stage meta-analysis was not evaluated because the models were fully saturated, so model fit in each case was essentially perfect according to standard goodness-of-fit indices. The analysis produces standardized parameter estimates for each effect in the model with accompanying Wald confidence intervals, with estimates considered non-zero if the lower bound of the confidence interval did not encompass zero. As in the first stage, we estimated each model using the covariate-adjusted and unadjusted correlation matrices. Missing data are imputed using full information maximum likelihood estimation. The two-stage multi-level MASEM analyses were implemented using the metafor (Viechtbauer, 2010) and metaSEM (Cheung, 2015b) packages in R.

Bias Assessment Methods

We evaluated the effect of selective reporting bias in the correlations among the proposed model constructs in our sample of studies using a panel of recommended bias-correction methods (Carter et al., 2019). One class of bias tests is based on a 'funnel' plot in which the effect size from each included sample is plotted against an estimate of its precision, such as the inverse its standard error. Bias is indicated by the extent to which plotted values deviate from the expected 'funnel' shape assumed by the plot under conditions of no bias. We used three methods based on the 'funnel' plot to estimate bias in the correlations in the current analysis: Begg and Mazumdar's (1994) rank correlation test, Duval and Tweedie's (2000) 'trim and fill' analysis, and a regression based method proposed by Egger et al. (1997). Substantive bias in an effect size is indicated by a significant rank correlation test based on Kendall's tau (τ), the number of studies imputed and 'corrected' value for the correlation from the 'trim and fill' analysis, and a significant estimate (z-test) of whether the intercept of Egger et al.'s regression model is different from zero. We also estimated two alternative regression methods: the precision effect test (PET) and the precision effect estimate with standard error (PEESE) (Stanley & Doucouliagos, 2014). The PET regresses study effect size on the inverse of its variance estimate while the PEESE uses the variance estimate. Both tests provide estimates of the extent of bias and the bias-corrected effect size. As the PET may underestimate the true mean effect size when there is evidence of a non-zero effect, Stanley and Doucouliagos proposed a conditional procedure: where the PET estimate is statistically significant, implying a non-zero effect, the PEESE estimate is taken, while in the absence of a statistically significant PET estimate, the PET estimate is used. Bias analyses based on the 'funnel' plot were implemented using the metafor package in R.

We also computed a series of tests based on selection methods including tests based on Hedges' (1984) original model (Iyengar & Greenhouse, 1988; Vevea & Hedges, 1995), and recent implementations, known as the p-curve (Simonsohn et al., 2014) and p-uniform* (van Aert & van Assen, 2018) procedures. Selection models involve the researcher specifying a 'data model', which describes how the data are generated, and a selection model, which specifies conditions that may lead to bias, such as, publication of only statistically significant effects. In the current analysis we used a form of the selection model that included a series of thresholds deemed relevant to the synthesis of zero-order correlations: 0.025, 0.050, 0.500, 1.000 (Carter et al., 2019; McShane et al., 2016). The analysis yields a corrected estimate of the effect size and a likelihood ratio ($\chi 2$) test of whether the selection model differs from the standard meta-analytic model, which should be non-significant in the absence of bias. The p-curve and p-uniform* procedures, which suggest that distributions of p-values in studies should assume a characteristic distribution under conditions of no bias. The p-curve of a 'bias free' effect size should exhibit significant right-skewness and non-significant estimates of flatness. The p-uniform provides corrected estimates of the averaged effect size and the between study variance ($\tau 2$) and a likelihood-ratio test of publication bias. The selection model, p-curve, and p-uniform* analyses were implemented using the weightr (Coburn & Vevea, 2019), dmetar (Harrer et al., 2019), and puniform (van Aert, 2020) functions, respectively, in R.

As most bias detection techniques have not been implemented with multi-level models, we implemented the bias correction methods for each correlation separately using conventional random effects meta-analysis using a maximum likelihood estimation method. We aggregated effect sizes within studies using Hunter and Schmidt's (2015) formula with the within-study correlation between effect sizes fixed to 0.50 using the MAc package (Del Re & Hoyt, 2018) in R.

