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Meta-analysis of the Theory of Planned Behavior in Physical Activity

A dissertation submitted in partial satisfaction of the requirements
for the degree Doctor of Philosophy

in

Psychological Sciences

by

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McNair Travel Grant *February 2019*

- Nine-hundred-dollar grant awarded to attend the annual Western Psychological Association conference.

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Warriors Excellence Textbook Scholarship *Fall 2018-May 2020*

- Two hundred and fifty dollars was awarded each semester.

President's Scholarship *Fall 2018-May 2020*

- Two-thousand and five-hundred dollars was awarded each semester.

SERSCA Undergraduate Assistantship *Fall 2019-May 2020*

- One thousand, one hundred and twenty dollars was awarded to complete research in the Healthy Aging Lab.

McNair Travel Grant *Fall 2019*

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California State University, Stanislaus Research Competition 1st Place *March 2020*

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Outstanding Student Award for Psychology *May 2020*

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Abstract

Objective: The theory of planned behavior is a prominent social cognition theory widely applied to predict physical activity. While prior meta-analyses of applications of the theory in this behavioral context have provided generalized support for its effects, limitations and evidence gaps have been noted such as syntheses of evidence on the unique effects of differentiated theory constructs, and effects of indirectly-measured belief-based constructs, on intentions and behavior. Further, there is a dearth of research on moderating conditions under which theory effects vary. To address these limitations and evidence gaps, we used synthesized data from a large-sample meta-analysis of applications of the theory in physical activity contexts to test effects of the basic theory and, importantly, particularly effects of differentiated and indirectly-measured theory constructs on physical activity intentions and behavior as well as examining effects of conceptually- and methodologically-salient moderators on theory effects including measurement correspondence and physical activity behavior types. **Method:** We identified studies reporting associations among measures of the attitude, subjective norm, and perceived behavioral control constructs, intentions, and behavior in a systematic literature search of theory applications in physical activity contexts. We tested theory effects and additional theory-implied effects in three models including versions adopting differentiated subcomponent constructs and directly- and indirectly-measured constructs, as well as effects of salient moderators, using optimal multilevel meta-analytic structural equation modeling techniques. **Results:** Model tests provided support for the theory-consistent patterns of effects for all three models including direct, and indirect intention mediated-effects, of core and differentiated constructs on physical activity behavior, and of the indirectly-measured constructs mediated by directly-measured counterparts. We also observed important theory-implied effects such as direct attitude-behavior effects. Moderator analyses revealed conceptually-salient differences in theory effects according to our moderators, particularly for measurement correspondence and behavior type. **Conclusion:** Beyond corroborating findings of prior meta-analyses of the theory, our analysis provides support for versions of the theory encompassing differentiated and indirectly-measured constructs, as well as moderators that represent key conditions that affect theory effects. Results provide support for key additional theory hypotheses not tested in previous research syntheses and set an agenda for future research applying the theory applications in physical activity contexts.

Introduction

Regular participation in physical activity, particularly of moderate-to-vigorous intensity, is associated with adaptive health-related outcomes, including reduction in risk factors for chronic disease (Centers for Disease Control and Prevention [CDC], 2020), promotion of positive physical and mental health outcomes (Biddle et al., 2019; Warburton & Bredin, 2017), and prevention of cognitive decline (Chase et al., 2016; Sofi et al., 2011). Despite substantive social epidemiological research in support of these health benefits, population level participation rates in regular physical activity fall far short of recommended guidelines (World Health Organization [WHO], 2022). Accordingly, governmental public health organizations and health promotion and communication advocates have made development of behavior change interventions targeting increased participation in physical activity a priority (e.g., Centers for Disease Control and Prevention [CDC], 2025; Sparling et al., 2000). Importantly, there is increased recognition that development of optimally efficacious interventions necessitates a basis in behavioral theory evidence purposed to identify determinants reliably associated with physical activity uptake and maintenance and the mechanisms involved (e.g., Glanz & Bishop, 2010; Rothman et al., 2015). Accordingly, evidence indicating the theory-based determinants reliably associated with physical activity and the purported theory-based mechanisms involved may signal potential targets for change via behavior change techniques of which behavioral interventions comprise (Hagger & Weed, 2019; Johnson et al., 2014; Sheeran et al., 2017). Such evidence may assist in informing the content of such interventions and subsequent research to assess their potential efficacy in physical activity promotion (Hagger et al. 2020; Kok et al., 2016; Michie et al., 2018).

Theories in the social cognition tradition, a particular class of theory derived from social psychology, have been widely applied to identify the determinants of physical activity and associated processes (Conner & Norman, 2015; Fishbein et al., 2001). Theories adopting this approach define psychological constructs that reflect individuals' beliefs with respect to their future performance of a given target behavior and are assumed to be directly implicated in the decision-making process that leads to subsequent adoption of a given target behavior. Accordingly, theories of this class adopt an information processing approach and assume that individuals' behaviors are a function of their reasoned processing of available and pertinent social information with respect to future actions (Hagger, 2025; Turner et al., 2021). Although many social cognition theories have been conceptualized as theories of behavioral prediction, theorists and associated empirical evidence have mounted contending that such theories have substantive utility in informing interventions designed to change behavior, elevating their societal value as means to guide practice (Ajzen & Schmidt, 2020; Hagger & Weed, 2019). Importantly, a substantive evidence base comprising predictive studies adopting these theories to predict behavior has amassed, particularly in health behavior contexts (e.g., Hagger, 2025), including physical activity (Rhodes et al., 2019).

Theory of Planned Behavior: Overview and Hypotheses

Of the multiple social cognition theories that have been applied to the prediction of health- related behavior, particularly physical activity, the theory of planned behavior (Ajzen, 1985, 1991) stands out as one of the most prominent. Prototypical of the social cognition approach, a central hypothesis of the theory is that intention is the most proximal determinant of a given target behavior. Intention is conceptualized as a motivational construct representing the extent to which an individual is motivated to engage in, or prepared to invest effort in pursuing, the behavior.

Intention is a function of three belief-based constructs: attitude, an individual's evaluation of whether the behavior will lead to salient outcomes; subjective norm, an individual's perception that others will approve or disapprove of their performance of the behavior; and perceived behavioral control, an individual's beliefs in their capacity to perform the behavior. Importantly, intention is proposed as the mechanism by which these sets of beliefs relate to behavior and is, consequently, expected to mediate the relationship between the belief-based constructs and behavior. Perceived behavioral control occupies a unique role in the theory in that it serves to moderate effects of the attitude and subjective norm constructs on intention, and of effects of intention on behavior.

Accordingly, in behavioral contexts where individuals perceive they have full control over the target behavior, attitude-intention, subjective norm-intention, and intention-behavior relations are proposed to be maximized. By contrast, in contexts where individuals perceive that their control over the behavior is compromised or limited, for example due to the presence of barriers or constraints or a lack of facilitating factors, individuals may be less likely to state intentions to act on the basis of their attitudes or subjective norms, and less likely to act on their intentions. With respect to prediction, therefore, attitude-intention, subjective norm-intention, and intention- behavior relations are predicted to be moderated downwards[1]. The formally-specified moderating function of perceived behavioral control notwithstanding, a substantive majority of predictive studies based on the theory have fixated on testing an indirect, intention mediated effect of perceived behavioral control on behavior with an accompanying direct effect. In behavioral contexts where perceived behavioral control represents perceived capacity to perform the behavior, behavioral effects are proposed to be mediated by intentions as the construct reflects individuals' personal judgment concerning perceived barriers and facilitating factors, while in cases where perceived behavioral control is precisely aligned with the actual level of control an individual has, the direct effect is expected (see Ajzen, 1991; Hagger et al., 2022).

Fundamental to the theory is the assumption that the attitude, subjective norm, and perceived behavioral control constructs represent global summarizes of the sets of beliefs salient to the individual with respect to their future performance of the target behavior (Ajzen, 1985, 1991). The specific sets of salient beliefs are proposed to capture the essence of their respective global construct in accordance with an expectancy-value model, which is reflected in the measurement methods proposed to capture them.

[1] Strictly speaking, under conditions of full perceived control the theory, the theory is effectively reduced to the theory of reasoned action (Ajzen & Fishbein, 1980), the predecessor and formative approach to the theory of planned behavior. For a full discussion, readers are directed to Ajzen's (1985, 1991) lucid treatment of the development of the theory.

Specifically, attitude is proposed to summarize a set of behavioral beliefs, reflecting expectations that performing the target behavior will result in meaningful outcomes relevant to the individual, and accompanying outcome evaluations of each belief, reflecting the extent to which the outcome is valued by the individual; subjective norm is proposed to comprise a set of normative beliefs, reflecting the perceived expectations of salient social agents with respect to the individual's performance of the behavior, and the individual's motivation to comply with the expectations of each social agent; and perceived behavioral control is proposed to encompass a set of control beliefs, reflecting expectations of acting in light of sets of salient barriers and facilitating factors, and associated control belief power, reflecting the extent to which each is expected to impede or facilitate action. The beliefs salient to the behavior and population are typically identified in advance via an open-ended elicitation procedure in a representative sample, with the most frequently cited beliefs adopted in subsequent measures. Each individual belief is weighted by its value in series of belief x value multiplicative composites, the sum of which forms the indirect measure of its respective global construct. In predictive models of the theory, the effect of each indirectly-measured construct on intention is proposed to be fully mediated by its directly-measured counterpart, and, by implication, their effects on behavior sequentially mediated by the directly-measured constructs and intention. The belief basis of the theory constructs is considered central to the role of the theory as a guide to intervention as they represent targets for change by persuasive communication messages (see Ajzen & Schmidt, 2020; Hamilton & Johnson, 2020).

The predictions of the theory have been tested in hundreds of studies spanning multiple populations, contexts, and behaviors (e.g., Armitage & Conner, 2001; Hagger & Hamilton, 2024), particularly in health behavior (e.g., McEachan et al., 2011; Rich et al., 2015) and physical activity- related contexts (e.g., Hagger et al., 2002; Symons-Downs & Hausenblas, 2005). Studies typically adopt predictive correlational designs in which directly- or indirectly-measured attitude, subjective norm, and perceived behavioral control constructs, or both, and intention, are measured on an initial occasion with a follow-up measure of the targeted physical activity behavior taken on a second, follow-up occasion sometime later. Meta-analytic syntheses of these data offer the most robust evidence for theory effects in physical activity (e.g., Hagger et al., 2002; McEachan et al., 2011; Symons Downs & Hausenblas, 2005). Specifically, these analyses have provided generalized support for averaged associations between the theory constructs across studies and demonstrated that the theory accounts for substantive variance in intention and behavior. In addition, using synthesized data from these analyses, research has provided support for the unique effects of the directly-measured global constructs of the theory on intentions, and of intentions and perceived behavioral control on behavior, and indirect effects of the constructs on behavior mediated by intention, as predicted by the theory (e.g., Hagger et al., 2002; Rich et al., 2015). However, the size of the averaged effects among theory constructs reported in these meta-analyses were associated with substantive residual heterogeneity after artifactual correction (e.g., sample size weighting) in all cases signaling the likely presence of moderating variables that represent possible conditions under which theory effects might vary. Although it should be noted that such variation reflects variance in the magnitude in effect sizes rather than the presence or absence of the effect (i.e., difference from the null). Moderator analyses conducted within these meta-analyses have identified contextual (e.g., behavior type) and methodological (e.g., time lag between measurement occasions, use of self- report behavior measures) conditions under which effect sizes among theory constructs likely vary (Hagger et al., 2002; Hagger & Hamilton, 2024; McEachan et al., 2011; Rich et al., 2015). Findings have indicated larger effect sizes for constructs such as attitude and perceived behavioral control on intention in self-focused behaviors that demand personally-driven decision making (e.g., physical activity, healthy eating) and larger effects of subjective norms in behaviors where group-level obligations and norms are more salience to decision-making takes (e.g., alcohol consumption; Armitage & Conner, 2001), and larger theory effect sizes of theory constructs in general in studies in which theory constructs were taken in close proximity to behavior (McEachan et al., 2011; Symons Downs & Hausenblas, 2005) and in studies employing self-report behavior measures (McEachan et al., 2011; Rich et al., 2015). However, such analyses typically do not fully resolve the residual variability observed in theory effects across studies.

Boundary Conditions, Theory Extensions, and Methodological Issues in Research Syntheses of the Theory

While there is robust evidence offered by research syntheses supporting the stipulated pattern of effects of the theory of planned behavior across predictive studies applied in health behavior contexts, including physical activity, subsequent conceptual and empirical work has identified boundary conditions, proposed extended versions and ancillary hypotheses related to the theory, and highlighted emergent methodological issues of concern. For example, researchers have suggested that the shortfall in explained variance in intentions and behavior may be attributable to certain boundary conditions, such as measurement correspondence. In addition, studies focused solely on theory tests employing based solely on directly-measured constructs tend to be overrepresented in the research literature and, consequently, in research syntheses, with a relative dearth of studies examining effects of indirectly-measured constructs. Further, there have been considerable advances in identifying specific forms of the core belief-based theory constructs, attitude, subjective norm, and perceived behavioral control, with the purpose of providing nuance in the specific belief-based determinants of behavior. This has resulted in the proposal and testing of extended versions of the theory adopting distinct constructs. Finally, research syntheses seeking to test theory predictions using multivariate analyses, including the unique direct and indirect theory- stipulated effects among its constructs and intentions and behavior, have tended to use sub-optimal analytic methods. Next, we review each of these issues with suggestions for possible solutions, and indicate how a new meta-analytic synthesis of research applying the theory in physical activity contexts that includes additional hypothesis tests and moderator analyses may provide resolution.

Correspondence in Measurement of Theory Constructs. Prior meta-analyses of the theory have led to substantive progress in knowledge of key contextual (e.g., behavior type) and methodological (e.g., measurement lag, use of self-report or non-self-report behavior measures) conditions that affect relations among theory constructs. This progress notwithstanding, the non- trivial residual variance in study effect sizes across studies points to the likelihood of other moderators. Tests of the level of correspondence in theory and behavior measures, and in intention and behavior measures, represent as yet untested candidate moderators of theory effects that possess considerable potential to advance conceptual and methodological knowledge on the theory, particularly to identify its boundary conditions and highlight requisite considerations in the design of construct measures. Specifically, in the original conceptualization of the theory, Ajzen (1985, 1991) specified the essentiality of the high correspondence in measures of the belief-based theory constructs, intention, and behavior to prediction. Steeped in prior research on attitudes indicating that attitude-behavior relations are highly dependent on the specificity of the attitude with respect to the attitude object (for example see Fishbein, 1967; Wicker, 1969), Ajzen outlined key elements on which measures of theory constructs, attitude, subjective norms, and perceived behavioral control and those used to measure intentions and behavior should correspond, namely, the target or objective of the action, the specific action or behavior of interest, the context in which the action occurs, and the time frame in which it is expected to occur, collectively summarized by the 'TACT' acronym. As a consequence, measures of constructs such as attitude would prompt individuals to respond to statements that encompassed as many, preferably all, of these elements. For example, the following physical activity attitude item: "Briskly walking in my local park for at least 30 minutes each day in the next fortnight would be…." encompasses three of the TACT correspondence elements, namely, action "brisk walking", context "my local park", and time " at least 30 minutes each day in the next fortnight " with responses provided on semantic differential scale anchored with bipolar adjectives (e.g., "highly unlikely" and "highly likely"). Measures of intention and behavior would be expected to attain high correspondence with each element, consider, for example the following accompanying intention item: "I plan to walk briskly in my local park for at least 30 minutes each day in the next fortnight".

Prediction of intention and behavior is expected to be optimized when the study measures adopted exhibit high correspondence with respect to the specified elements and attenuated when measurement correspondence is low or even absent. However, this basic premise has surprisingly received only relatively limited attention in primary research studies applying the theory, with little resolution or consensus on the extent to which measurement correspondence affects relations among theory constructs in predictive studies (e.g., Courneya, 1994; Courneya & McAuley, 1994). The proliferation in research studies applying the theory in physical activity contexts since the publication of prior reviews offers a unique opportunity to test the effects of measurement correspondence in terms of the direct measures of theory constructs and intention, and of intention and behavior, on theory effects.

We therefore proposed to conduct a meta-analysis of research aimed at indicating the extent to which measurement correspondence explains observed variance in averaged effect sizes in syntheses of applications of the theory in this context. Specifically, we proposed to test differences in the averaged effects of theory constructs across eligible studies according to the degree of measurement correspondence in the construct measures according to Ajzen's elements. The analysis is expected to provide a first meta-analytic test of measurement correspondence on theory effects, yielding salient information with respect to the conceptual imperative of adhering to Ajzen's correspondence specifications and recommendations for researchers developing measures for use in future theory tests in this context.

Effects of Indirectly-Measured Constructs. Although prior meta-analytic reviews have tested the unique direct and indirect effects of theory constructs on intention and behavior, these analyses have largely been confined either to data from studies solely adopting directly-measured theory constructs, or in some cases, pooled data across studies adopting directly- and indirectly-measured constructs. There are also prior meta-analyses of theory tests that have reported averaged effects of the indirectly-measured theory constructs on intentions, but these have exclusively focused on bivariate correlations with intention or with the directly-measured constructs themselves (Armitage & Conner, 2001). To date, current syntheses of theory applications have not formally tested theory- stipulated indirect effects of indirectly-measured theory constructs on intentions and behavior mediated by the directly-measured constructs. Concurrently, it is worth noting that relatively few primary studies offer formal tests of these effects, with many either confined to bivariate associations between the directly- and indirectly-measured constructs, or between the indirectly- measured constructs and intentions (e.g., Armitage & Conner, 1999; Hagger et al., 2001).

We therefore sought to resolve this evidence deficit in the current analysis by leveraging synthesized data from research applying the theory in physical activity contexts, which has greatly expanded since previous reviews, to conduct a large-sample test of the proposed theory effects, particularly indirect effects of the indirectly-measured constructs on intentions and behavior mediated by their respective global, directly-measured counterparts. Our analysis is expected to provide estimates of the size and variability of these effects that researchers conducting future comprehensive tests comprising both directly and indirectly-measured theory constructs would expect to observe.