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Table S4

Results of Multi-Level Multivariate Meta-Analysis of Zero-Order Correlations Among Habit Measures, Intention, Behavior, and Past Behavior for Models Including and Excluding Past Behavior and With and Without Adjustment for Covariates

Effect	Model including past behavior				Model excluding past behavior			
	r^{+a}	SE	95% CI		r^{+a}	SE	95% CI	
			LL	UL			LL	UL
Intention-Behavior	.415	.017	.381	.449	.424	.016	.392	.456
	.362	.017	.328	.395	.368	.016	.337	.399
Intention-Habit	.403	.014	.375	.431	.434	.014	.407	.461
	.352	.014	.325	.379	.379	.013	.353	.405
Intention-PB	.452	.017	.420	.484	–	–	–	–
	.401	.016	.369	.433	–	–	–	–
Behavior-Habit	.371	.016	.340	.403	.384	.015	.354	.414
	.320	.016	.289	.351	.330	.015	.301	.359
Behavior-Past behavior	.488	.021	.447	.529	–	–	–	–
	.436	.021	.395	.477	–	–	–	–
Habit-Past behavior	.485	.014	.459	.512	–	–	–	–
	.433	.013	.407	.459	–	–	–	–

Note. Values printed on upper line are for models unadjusted for covariates, values printed on lower line are for models adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. [a]All parameter estimates are non-zero with confidence intervals that do not encompass zero ($p < .001$). r^+ = Zero-order correlation corrected for sampling error; 95% CI = 95% confidence interval of r^+; LL = Lower limit of 95% confidence interval; UL = Upper limit of 95% confidence interval; SE = Standard error.

Table S5

Heterogeneity Statistics for Multi-Level Multivariate Meta-Analytic Models for the Full Sample and Moderator Analyses

Model	L2 σ^2	L3 σ^2	Q^a	df	I^2	L2 var	L3 var
Full model							
Including past behavior	0.020	0.022	20625.517***	1302	93.37	44.34	49.03
	0.018	0.022	19813.821***	1302	93.12	42.12	51.00
Excluding past behavior	0.021	0.015	8514.808***	641	91.66	59.25	32.41
	0.019	0.012	8304.719***	641	91.11	56.48	34.63
Moderator: Opportunity to develop behavior as a habit							
High opportunity	0.013	0.022	23357.532***	1749	92.97	34.46	58.51
	0.012	0.022	22357.087***	1749	92.72	32.06	60.66
Low opportunity	0.013	0.018	8248.786***	597	91.11	38.98	52.13
	0.010	0.018	7005.683***	597	90.07	31.79	58.29
Moderator: Behavioral complexity							
High complexity	0.017	0.012	17843.097***	1365	91.71	54.17	37.55
	0.017	0.010	17532.977***	1365	91.31	57.00	34.31
Low complexity	0.024	0.015	13559.517***	981	93.20	57.17	36.03
	0.024	0.013	12652.611***	981	92.94	59.47	33.47
Moderator: Habit measure							
SRH	0.025	0.016	7087.324***	512	91.31	67.34	23.98
	0.022	0.009	6855.494***	512	90.69	64.87	25.82
BFCS	0.006	0.018	1087.487***	106	90.72	23.93	66.80
	0.001	0.018	876.713***	106	87.85	0.42	87.43
RFM	0.006	0.021	1032.878***	91	91.60	20.38	71.22
	<0.001	0.021	859.442***	91	89.44	<0.01	89.42
Moderator: Habit measure x opportunity†Δ							
High opportunity x SRH	0.028	0.009	5666.891***	360	92.48	69.19	23.29
High opportunity x BFCS	0.006	0.021	1032.878***	91	91.60	20.379	70.22
High opportunity x RFM	0.008	0.091	86.405***	14	82.87	59.29	23.57
Low opportunity x SRH	0.022	0.006	1276.648***	149	87.44	69.01	18.43
Low opportunity x BFCS	0.011	<0.001	50.227***	12	77.80	77.80	<0.01
Moderator: Habit measure x Complexity††‡							
High complexity x SRH	0.021	0.009	3204.160***	279	89.17	62.96	26.21
High complexity x BFCS	0.011	0.007	396.652***	56	88.71	54.26	34.45
Low complexity x SRH	0.032	0.007	3774.149***	230	92.99	76.73	16.26
Low complexity x BFCS	0.011	<0.001	50.227***	12	77.80	77.80	<0.01
Moderator: Inclusion vs. exclusion of frequency items							
SRHF	0.020	0.014	16145.989***	1112	93.06	54.15	38.91
	0.020	0.014	16149.237***	1112	93.01	54.46	38.55
SRHE	0.024	0.015	20555.099***	1600	91.59	56.49	35.11
	0.024	0.012	18648.966***	1600	91.04	60.43	30.61
Moderator: Behavior type							
Dietary behaviors	0.021	0.012	8037.029***	617	92.76	60.10	32.67
	0.022	0.010	7944.679***	617	92.41	63.26	29.15
Physical activity	0.011	0.011	4030.307***	512	87.96	44.16	43.81
	0.012	0.008	3392.752***	512	86.38	51.54	34.83