Differentiated Construct Sub-Components. The enduring attraction of the theory of planned behavior is its inherent parsimony and clarity in conceptualization and measurement, a likely factor in its wide application and popularity. However, there are conceptual and empirical contentions that the theory constructs may not adequately distinguish between more fine-grained, nuanced beliefs relevant to behavior intentions, and researchers have conceptualized differentiated subcomponents of the attitude, subjective norm, and perceived behavioral control constructs and tested their effects on intention and behavior in the context of theory tests[2]. Specifically, distinctions have been made between cognitive and affective sub-components of the attitude construct, in recognition that individuals' beliefs about outcomes encompass those focused on the instrumentality or utility of the action or emotional expectations, respectively. The

[2] It should be noted that differentiation of theory subcomponents may be a function of researchers' generalized fixation on the direct, global measures of theory constructs, and there is a suggestion that the subcomponents may be reflected in the specific beliefs that comprise the indirect, belief- based measures of theory constructs (Fishbein & Ajzen, 2010).

distinction is consistent with mounting evidence that anticipated affect or emotional consequences are a unique behavioral determinant, particularly for behaviors that tend to be more impulsive or inherently rewarding (e.g., alcohol consumption, snacking), relative to those that necessitate more deliberate consideration, such as those that are more complex or demand substantive planning or processing to enact (e.g., physical activity, keeping medical appointments) (e.g., Conner et al., 2013; Lawton et al. 2009). A distinction has also been made between injunctive and descriptive sub-components of the subjective norm construct. While injunctive norms reflect the prototypical conceptualization of subjective norms as perceived expectations of significant others with respect to performing the target behavior, descriptive norms reflect expectations with respect to what is perceived as normative with regarding performing the target behavior among salient social agents and social groups. This aligns with the conceptual proposition that beliefs with respect to typical, normative group behaviors is a salient source of information for intention formation and decision making (e.g., Cialdini et al., Deutsch & Gerrard, 1955). Finally, researchers have distinguished between perceived controllability, sometimes labelled autonomy (Fishbein & Ajzen, 2010), and self-efficacy as subcomponents of the perceived behavioral control construct, which represent perceptions relating to actual control over the behavior and the degree to which they are able to perform it relative to barriers or obstacles and their estimation of personal capacity or confidence in performing, respectively. This is consistent with research indicating that beliefs with respect to the ease of performance of enacting a behavior and estimates of capacity represent distinct constructs and have differential effects on behavior. Recognizing an emergent literature supporting formal distinctions between the attitude, subjective norms, and perceived behavioral control subcomponents (Trafimow & Fishbein, 1995; Trafimow & Sheeran, 1998; Trafimow et al. 2002) and their unique effects on intention and behavior (e.g., Conner et al., 2015; Grube et al., 1986; Terry & O'Leary, 1995), a respecified, generalized version of the theory has been proposed by its originators that has become known as the reasoned action approach (Fishbein & Ajzen, 2010).

Cumulative evidence in the form of meta-analyses has also been forthcoming supporting unique effects of the differentiated subcomponents of the attitude (Conner et al., 2015), subjective norm (Rivis & Sheeran, 2002), and perceived behavioral control (Hagger et al., 2002) constructs on intentions and, indirectly, behavior across studies in health behavior contexts including physical activity, the culmination of which has been recent meta-analyses testing differentiated subcomponent effects simultaneously in a fully-differentiated model of the theory, effectively testing the reasoned action approach (Hagger et al., 2018; McEachan et al., 2016). Further, multi-behavior studies have indicated divergence in the predictive patterns of effect of key subcomponents consistent with the theory, providing further evidence of predictive validity. For example, affective attitudes have consistently demonstrated larger effects among risk behaviors and those more likely to be driven by impulsive processes such as illegal drug use, binge drinking, and smoking, relative to behaviors that are more likely to necessitate greater reasoning and planning to enact such as physical activity (Conner et al., 2015; Lawton et al., 2009). These data have also provided evidence of direct affective attitude-behavior relations unmediated by intentions observed in the more impulsive behaviors consistent with the notion that these behaviors are more likely to be enacted through less reasoned processes. Similarly, there is also evidence of larger effects of the descriptive norm subcomponent on health behavior intentions, including for physical activity, relative to injunctive norms, among individuals who strongly identify with the social group to which they belong, an indicator of the greater likelihood that the behavioral norms of social agents in the groups are likely to be highly salient in making decisions (Åstrøm & Rise, 2001; Terry & Hogg, 1996). Taken together, the extant research has provided broad support for the construct and predictive validity of separate subcomponent models of the key constructs from the theory of planned behavior, providing indication that making this distinction may assist in elucidating further specific judgements implicated in intention formation and subsequent action in health contexts including physical activity[3].

In the current study, we aimed to provide a further test of the differentiated construct approach across the extant literature in the physical activity domain. The analysis will offer an advance on prior syntheses by offering a test of the predictive validity of each construct subcomponent through large sample estimation of the unique subcomponent effects on intention and, indirectly, behavior that such a synthesis affords. This represents an incremental advance on prior analyses, which were not able to conduct behavior-specific analyses of the differentiated construct model due to insufficient available studies.

Meta-Analytic Methods. It is important to acknowledge that prior meta-analyses of research applying the theory in physical activity contexts have tended to use sub-optimal analytic methods to estimate the unique effects of theory constructs on intentions and behavior across studies. These methods are likely to have resulted in imprecise effect size and, particularly, variance estimates. This is because prior analyses used meta-analytic path analysis, also known as ‘univariate’ meta-analytic structural equation modeling, to estimate model effects (Cheung, 2015; Jak et al., 2021; Hagger & Hamilton, 2024). In such analyses, models representing the theory effects are fit to a matrix of meta-analyzed correlations, which may arise from different numbers of studies, presenting researchers with the vexing problem of identifying a reasonable estimate of the sample size, with many falling back on a ‘rule of thumb’ values such as the harmonic mean (e.g., Hagger et al., 2016; Viswesvaran & Ones, 1995). Such an approach is highly likely to yield imprecise variability estimates, confirmed in recent simulation research (Jak & Cheung, 2024). Methodological developments have produced updated implementations of these procedures, collectively known as meta-analytic structural equation modeling, that allow the matrix of meta-analyzed bivariate correlations among theory constructs to

[3] Several caveats to the differentiated construct approach should be noted. There is evidence to suggest that the subcomponents are substantive indicators of their respective higher order constructs (Hagger & Chatzisarantis, 2005; Rhodes et al., 2006), which is to be expected given they tend to substantively intercorrelate. Further, the distinction between the specific subcomponents may also be moot at the practical level as intervention techniques and messaging may affect change in each subcomponent simultaneously.

be analyzed as covariance matrices (Cheung, 2015; Jak & Cheung, 2024). These analytic approaches permit researchers' capacity to fit models representing the nomological network of relations among theory constructs and estimate the theory-specified unique direct and indirect effects among constructs and their associated variability with optimal precision. Importantly, these approaches are directly commensurate with the multivariate analytic procedures used in primary studies and circumvents the sample size issue. As a consequence, the adoption of such procedures is considered de rigueur when testing theory-implied predictions using meta-analytic data and offers a considerable advance on the univariate approaches adopted in prior meta-analyses of the theory in physical activity contexts (e.g., Hagger et al., 2002; Symons-Down & Hausenblas, 2005).

The Present Study

The purpose of the present meta-analysis was to provide large-sample tests of a series of models specifying the key hypotheses of the theory and, importantly, seeking to address salient outstanding issues, specifically, measurement correspondence as an identified boundary condition of the theory; previously untested and extended versions of the theory focused on directly- and indirectly-measured constructs and differentiated constructs, respectively; and sub-optimal analytic techniques. We aimed to do so by leveraging synthesized data from meta-analyses of theory applications in physical activity contexts identified in systematic literature searches.

We acknowledge the existence of multiple prior meta-analyses of the theory conducted in a number of health behavior contexts (e.g., McEachan et al., 2011; Rich et al., 2015), including those related to physical activity behaviors (e.g., Hagger et al., 2002; Symons-Downs & Hausenblas, 2005), that have provided robust, consistent, converging evidence in support of core theory predictions as well as differentiated construct versions that distinguish between attitude (Conner et al., 2015), subjective norm (Rivis et al., 2003), and perceived behavioral control (Hagger et al., 2002) construct subcomponents, commonly referred to as the reasoned action approach (Conner et al., 2015; Hagger et al., 2002, 2018; McEachan et al., 2016; Rivis et al., 2003). Given the prevalence and breadth of these prior syntheses, we recognize the bar is set high for the potential of new meta-analyses to extend current knowledge and broaden beyond mere corroboration in an updated database of studies. However, we contend that our analysis meet and exceeds these high standards, beyond the requisite meta-analytic test of core study hypotheses in an updated sample of studies. Specifically, it offered meta-analytic tests of additional moderators of theory effects with conceptual relevance and hypotheses of versions of the theory that have not previously been tested in synthesized data, as well as employing appropriate analytic techniques to test unique theory effects commensurate with those used in primary studies. We did this by estimating three models each specifying a set of hypothesized effects of the theory in meta-analytically synthesized matrices of correlations among theory constructs extracted from empirical applications of the theory in physical activity contexts identified in a systematic literature search.

Beyond corroborating hypotheses of the theory tests in previous syntheses in the updated database, notable innovations of our analysis include: the first test of the effects of moderators focused on measurement correspondence on theory effects, which has conceptually-relevant implications for the efficacy and predictive validity of the theory; a first meta-analytic test of a version of the theory encompassing directly- and indirectly-measured belief-based constructs simultaneously and their theory-stipulated effects on intentions; and a first comprehensive and comparative test of differentiated theory constructs on behavior, including effects with high conceptual relevance, such as direct and indirect intention-mediated effects of affective attitude on behavior considered indicative of an impulsive process involved in behavioral uptake. Finally, our analysis is also innovative in that we estimated our models using the most recent implementations of multivariate meta-analytic techniques that mirror those used in primary studies and are expected to provide the most precise estimates yet of theory hypotheses across studies. Next, we outline the specific hypotheses of each model, documented in an accompanying table (Table S1.1, supplemental materials, S1) and illustrated in the causal-directional acyclic model diagrams presented in Figure 1 (see Poppe et al., 2024).