Alcohol behaviors	0.012	0.004	612.818***	119	80.03	61.63	18.40
	0.011	0.001	540.303***	119	75.88	68.07	7.82
Protection behaviors	0.018	0.007	2581.479***	353	85.87	61.29	24.58
	0.018	0.006	2453.349***	353	85.02	64.96	20.05
Transport behaviors	0.017	0.015	4796.716***	246	95.64	50.48	45.16
	0.017	0.008	3515.170***	246	94.51	63.45	31.06
Moderator: Behavior measure							
Self-reported behavior	0.022	0.012	30224.338***	2154	92.89	59.42	33.47
	0.022	0.011	29781.951***	2154	92.66	61.39	31.27
Non-self-reported behavior	0.000	0.004	71.265*	48	25.17	<0.01	25.17
	0.000	0.002	64.670	48	14.61	<0.01	14.61
Moderator: Measurement lag							
Distal	0.021	0.009	6497.574***	369	93.71	66.73	26.98
	0.021	0.007	6050.517***	369	93.26	71.37	21.89
Proximal	0.014	0.016	9302.216***	1008	89.83	41.95	47.89
	0.014	0.014	9104.674***	1008	89.23	44.48	44.75
Habit measure correlations/CFA							
	0.009	0.009	331.165***	63	73.28	37.04	36.24
	0.007	<0.001	137.622***	63	52.10	52.10	<0.01

Note. Values printed on upper line are for models unadjusted for covariates, values printed on lower line are for models adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. [†]Interaction effects of the opportunity to develop behavior as a habit and the habit measure type moderator variables on model effect sizes. These models are not adjusted for covariates due to small numbers of studies in a majority of the moderator groups. [††]Interaction effects of the behavior complexity and the habit measure type moderator variables on model effect size. These models are not adjusted for covariates due to small numbers of studies in a majority of the moderator groups. [Δ]Heterogeneity statistics could not be generated for the model estimated in the low opportunity to form as a habit x RFM moderator group because there was only one available study; [‡]Heterogeneity statistics could not be generated for the model estimated in the low behavioral complexity x RFM moderator group because there was only one available study, and the model in the high behavioral complexity x RFM moderator group could not be estimated due to a lack of available studies resulting in empty cells in the input correlation matrix. L2 = Level 2 variance component of multi-level model (variance between effect sizes within studies); L3 = Level 3 variance component of the multi-level meta-analytic model (variance between studies); σ^2 = Estimate of 'true' variability in the effect; Q = Cochran's Q test; df = Degrees of freedom for Q; I^2 = Higgins and Thompson's (2002) I^2 statistic; L2 var. = Percentage of total variability attributable to variability between effect sizes within studies (level 2); L3 var. = Percentage of total variability attributable to variability between studies (level 3); SRH = Self-report habit measure; BFCS = Behavioral frequency x context stability habit measure; RFM = Response frequency habit measure; SRHF = Self-reported habit measures including behavioral frequency items; SRHE = Self-reported habit measures excluding behavioral frequency items; CFA = Meta-analytic confirmatory factor analysis.

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

Table S6

Standardized Parameter Estimates for Effects of Habit and Intention on Behavior from Multi-Level Meta-Analytic Structural Equation Modeling Analysis at Each Level of Key Moderator Variables (Adjusted and Unadjusted for Covariates)

Moderator	Effect								
	Hab→Beh			Int→Beh			Hab↔Int		
	β	95% CI		β	95% CI		β	95% CI	
		LL	UL		LL	UL		LL	UL
Opportunity to develop behavior as a habit									
Low opportunity	.198[a]	.152	.243	.337	.285	.388	.436	.393	.478
	.180[b]	.137	.223	.308	.259	.356	.397	.358	.437
High opportunity	.265[a]	.229	.302	.311	.272	.350	.436	.403	.469
	.257[b]	.222	.292	.298	.260	.336	.414	.381	.446
Behavioral complexity									
Low complexity	.293[a]	.251	.336	.312	.266	.358	.437	.396	.479
	.291[b]	.249	.333	.308	.263	.354	.429	.389	.469
High complexity	.208[a]	.172	.244	.328	.288	.368	.438	.405	.471
	.178[b]	.145	.212	.276	.240	.313	.365	.333	.396
Habit measure									
SRH	.259	.228	.290	.293[a,b]	.259	.327	.434	.405	.463
	.226[a]	.197	.255	.254[c]	.222	.285	.366[a]	.338	.394
BFCS	.204	.120	.287	.413[a]	.329	.496	.442	.371	.512
	.124[a]	.060	.189	.276	.215	.336	.257[a,b]	.215	.299
RFM	.205	.107	.302	.419[b]	.323	.514	.450	.374	.525
	.169	.086	.252	.354[c]	.277	.432	.370[b]	.323	.417
Habit measure x opportunity[†Δ]									
High opportunity x SRH	.286[a,b]	.248	.324	.284[a,b,c]	.243	.325	.434	.398	.471
High opportunity x BFCS	.205	.107	.302	.419[a,d]	.323	.514	.450	.374	.525
High opportunity x RFM	.304	.197	.412	.226[d,e,f]	.106	.345	.395	.299	.491
Low opportunity x SRH	.198[a]	.148	.247	.317[g,h]	.260	.373	.435	.389	.480
Low opportunity x BFCS	.182[b]	.112	.252	.428[b,e,g]	.336	.519	.426	.323	.530
Low opportunity x RFM	.203	.076	.330	.505[c,f,h]	.385	.624	.470	.386	.554
Habit measure x Complexity[††‡]									
High complexity x SRH	.214[a]	.173	.256	.319[a,b]	.273	.364	.436	.399	.472
High complexity x BFCS	.187[b]	.106	.269	.364	.280	.447	.451	.364	.538
Low complexity x SRH	.314[a,b]	.270	.359	.272[c,d]	.225	.318	.437	.392	.482
Low complexity x BFCS	.205	.081	.329	.524[a,c]	.385	.663	.436	.322	.551