We first tested a basic model (Model 1) comprising unique direct effects of the core, directly-measured belief-based theory constructs, attitude (H1.1), subjective norm (H1.2), and perceived behavioral control (H1.3) on physical activity intentions, of intention on behavior (H1.4), and, indirectly, of each construct on behavior mediated by intention (H1.6-H1.8). We also specified a direct effect of perceived behavioral control on behavior (H1.5) and a linked total effect comprising the direct and indirect effects (H1.9). Next, we tested a differentiated construct model (Model 2), which has become known as the reasoned action approach (Fishbein & Ajzen, 2010), comprising unique direct effects of differentiated subcomponents of the core theory constructs, namely, affective (H2.1) and instrumental (H2.2) attitude, injunctive (H2.3) and descriptive (H2.4) norms, and perceived controllability (H2.5) and self-efficacy (H2.6), on physical activity intentions, of intention on behavior (H2.7), indirect effects of each differentiated construct on behavior mediated by intention (H2.10-H2.15). We also specified a direct effect of perceived control-behavior effect (H2.8) with matched total effect (H2.16), and, importantly, a direct effect of affective attitude (H2.9) and accompanying total effect (H.17), consistent with prior conceptual and empirical work demonstrating spontaneous behavioral engagement based on affective responses (e.g., Conner et al., 2015).

We then tested an extended model that encompassed both directly- and indirectly-measured theory constructs (Model 3). In this model, we specified effects of the belief-based, indirect measures of the core theory constructs, behavioral (H3.1), normative (H3.2), and control (H3.3) beliefs, on their global, directly-measured counterpart constructs, of each directly-measured construct on intention (H3.4-H3.6), and of intention on behavior (H3.7). We also specified indirect effects of each belief-based construct on intentions mediated by their directly-measured counterpart (H3.9-H3.11) and on behavior mediated by the directly-measured constructs and intention (H3.12-H3.14). Consistent with the prior models, we also specified a direct effect of the directly-measured perceived behavioral control construct on intention (H3.8) with an associated total effect (H3.15) and a total effect of the indirectly-measured control belief construct (H3.16).

Importantly, we expected substantive residual between-study variability in the averaged effects from our tests after artifactual correction from the meta-analysis signaling the likely presence of moderators. As a consequence, we tested the effects of candidate moderator variables that reflect methodological conditions that have highly salient implications for the theory conceptually on which the pattern of key effects of the belief-based theory constructs on physical activity intentions and behavior, and of intentions on behavior, are expected to depend. Specifically, our moderators encompassed: (a) the degree of correspondence in measures tapping the belief-based constructs of the theory with measures physical activity intention and behavior; (b) the degree of correspondence in the intention and behavior measures; (c) the type of targeted physical activity behavior, categorized as structured and unstructured forms; (d) the temporal lag between measures of the belief-based constructs and follow-up measures of behavior; (e) the type of behavior measure adopted, categorized as measures using self-report or non-self-report methods; and (f) whether or not measures of study constructs had been subject to a pilot or prior development study purposed to provide support for their validity prior to their subsequent adoption in the study. Next, we outline our proposed conceptual or methodological, or both, basis for the effect of each moderator on theory effects. All moderator effects were tested in the basic model (Model 1) comprising the core, directly-measured theory constructs, intention, and behavior to maximize the sample size of each moderator group.

Consistent with Ajzen's (1991) original proposals, and the relatively sparse accompanying research literature (e.g., Courneya, 1994; Courneya & McAuley, 1994), high measurement correspondence in terms of the TACT elements is a requisite condition to maximize the predictive validity of measures of the theory constructs, including the belief-based constructs on intentions and behavior, and of intentions on behavior. As a consequence, we predicted that effects of the belief- based constructs on intentions, of perceived behavioral control on behavior, and, effects of each belief-based construct on behavior mediated by intentions would be larger in studies classified as high in measurement correspondence, defined as the number of TACT elements that measures fulfill, relative to those classified as low in measurement correspondence (H1.10). Analogously, we expected larger intention-behavior effects in studies classified as high on intention-behavior measurement correspondence relative to those classified as low in correspondence (H1.11).

Alongside measurement correspondence, there is also precedence for researchers to examine the moderating effects of target behavior type on theory effects in meta-analyses of the theory. For example, analyses of theory applications in health behavior contexts have classified studies according to whether the behaviors targeted present a health risk or represent a behavior offering protection from illness or chronic disease, or studies targeting specific behaviors for which there is a critical mass of evidence sufficient to conduct an independent test, including physical activity. However, given the current analysis was conducted in studies targeting a relatively homogenous behavior, we distinguished between structured or formal forms of physical activity, which are usually purposed toward a health, fitness, or wellness goal, such taking an exercise class or participating in organized sport activities, and unstructured forms of activity that did not have a specific health goal, such as casual walking or active transport. We expected that participants in studies targeting structured activities with a formal purpose would exhibit larger effects of belief- based theory constructs on behavior, and of intentions on behavior, because such activities are more likely to demand elaborate planning and effortful, reasoned decision making to perform relative to those in studies targeting unstructured activities, that are less likely to pose such demands on participants (H1.12).

In addition, Ajzen (1991) indicated that predicted theory effects would be optimized if measures of theory constructs and subsequent measures of the target behavior were taken in close temporal proximity to each other. This is based on the premise that the greater the lag in measurement the greater the likelihood that new information or contextual change would lead individuals to adjust or modify their beliefs with respect to behavioral performance. This notion is consistent with the social cognition basis of the theory that assumes an information-processing metaphor for human cognition and decision making. As a consequence, we predicted larger effects of intentions and perceived behavioral control on behavior and, indirectly, the belief-based constructs on behavior mediated by intentions, in studies adopting a short lag period in which between measures of physical activity behavior and measures of the theory constructs and intention were taken in close proximity relative to those adopting a more distal lag (H1.13), an expectation consistent with predictions and observations of prior meta-analyses (e.g., McEachan et al., 2011).

There is evidence to indicate that adoption of self-report behavior measures in predictive studies introduces substantive method variance in effect estimates attributable to recall and social desirability biases, biases that are not associated with the adoption of non-self-report behavior measures. Given suggestions that these sources of bias could both inflate or attenuate associations among constructs, we anticipated differences in the pattern of theory effects, including intention-behavior effects and indirect effects of belief-based constructs on behavior mediated by intentions, across studies classified according to their adoption of self-report and non-self-report behavior measures, but did not specify a direction for the moderating effects (H1.14). In addition, we anticipated that studies reporting conducting an initial methodological development study designed to pilot construct measures to gain perspective on their appropriateness and face validity would exhibit larger effects of study constructs on intentions and, indirectly, behavior than those that did not report conducting a development or pilot study (H1.15). This is consistent with the general expectation that measure piloting assists researchers in identifying errors and anomalies in measures (e.g., inconsistencies in wording or framing of items) that may contribute to measurement imprecision or lack of comprehensions so as to introduce additional method variance.

Finally, we also accounted for a series of demographic characteristics of the samples of the included studies as study-level covariates in our model tests: (a) sample age distribution; (b) sample sex distribution; (c) sample clinical status; and (d) sample student status. Given the general assumption that social cognition theories purport to map universal decision-making processes likely to generalize across populations and contexts, we assumed that the theory predicted pattern of effects would hold regardless of sample characteristics. Nevertheless, there is precedent in primary studies applying theories like the theory of planned behavior in health behavior to include statistical controls for these variables (see Hagger, 2019). As a consequence, we followed suit in our current analysis and adjusted the synthesized correlations for these sample-specific covariates, an approach that has been adopted elsewhere (e.g., Hagger & Hamilton, 2024). Finally, we also assessed each study against a set of key study quality criteria and included quality score as a further covariate, consistent with prior suggestions on the potential for variation in study quality to bias effect size estimates (Johnson et al., 2015).

Method

Search Strategy

Eligible research items were located in a systematic search of four digital databases (Web of Science, ProQuest, EBSCO, and PubMed) covering the period from January 1953 to September 2024. The following keyword terms were used in accordance with the search standards of each database: "theory of planned behavio*" OR "theory of reasoned action" OR "reasoned action approach" OR "social cognition*" OR "attitud*" OR "intentio*" OR "self-efficacy" OR "subjective nor*" OR "perceived behavio* control" OR "past behavio*" AND "exercise" OR "physical activit*" OR "sport." To supplement these searches, we manually reviewed the reference lists of key reviews and meta-analyses (e.g., Hagger et al., 2002; McEachan et al., 2011; Symons Downs & Hausenblas, 2005), conducted additional cross-checks via Google Scholar, and posted calls for unpublished data on the email listservs of relevant professional organizations (e.g., Society of Behavioral Medicine, Society for Personality and Social Psychology).

Inclusion and Exclusion Criteria and Screening Procedure

To be included in the current analysis, studies were required to report at least one quantitative estimate of an association between a measure or manipulation of one or more constructs of the theory of planned behavior, directly-measured (e.g., attitude, subjective norm, perceived behavioral control) or indirectly-measured (e.g., behavioral, normative, or control beliefs), and a measure of physical activity intention or behavior or both. Eligible study designs included cross-sectional, prospective, longitudinal, experimental, or intervention designs. Studies were excluded if they did not report a quantitative association between at least one theory construct measure or manipulation and a measure of intention or behavior, or if the raw or processed data necessary to estimate effect sizes from eligible studies reporting such effect sizes could not be located after reasonable attempts to contact the authors. Studies adopting case study, qualitative, or *n*-of-1 designs, conceptual or narrative reviews, and non-empirical commentaries were excluded. Studies targeting samples comprising participants with mental health conditions or diagnoses were excluded due to their potential to bias responses to study measures.

Initial screening of the titles of the research items located via the search strategy after duplicate removal against eligibility criteria was performed by two members of the research team with training in research synthesis methods. A third reviewer independently double-screened 25% of titles to provide concurrent validity of the screening procedure. Subsequent screening of the abstracts and full-texts versions of the remaining items was conducted using the same procedure.

For title, abstract, and full-text screening, agreement between reviewers was estimated using Gwet's AC1/AC2 inter-rater reliability statistic (Gwet, 2008). Any substantive disagreements flagged were resolved through discussion and consensus between the researchers, with independent adjudication provided by the principal investigator where a resolution could not be reached, followed by any necessary refinements to the screening procedure. A PRISMA flow diagram, a list of studies that included multiple samples and within-study effect sizes and how they were treated in our analysis, and list of included studies are available in our supplemental materials (S2-S4).

Construct and Behavior Measure Classification

To ensure that measures used in studies identified as eligible for inclusion appropriately conformed to the definition and conceptualization of theory of planned behavior constructs, we developed a structured classification system. This was informed by established definitions of theory constructs derived from key conceptual and review sources (e.g., Ajzen, 1991, 2002; Fishbein & Ajzen, 2011; Francis et al., 2004; Hagger, 2019) and consistent with procedures developed and adopted in prior meta-analyses (e.g., Hagger et al., 2023; McEachan et al., 2011). A similar procedure was used to confirm the appropriateness of measures used to quantify physical activity participation, usually conceptualized as measures of frequency of performance or participation.

Specifically, for the construct classification, the research team conducted an initial discussion session in which operational definitions of the salient constructs from the theory of planned behavior were developed, encompassing the directly-measured (attitude, subjective norm, perceived behavioral control) and indirectly-measured (behavioral beliefs and outcome evaluations, normative beliefs and motivation to comply, control beliefs paired with control belief power), including their differentiated forms (affective and instrumental attitudes, injunctive and descriptive norms, and perceived controllability and self-efficacy) theory constructs. Next, an experienced researcher with familiarity in behavioral theory including the theory of planned behavior and with prior training on research synthesis methods, identified, located, and collated sample measures of each defined construct. They subsequently applied a matching procedure requiring a review of the items used in the measures of each construct reported in the included studies alongside the definitions and sample items and assigning them to their appropriate construct based on their goodness-of-fit. In the cases adopting experimental or intervention designs, manipulations of theory-based constructs were similarly reviewed and assessed against the evidence base behind the technique used and its capacity to affect change in the targeted construct from the theory implicated in its mechanism of action (see Johnston et al., 2021; Marques et al., 2024).

Similarly, for the classification of behavior measures, the research team held an initial meeting to develop an a priori definition of physical activity based on definitions provided in the extant research on health promoting physical activity (e.g., Colbert et al., 2011; Lee et al., 2011; Taylor et al., 2013) with specific reference to prior measures used in predictive studies applying the theory of planned behavior (e.g., Courneya, 1994; Hagger & Chatzisarantis, 2005; Hagger et al., 2003; Rhodes & Courneya, 2003), as well as other social cognition theories, in this behavioral context (e.g., Godin et al., 2011). Given the number of available measures of physical activity and the variation in measures used ranging from self-report including questionnaire and diary measures and non-self- report including observation and device-based measures (e.g., pedometers, accelerometers, internet and GPS enabled devices such as smartwatches), we did not develop a priori sample measures. A trained member of the research team then applied a similar matching procedure to that adopted for the construct classification in which physical activity measures were evaluated for their goodness-of-fit with the a priori definition and assigned accordingly. A summary of the definitions and example items, where appropriate, for the theory constructs and physical activity behavior measures and the matched measures used to tap each identified from our review of the included study methods is presented in Table S5.1 (supplemental materials, S5).

Moderator and Covariate Coding

Moderator Coding

We examined the effects of several methodological moderator variables on theory effects in the current analysis, namely, correspondence in measures of the belief-based constructs and intention and behavior, correspondence in measures of intention and behavior, the target physical activity behavior type (structured vs. unstructured), measurement lag between predictors and behavioral outcomes, behavioral measure type (self-report vs. non-self-report), and whether or not the study construct measures had been piloted in advance. We therefore applied a formal procedure to code each study into categories corresponding to levels of each moderator. The procedure was based on explicit a priori operational definitions of each moderator and their potential distribution across the included studies so as to be appropriate for moderator analysis. Next, we summarize our coding procedure for each moderator. The coding of included studies into categories according to each moderator category is summarized in Table S6.1 (supplemental materials, S6)[4].

Measurement Correspondence. Ajzen (1991, 2002) provided explicit guidance on the requisite criteria for measurement correspondence in studies employing theory of planned behavior measures, summarized in the TACT acronym. We therefore developed a brief checklist with four simple items to evaluate whether or not measures and intention and behavior outcomes of each included study that supplied data for the current analysis conformed to each of the target, action, context, and time criteria. For each study, measures and outcomes were afforded a point for each criteria fulfilled, which was summed to produce a score out of four. To ensure we had sufficient numbers of studies to estimate our model (e.g., to obviate the concerns over missing correlations in pooled correlation matrix among study constructs and outcomes) we computed a binary moderator variable. Studies assigned a score of three or more points on our checklist, indicating that their measures and outcomes fulfilled at least three of Ajzen's TACT criteria, were classified as high in correspondence, while those scoring fewer than three were classified as low in correspondence.

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[4] A spreadsheet providing full details of study characteristics and moderator coding is available online: https://osf.io/wcymg/

Similarly, we applied an identical procedure to assess correspondence in intention and behavior measures, also yielding a binary moderator variable representing high or low correspondence across intention and behavior measures.

Behavior Type. We coded a binary moderator variable according to type of physical activity behavior targeted by the included studies, with studies assigned to either structured or unstructured activity category. Structured activities were defined as those that were planned and organized with a clear health, fitness, or wellness-related goal (e.g., formal exercise such as gym workouts or exercise classes, or organized sport activities), while unstructured activities comprised those that were informal or did not have a clear health-related goal (e.g., casual walking, incidental activity such as commuting or active transport).

Measurement Lag. A binary measurement lag moderator was coded with included studies adopting a prospective or longitudinal design assigned to proximal or distal categories based on time elapsed between measurement occasion for theory constructs and the follow-up occasion for the measure of behavior. Consistent with prior meta-analyses of the theory in health-related contexts, studies were assigned to proximal category if the measurement lag was four weeks or to the distal category if the lag was greater than four weeks[5].

Behavior Measure Type. We classified studies according to whether a self-report method was adopted to measure physical activity behavior (e.g., questionnaires, diaries) or non-self-report (e.g., device-based measures such as accelerometers or pedometers). Again, we were able to account for studies that employed both self-report and non-self-report behavior measures using a multi-level analytic approach.

Pilot Testing of Measures. We assessed whether adopting measures with prior evidence of piloting or developmental work in support validity moderated proposed theory effects in our models by coding a binary pilot testing moderator variable. Included studies that reported having conducted a pilot test or developmental study to support the validity of the theory construct measures adopted were assigned to the 'piloted' category while those that did not report pilot testing or conducting a developmental study to support the validity of their measures were assigned to the 'no pilot' category.

Covariates

We coded a series of variables representing key sample characteristics for which we adjusted for in our model tests: sample age and sex distribution, and sample clinical and student status.

Included studies were assigned to a three-level categorical covariate according to the reported average age of participants in the sample. Studies on samples comprising participants with a mean age of less than 40 years and a relatively narrow standard deviation (approximately < 10), a mean age equal to or older than 40 years with similar variability, and samples comprising samples of participants whose average age fell

[5]In case where studies included multiple behavioral follow-up occasion, we were able to assign effect size data to the corresponding lag and account for within-study variation in lag using a multi- level meta-analytic approach.

outside these categories, were assigned to 'younger', 'older', and 'balanced' aged samples, respectively. Where studies did not report the sample average age, we used available information to make a reasonable inference of the sample age (e.g., samples comprising undergraduate students were assigned to the 'younger' category) or were assigned to the balanced category by default. Studies on samples comprised predominantly of women (≥ 75% women), predominantly men (≤ 25% women), or a relatively even distribution of men and women were assigned to 'majority women', 'majority men', or 'balanced' for our three-level sex distribution covariate. The sample clinical status covariate distinguished between studies on samples comprising participants with a formally-diagnosed clinical condition (e.g., diabetes, cancer) and those on samples without such a diagnosis. The sample student status covariate was coded as studies on samples comprising students in full or part-time high school or university education and those comprising non-student participants. Finally, we assessed the quality of each included study and included it as a continuous covariate in our analysis. To do so, each study was assessed by three trained researchers using Quality of Survey Studies in Psychology (Q-SSP) checklist that comprises 20 items assessing quality criteria against an evidence-based standard in four broad categories: (Protogerou & Hagger, 2020). Each checklist item was scored as 1 (meets standard) or 0 (does not meet standard or not reported), with total scores computed for each study. A subset of studies was initially assessed by each researcher to ensure calibration and consistency in checklist application (average AC1/AC2 for item scores = .82; average inter-class correlation for total scores = .88), where discrepancies were identified we resolved them through discussion among the researchers with revisions made to the procedures based on the consensus. Checklist items and scoring criteria are reported in the supplemental materials (S7) and quality scores for each included study summarized in a spreadsheet archived online (https://osf.io/72mtu/).