Low complexity x RFM	.203	.076	.330	.505[b,d]	.385	.624	.470	.386	.554
Inclusion vs. exclusion of frequency items									
SRHE	.274	.227	.320	.260	.208	.311	.428	.387	.469
	.298[a]	.250	.346	.279	.226	.333	.463[a]	.422	.503
SRHF	.244	.203	.285	.321	.277	.365	.440	.400	.481
	.224[a]	.185	.263	.288	.246	.330	.392[a]	.355	.430
Behavior type									
Dietary behaviors	.277[a]	.224	.331	.286[a]	.230	.343	.378[a,b,d]	.332	.424
	.285[b]	.232	.339	.293[b]	.235	.350	.394[c]	.350	.437
Physical activity	.195[a,c,d]	.152	.238	.334[c]	.284	.383	.443[a,e]	.398	.487
	.187[b]	.146	.228	.308[d]	.262	.354	.408[f]	.367	.449
Alcohol behaviors	.246	.180	.313	.422[a,c,e]	.349	.495	.540[b,e]	.463	.616
	.256	.184	.328	.460[b,d,f,g]	.387	.533	.601[c,f,g,h]	.546	.656
Protection behaviors	.311[c]	.219	.403	.252[e]	.160	.344	.478[d]	.407	.549
	.264	.181	.347	.220[f]	.137	.304	.399[g]	.334	.464
Transport behaviors	.284[d]	.211	.357	.351	.274	.428	.441	.361	.520
	.238	.173	.304	.290[g]	.222	.358	.356[h]	.297	.415
Behavior measure									
Self-reported behavior	.250	.219	.281	.324[a]	.291	.358	.447[a]	.418	.475
	.224	.195	.253	.287[b]	.256	.318	.384[b]	.357	.412
Non-self-reported behavior	.227	.162	.291	.190[a]	.104	.275	.315[a]	.244	.386
	.229	.164	.293	.182[b]	.097	.267	.294[b]	.224	.365
Measurement lag									
Proximal	.272[a]	.239	.305	.307	.271	.342	.463	.426	.501
	.301[b]	.265	.336	.337	.299	.375	.526[a]	.490	.562
Distal	.183[a]	.124	.242	.359	.292	.427	.400	.338	.462
	.170[b]	.115	.225	.323	.260	.387	.350[a]	.290	.409

Note. Parameter estimates printed on the upper line are unadjusted for covariates, parameter estimates on the lower line are adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study quality, and study design. All parameter estimates are non-zero with confidence intervals that do not encompass zero ($p < .01$). Parameter estimates with matching superscripted letters are statistically significantly different ($p < .05$) using Schenker and Gentleman's (2001) 'standard method' based on confidence intervals. †Interaction effects of the opportunity to develop behavior as a habit and the habit measure type moderator variables on model effect sizes. These models are not adjusted for covariates due to small numbers of studies in a majority of the moderator groups. ††Interaction effects of the behavior complexity and the habit measure type moderator variables on model effect size. These models are not adjusted for covariates due to small numbers of studies in a majority of the moderator groups. ΔOnly one study was available the model in the low opportunity to form as a habit x RFM moderator so the parameter estimates are from a single study and are not meta-analytic estimates; ‡Only one study was available the model in the low opportunity to form as a habit x RFM moderator so the parameter estimates are from a single study and are not meta-analytic estimates, and the model in the high behavioral complexity x RFM moderator group could not be estimated due to a lack of available studies resulting in empty cells in the input correlation matrix. SRH = Self-report habit measure; BFCS = Behavioral frequency x context stability habit measure; RFM = Response frequency habit measure; β = Standardized path coefficient; 95% CI = 95% confidence interval of parameter estimate; LL = Lower limit of 95% CI; Int = Intention; Beh = Behavior; Hab = Habit.