Effect Size Extraction

Our analytic strategy required extraction of effect sizes expressed as zero-order correlations among theory constructs, intention, and physical activity behavior measures that were available in each included study. As most studies employed correlational study designs, we were able to directly extract the requisite correlations in most cases, if reported. In cases where the zero-order correlations were not reported, we extracted effect size data expressed in other metrics and converted them to a correlation coefficient (e.g., Cohen's d or f^2), or used other available data to compute a correlation (e.g., t-values, F-ratios, odds ratios, means and standard deviations), using standard formulae (Borenstein et al., 2009; Digby, 1983). The sample size associated with each effect size was extracted and used in our analysis to weight samples and compute variance estimates using meta-analytic methods. In the case of studies adopting experimental or intervention designs that directly manipulated the construct of interest and examined their effects on an outcome such as intention or physical activity behavior, we computed an effect size based on the standardized mean difference across intervention and control groups, or across time in pre-post designs, and converted to a correlation. In cases where studies included a manipulation that was not purposed to directly affect change in the theory construct of interest, we used data from baseline measures prior to the introduction of the manipulation, or we used data from the control group that did not receive the intervention, so as to avoid bias in the effect size due to the intervention.

In addition to effect size and sample data, we extracted additional study characteristics: study author(s), year of publication or dissemination, country of origin, age and gender distribution data, study design, theory constructs assessed, time lag in weeks between construct and behavior measures, and definitions and operationalization of physical activity behavior where available. In cases where insufficient data were available to compute a useable effect size, we contacted study authors to request the missing data with a two-week window provided for a response. Extracted data were archived in a spreadsheet which was independently verified for accuracy by a second researcher. The final dataset including all extracted effect size data and study characteristics is archived online at: https://osf.io/72mtu/?view_only=70dd2ac795cc482d9ab6306b2514ce01 and a summary table of study characteristics presented in the supplemental materials (S6).

Data Analysis

Model Tests

We adopted Wilson et al.'s (2016) multi-level implementation of Cheung's (2015) two-stage meta-analytic structural equation modeling (MASEM) method to estimate a pooled correlation matrix comprising averaged, sample-weighted associations between theory of planned behavior constructs, intentions, and behavior, which was, subsequently used as input to provide simultaneous tests of our proposed models purposed to test theory predictions. In the first stage of the analysis, a multivariate multi-level meta-analytic model was adopted to produce pooled correlation matrices for each model such that each correlation in the matrix was corrected for random effects with associated pooled variance-covariance matrices estimated using Cheung's method. The elegance of the analysis is that it allows for variation in the numbers of studies that contribute effect size data for each matrix cell, permits the produced matrices to be treated in the same way as covariance matrices in subsequent estimation of structural equation models, and accounts for dependency arising from the presence of multiple within-study effect sizes reported in the included studies using the multi-level approach. In addition, Wilson et al.'s method enables adjustment of each matrix correlation for covariates using a novel regression approach, so we produced versions of the correlation matrices for each model that were adjusted for our sample age and sex distribution, sample type (clinical and student status), and study quality covariates alongside the unadjusted versions. In stage two, each matrix and its associated variance-covariance matrix was used as input for structural equation model estimation such that models specifying their respective theory-implied pattern of predictions were fit to the appropriate matrices. The analysis yields estimates of overall model fit with the data along with standardized parameter estimates, effectively equivalent to regression coefficients, and associated Wald standard error and 95% confidence interval estimates for each hypothesized model effect. Model fit was evaluated using the goodness-of-fit chi-square and, given that the chi-square tends to be oversensitive to model misspecification, a set of incremental fit indices, including the comparative fit index (CFI), Tucker–Lewis index (TLI), standardized root mean square residual (SRMR), and the root mean square error of approximation (RMSEA) and the associated 90% confidence interval. Based on conventional criteria (e.g., Hu & Bentler, 1999), a chi-square value that is not statistically significant, CFI and TLI values approaching or exceeding 0.950, an SRMR of less than 0.080, and an RMSEA of less than 0.060 with narrow confidence intervals are considered indicative of good model fit with the data. We also compared our unadjusted models with those adjusted for our covariates – given these were non-nested models, we made comparisons using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Lower values for these criteria are considered indicative of an optimal model, although a relative perspective in multi-model approaches is recommended to acknowledge the comparison models (e.g., their relative closeness or deviation) when making judgements (Burnham & Anderson, 2004). Moderator analyses were conducted by estimating each proposed model in subgroups of studies defined by levels of each moderator variable. Pairwise comparisons of standardized parameter estimates across moderator groups were made using the confidence interval about the mean difference in the estimate following Schenker and Gentleman's (2001) method. Analyses were conducted in R using the metafor (Viechtbauer, 2010) and metaSEM (Cheung, 2015) packages.

Bias Assessment

Small-study bias, often attributed to publication bias, was assessed using two panels of bias analyses recommended by Carter et al. (2019) – one panel was based on the funnel plot of each study effect size on a precision estimate (e.g. the inverse of its standard error) and the other was based on selection models that compares the model represented by the data with one or more selection models that model different conditions of bias. Tests based on the funnel plot included a basic estimate of asymmetry using a rank correlation test (Begg & Mazumdar, 1994), Duval and Tweedie's (2001) trim and fill analysis, and a basic regression-based analyses of funnel plot asymmetry (Egger & Sterne, 2005) with two alternative implementations that use different precision estimates, known as the precision effect test (PET) and the precision effect estimate with standard error (PEESE; Stanley & Doucouliagos, 2014). A statistically non-significant Kendall's tau from the rank correlation test, and a low number or, preferably, zero imputed studies from the trim and fill analysis, along with 'bias-corrected' effect size estimates from the trim and fill and PET and PEESE analyses[6] that are comparable to the naïve meta-analytic effect size are indicative of a low likelihood of bias. Tests based on selection methods included Vevea and Hedges implementation of Hedges original model with selection models estimating bias under stringent conditions (e.g., lower statistical significance of included effects) and two recent implementations, one based on statistically significant effects only, known as the *p*-curve analysis and the other an adapted version known as the *p*-uniform and its modified version, *p*-uniform*, which focus on the distribution of *p*- values associated with statistical significance tests. A non-

[6]Based on simulated data, Stanley and Doucouliagos (2014) provide a rule of thumb for selection of the PET and PEESE estimates, where the PET estimate is statistically significant, the PEESE estimate is taken, while when the PET estimate is statistically non-significant, the PET is preferred.

significant chi-square value for the Hedges and Vevea selection model, statistically significant right-side skewness and statistically significant flatness estimates for the *p*-curve, and a non-zero likelihood ratio test for bias from the *p*-uniform analysis are indicative of minimal bias. The selection model and *p*-uniform methods also provide 'bias-corrected' estimates, which, again, should bear resemblance to the naïve estimate to infer low bias. The metafor package was used to conduct analyses based on the funnel plot, while the specialized weight (Coburn & Vevea, 2019), dmetar (Harrer et al., 2019), and *p*-uniform* (van Aert, 2020) functions were used to conduct the selection model, *p*-curve, and *p*-uniform* analyses, respectively, in R[7].

Results

Full-Sample Tests of Theory Hypotheses

Our first set of analyses estimated the fit and accompanying theory-stipulated patterns of effects with variability estimates specified in three separate models in meta-analytically synthesized data from our sample of studies applying the theory of planned behavior in physical activity contexts. These included our models specifying the basic 'core' theory predictions (Model 1), an extended version differentiating between subcomponents of the theory constructs, also known as the reasoned action approach (Model 2), and a version encompassing the indirectly-measured theory constructs alongside direct measures (Model 3). Here we summarize results of each estimated model. To accompany our summaries, we present zero-order correlations and heterogeneity estimates yielded by the first-stage multivariate meta-analytic model in Tables S9.1-9.4 (supplemental materials, 9), and model fit statistics for each second-stage structural equation model in Table 10.1 (supplemental materials, S10) with accompanying standardized parameter estimates and 95% confidence intervals for each hypothesized effect in Tables 1-4. In addition, for the basic model (Model 1), we present estimates for unadjusted and covariate-adjusted versions of the model, as well as versions that enabled evaluation of ancillary predictions, that is, models that include and exclude control for past behavior and models that include a direct attitude-behavior effect. Analogously, we present unadjusted and adjusted versions of Models 2 and 3, alongside versions that include and exclude direct effects of affective attitude (Model 2) and attitude (Model 3) on behavior.

Multilevel Meta-Analytic Structural Equation Models

Model 1: Basic Model

Our first model, representing the core or 'basic' version of theory, exhibited good fit with the data according to multiple criteria adopted, albeit with substantive heterogeneity. We noted virtually nil differences in the AIC and BAIC selection criteria for the unadjusted and covariate adjusted versions, indicating little evidence that covariate correction altered the size and pattern of model effects. We therefore focus our

[7]Most of the bias detection analyses have no implementations for multilevel meta-analytic models, so we computed standard meta-analytic estimates for the purpose of the bias analyses by aggregating multiple within-study effect sizes using recommended formulae (Hunter & Schmidt, 2015) using the MAc package in R (Del Re & Hoyt, 2018).

discussion on the unadjusted estimates. With respect to theory-specified effects (Table 1), consistent with hypotheses we observed non-zero averaged direct effects of the attitude, subjective norm, and perceived behavioral control constructs on intention, and of intention on physical activity behavior, with small- to-medium effect sizes. The direct perceived behavioral control-behavior effect was also non-zero but considerably smaller in size than the intention-behavior effect. We also noted non-zero indirect effects of each construct on behavior mediated by intention, and a non-zero total effect of perceived behavioral control on behavior comprising both direct and indirect effects, again consistent with expectations. In addition, while we noted non-zero attenuation of the majority of model effects in the version of the model that included past behavior, consistent with observations from previous meta-analyses of the theory in this context, the pattern of effects remained unaltered, providing evidence in support of theory sufficiency. Finally, as an ancillary analysis, we also estimated a model that included a direct attitude-behavior effect, which identified a non-zero effect albeit substantially smaller in size than effects of intention.

Model 2: Differentiated Construct Model

Our second model testing hypotheses of a version of the theory differentiating between subcomponents of each belief-based theory construct, also exhibited good fit with the data and substantive heterogeneity. Covariate adjustment indicated little variation in selection criteria, so we focused on unadjusted models consistent with Model 1. The analysis revealed non-zero averaged direct effects of affective and instrumental attitudes, subjective and descriptive norms, and self-efficacy on intention, and of intention on physical activity behavior with small-to-medium effect sizes, consistent with hypotheses. However, contrary to predictions, the direct effects of perceived controllability on intention and behavior were small and no different from the null. In addition, we observed non-zero averaged indirect effects of each construct on behavior mediated by intention, the perceived controllability construct excepted. This translated to a non-zero total effect of the attitude-related subcomponents on intention, but not of the control- related subcomponents, on behavior. It is also important to note that medium-to-large sized zero- order intercorrelations were observed between the subcomponents of each construct (r range = .353 to .535, $p < .001$). Finally, inclusion of a direct affective attitude-behavior effect, as recommended in previous research and represents the most conceptually consistent test of this impulsive route to behavior (e.g., Conner et al., 2015), revealed a non-zero, small-to-medium sized effect.

Model 3: Directly- and Indirectly-Measured Constructs Model

Our third model tested effects of directly- and indirectly-measured belief-based theory constructs on intention and physical activity behavior. As with prior models, model fit was acceptable, with substantive heterogeneity, and covariate adjustment had a relatively effects leading us to take the unadjusted estimates. We observed non-zero averaged direct effects of the behavioral, normative, and control belief constructs on their respective directly-measured counterparts, and of each of the directly-measured constructs on intention. We also noted non-zero averaged direct effects of intention and perceived behavioral control on physical activity behavior, which was reflected in the non-zero total effect of the latter construct on behavior. Importantly, and central to the rationale underpinning this model test, we observed non-zero averaged indirect effects of each indirectly-measured construct on behavior sequentially mediated by their respective directly-measured construct and intention. Finally, as with the other models, the direct attitude-behavior effect was non-zero albeit small in size, mirrored in a non-zero total effect of this construct on behavior.

Moderator Effects

Given the substantive residual heterogeneity observed for each meta-analytic model estimated in the full sample analyses, we tested the effects of our moderator variables, namely, correspondence in theory construct and intention-behavior measures, behavior type (structured vs. unstructured), behavior measure type (self-report vs. non-self-report), measurement lag (proximal vs. distal) and pilot testing of theory measures (piloted vs. no pilot) on theory effects. Models were estimated in the basic model comprising core theory predictions (Model 1) to maximize numbers of studies at each level of the moderator and unadjusted for covariates given the minimal differences in selection criteria across unadjusted and covariate adjusted models in the full sample analysis[8]. Model fit statistics and heterogeneity estimates for the model estimated at each level of the moderator are presented in Tables S9.4 and S10.1 in our supplemental materials (S9, S10) and standardized parameter estimates and 95% confidence intervals for effects of the model in each analysis at all levels of the moderator are presented in Tables S11.1-11.6 (supplemental materials, S11), with formal tests of difference (Schenker & Gentleman, 2001). Given the minimal differences across unadjusted and covariate adjustment in the full sample analyses, we evaluated moderator effects in the unadjusted models. Each moderator model exhibited good fit with the data according to adopted criteria. Each was also associated with substantive residual heterogeneity, although expecting for the effects of an individual moderator to fully resolve observed heterogeneity of complex models would be unrealistic. Next, we summarize key differences in the theory-stipulated effects across moderator models. It is worth noting that when assessing moderator effects, rather than focusing on idiosyncratic differences in effects across moderator levels, we focused on expected hypothesis-driven differences relevant to the moderator as well as exploring any emergent systematic differences identified.

Focusing first on correspondence in the measures of the belief-based constructs and intention and behavior moderator analysis, contrary to expectations we observed no differences in theory effects in models estimated in groups of studies classified as high

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[8]While we directed our primary focus on the unique and conceptually-relevant moderators in the current analyses, we recognize that prior meta-analyses had treated some of the covariates for which we adjusted in our current analysis as moderators. For completion, therefore, we conducted ancillary analyses in which we treated each covariate as a separate moderator and estimated our model separately at each moderator level. Model fit statistics and heterogeneity estimates for each model are presented in Tables S9.4 and S10.1 (supplemental materials S9, S10) and standardized parameter estimates and 95% confidence intervals for the model in each analysis summarized in Tables S11.7-11. Finally, a full summary of the findings of these analyses is presented in our supplemental materials (S12).

and low in measurement correspondence. By contrast, we observed larger indirect effects of attitude and subjective norm on behavior mediated by intention in groups of studies with high correspondence in intention and behavior measures. It should be noted that although we observed larger intention-behavior, attitude-intention, and subjective norm-intention effects in the high correspondence group, differences across moderator groups did not differ from the null. However, these relatively modestly-sized component effects translated to an effect size large enough to exhibit a non-zero difference for the indirect effect, a notable finding indicating the behavioral relevance of ensuring adequate correspondence in intention and behavior measures.

We also noted differences in theory effects across groups of studies targeting structured (e.g., sport activities, exercise) and unstructured (e.g., active transport, incidental walking) forms of physical activity. Specifically, we observed larger attitude-intention effects in the model estimated in studies targeting structured activity relative to studies targeting unstructured forms, which was translated into a larger indirect effect of attitude on behavior mediated by intentions. In addition, we observed larger intention-behavior, and, interestingly, perceived behavioral control-intention, effects in studies utilizing a proximal measurement lag relative to those with a more distal lag, which was also reflected in larger indirect and total effects of perceived behavioral control on behavior in the proximal group. In addition, we observed larger intention-behavior effects in studies employing self-report behavior measures relative to those employing non-self-report measures, which translated to larger indirect effects of attitude, subjective norm, and perceived behavioral control on behavior mediated by intention, and a larger total effect of perceived behavioral control on behavior. By contrast, we observed no notable variations in model effects across groups of studies categorized according to levels of our piloting of study measures moderator.

Bias Analyses

Application of our panel of funnel plot-based and selection model bias analyses to each separate meta-analyzed correlation of the correlation matrices used to estimate our models revealed no converging evidence of systematic small-study bias. Some idiosyncratic exceptions aside, most analyses returned findings indicative of low or no bias and reproduced ostensibly bias- corrected correlation estimates did not deviate substantially from the naïve meta-analytic estimate. Full results of the bias analyses are presented in Tables S13.1 and S13.2 (supplemental materials S13). As before, a caveat to these analyses is that they were implemented by aggregating multiple within-study effect sizes and in the face of substantive heterogeneity as these analyses have typically not been implemented using a multi-level approach and may also not return precise estimates in heterogenous cases (Carter et al., 2019).

Discussion

In the current research, we tested a series of models specifying key hypotheses of, and additional ancillary predictions derived from, the theory of planned behavior, a prototypical social cognition approach to behavior, in data from a meta-analytic synthesis of applications of the theory in physical activity contexts. Beyond corroborating the findings of prior meta-analyses of the theory, our analysis uniquely provides first tests of a comprehensive version of the theory stipulating effects of the directly- and indirectly-measured belief-based constructs on physical activity intentions and behavior in synthesized data, tested an elaborated version comprising differentiated subcomponents of theory constructs, and compared theory effects across conceptually-salient moderating conditions not hitherto tested in meta-analyses of the theory such as correspondence in construct, intention, and behavior measures and type of physical activity behavior. Our hypothesized sets of effects were tested in three models, the first representing core predictions of the basic theory using directly-measured theory constructs, the second specifying an elaborated version of the theory differentiating between subcomponents of the core constructs, and a third comprising directly- and indirectly-measured belief-based theory constructs. Models were tested in synthesized data extracted from studies meeting inclusion criteria identified in a systematic literature search of theory applications in physical activity contexts. Included studies were also segregated into subgroups according to our key moderator variables: measurement correspondence, physical activity type, measurement lag, and pilot testing of measures. Comparisons of theory effects across moderators was performed by estimating the basic model at each level of the moderator. Finally, in an additional innovation, we employed state-of-the-art multivariate, multi-level analytic techniques to estimate our models in the synthesized data, including adjustment for covariates, commensurate with those used in primary research, expected to yield the most precise estimates of model effects to date.

Overall, our model tests lent support for theory hypotheses, and corroborated findings of prior meta-analyses of theory applications in health behavior contexts and, particularly, physical activity. Specifically, model tests in data from the full sample of studies revealed theory-consistent direct and indirect effects of core, directly-measured (Model 1), differentiated subcomponent (Model 2), and directly- and indirectly-measured (Model 3) theory constructs on intentions, of intentions on behavior, and indirect effects of the constructs on behavior, with effect sizes ranging from small to medium. We also found support for direct and indirect effects of the perceived behavior control and the attitude, construct, on physical activity behavior in all three models – and, of particular conceptual salience, the direct behavioral effect for the affective attitude construct in the differentiated construct model (Model 2). Effect sizes for these construct-behavior direct effects were small relative to the intention-behavior effects. In addition, theory effects held, and the overall pattern of effects retained, with the inclusion of past behavior in the model, corroborating findings of prior analyses and providing indication of theory sufficiency, some relatively modest effect size attenuation notwithstanding. Key emergent findings from analyses of our conceptually-relevant moderators included: larger indirect effects of attitude and subjective norm constructs on physical activity behavior in studies with high intention-behavior measurement correspondence; larger attitude-intention, and indirect attitude-behavior, effects in studies targeting structured physical activity form; larger intention-behavior and indirect and total perceived behavioral control-behavior effects in studies utilizing a proximal measurement lag; and larger intention-behavior effects in studies employing self-report behavior measures. Next, we outline the conceptual implications of these headline findings, with particular emphasis on the novel aspects of the current analysis and its ramifications for theory, research, and informing intervention efforts in physical activity contexts.

Theory of Planned Behavior: Corroboration and Extension

Unsurprisingly, given the number of prior meta-analyses testing the unique hypotheses of the applications of the theory of planned behavior in physical activity contexts, current findings of our models estimated in the full sample of included studies yield further support for the proposed direct and indirect effects. Specifically, our findings corroborate the efficacy of the theory constructs in accounting for unique variance in physical activity behavior, and the proposed candidate mechanism involved, that is, the mediation of effect of the belief-based constructs on behavior by intention, a central motivational construct. The latter effect provides sharp confirmation of the basis of the theory in the social cognition approach (Hagger, 2025; Mitchell, 2006; Turner et al., 2021), particularly the generalized assumption that performance of behaviors is the consequence of a deliberative, reasoned process based on individuals' evaluation of the utility of the behavior (e.g., physical activity viewed as likely to promote adaptive desirable outcomes), perceptions of social influence (e.g., the perceived support or pressure from salient social agents to perform physical activities), and an evaluation of personal capacity (e.g., perceived confidence in performing physical activities and capacity to overcome potential obstacles; Ajzen, 1885, 1991). Given intentions reflect level of planning or readiness to perform the behavior, its function as a mediator of these belief- based expectations directly implicates reasoned deliberation as the key process involved (Ajzen, 1985, 1991; Ajzen & Fishbein, 1980). This is further reinforced by the consistent effects in the differentiated construct model, effectively the reasoned action approach (Fishbein & Ajzen, 2010), which also corroborates the role of intention as the mediator. That our findings replicate previous meta-analytic findings in a substantially larger sample of studies, our analyses provide the most comprehensive and precise estimates of theory effects in this context to date. These effects have value insofar as they offer robust guideline size and variability estimates that a researcher would expect when applying the theory to predict physical activity in a given sample and context. Such estimates could, for example, serve as prior values in new studies aiming to test theory predictions in a novel population or context using a Bayesian analytic approach (Depaoli et al., 2017).

We should also note that our analysis corroborates prior findings that lend support to other key hypotheses in the theory and theory-implied predictions. For example, we note that theory effects held when controlling for the effects of past behavior. At a basic level this provides confirmation of Ajzen's (1991) premise of theory sufficiency. Basically, a theory purposed to predict behavior, as is eminently the case in the theory of planned behavior, should provide an account of behavioral consistency over time and, therefore, its component constructs and their predicted effects on subsequent behavioral performance should hold even when included as predictors of behavior alongside measures of prior behavior. If this were not the case, the theory would be rendered insufficient as a means to explain unique variance in behavior. Of course, individuals also draw from past experience when estimating their expectations or beliefs about performing the behavior in future (c.f., Bem, 1972), so the theory constructs would be expected to account, at least in part, for past-future behavior associations. However, the non-trivial residual unique effect of past behavior on behavior observed here, and in previous analyses, indicates that the theory does not fully account for behavioral consistency over time (see also Hagger & Hamilton, 2024), and is suggestive of other constructs that may, for example, represent other, unmeasured processes that lead to subsequent behavior, such as habit (see Oullette & Wood, 1998). This issue has been subsequently met by theoretical and empirical work aimed at rationalizing past-future behavior effects and identifying candidate constructs that may account for the effects beyond constructs from theories like the theory of planned behavior (for a broader discussion of these issues, see Ajzen, 2002; Hagger et al., 2023; Ouellette & Wood, 1998; Sutton, 1994).

Beyond the general corroboration of prior meta-analytic findings, our analysis offers a number of unique advances that contribute to existing knowledge on the determinants of physical activity and the mechanisms involved, as implied by the theory, but also for more broadly for the theory as a means to explain behavior and its potential to inform future research and practice (e.g., Hagger & Hamilton, 2024; Hardeman et al., 2002; McEachan et al., 2011). Foremost among these was our test of a comprehensive version of the theory that included effects of indirectly-measured versions of the theory constructs alongside the direct measures. Specifically, consistent with Ajzen's (1985, 1991) original proposals, we predicted that indirectly-measured constructs, that represent the specific sets of behavioral, normative, and control beliefs that underpin the core attitude, subjective norm, and perceived behavioral control constructs, respectively, would predict intentions and behavior mediated by their directly-measured counterparts. The directly-measured constructs are, effectively, purported to represent summaries of the belief sets of which the indirectly-measured versions comprise. To our knowledge, there have been no tests of these hypothesized effects in previous meta-analyses in physical activity, or in other behavioral contexts, save univariate associations of the directly- and indirectly-measured constructs (see Armitage & Conner, 2001). The lack of a prior meta-analysis is likely due to a fixation of research in the field on theory tests adopting directly-measured constructs alone with a relative dearth in studies, by comparison, utilizing indirectly-measured constructs. Our comprehensive search strategies yielded a sufficiently large database of studies for inclusion in the current analysis to conduct current test of this comprehensive version encompassing both sets of measures, so our analysis stands as the first meta-analytic test of this version.

The primary implication of this model is that constructs directly inferred from specific sets of salient beliefs are related to the belief-based constructs, and so mediated by their respective directly-measured constructs and intentions. This pattern of effects indicates a convergence in empirical support for Ajzen's (1991) predictions for this version and corroborates prior primary research studies testing its effects in specific behaviors and populations (e.g., Courneya, 1994; Rhodes & Courneya, 2003; Hagger et al., 2003). Our finding has both conceptual and practical relevance and utility. Conceptually, it provides indication that directly-measured theory constructs sufficiently and fully account for indirectly-measured construct effects on intentions and behavior, providing indication that such measures adequately capture and summarize sets of specific beliefs salient to the population and the behavior. This provides a level of justification for researchers applying the theory who have tended to test theory effects with a sole focus on directly-measured constructs, with ramifications for future applications, at least in physical activity contexts. If prediction is the research goal, researchers essentially need only to adopt directly-measured constructs.

However, in cases where the theory is utilized to guide intervention efforts offer a point of mitigation. Eliciting the sets of specific, salient beliefs of which, ultimately, the indirectly-measured theory constructs comprise when developed according to guidelines, specification of the salient outcomes, social agents or significant others, and facilitating and inhibiting factors that should be targeted in interventions purposed to change behavior. Specifically, the salient beliefs have been proposed as those that should be referred to in, for example, messages that comprise persuasive communications seeking to affect behavior change through change in the beliefs that are reliably linked to behavior, as stipulated in the theory (see Ajzen & Schmidt, 2020; Hamilton & Johnson, 2020). Such beliefs, therefore, represent the mental processes expected to be activated or changed as a result of exposure to the message and are, therefore, implicated in the mechanism of action by which the intervention leads to individuals' subsequent behavior change. Of course, this is based on the assumption that the effects reported in theory tests not only represent causal, directional effects, but also indicate the possibility that change in the constructs leads to concomitant change in behavior (for discussions see Hagger & Hamilton, 2024; St. Quinton et al., 2021). While this is not the case for the majority of theory applications, as many adopt correlational designs for which such inferences are contraindicated including the vast majority of studies included in the current analysis (Hagger, 2025; Hagger & Hamilton, 2025), recent meta-analyses of theory applications employing experimental or intervention designs as provided cumulative evidence of these effects and lend support these mechanistic predictions (see Sheeran et al., 2016; Steinmetz et al., 2016). This means that researchers applying theory with the expressed goal of guiding intervention to promote physical activity should embrace the recommended approaches to belief elicitation and procedures for producing indirect theory constructs measures. This would pave the way for tests that focus on identifying the most salient specific beliefs expected to be associated with the direct theory construct measures and measures of the target behavior (for examples see Ajzen & Driver, 1992; Armitage & Conner, 1999; Hamilton & White, 2010), informing the content of the messages that may be employed in persuasive communications or manipulations purposed to affect change in behavior through change in the targeted construct (see Ajzen & Schmidt, 2020; de Leeuw et al., 2015; Hamilton & Johnson, 2020), and in evaluating the efficacy of the intervention and, most presciently, the intervention mechanism of action involved (see Hagger et al., 2020; Sheeran et al., 2017). Accordingly, an implication of current findings is that researchers should consider the specific purpose of their study when selecting the measures to be used in theory tests in physical activity and other health behaviors more broadly - those seeking to merely apply the theory in studies purposed to establish behavioral prediction may consider a sole focus on directly-measured constructs. By contrast, those seeking to develop, test, and evaluate manipulations or interventions based on the theory and their associated mechanisms should consider eliciting and forming indirectly-measured versions, particularly when developing studies seeking to identify the specific beliefs that might be most salient to prediction and that should be the targets of intervention content (e.g., persuasive messages).

Of course, there are caveats to this analysis that should be taken into account. First, we made no distinction between researchers that adopted Ajzen's (1991) proposed method to produce the indirectly-measured constructs, that is, by averaging the expectancy x value composites for each salient belief – effectively weighting each belief by its perceived salience – and approaches that focus solely on alternatives, the most frequent of which involves mere averaging the beliefs themselves without the value weighting. This is relevant because there is some debate in the research literature on the theory over the most optimal method to conceptualize and measure the beliefs underlying the core theory constructs (e.g., Schmidt et al., 2010), derived from concerns that the expectancy x value approach can lead to under- or over-estimation of individual beliefs (e.g., French & Hankins, 2003). Second, it should be noted that summaries of beliefs through averaging do not provide indication of the most relevant beliefs to individuals, and there is evidence to suggest that it is only one or two specific beliefs that are relevant to individuals' decisions and their capacity to make belief-to-behavior inferences that inform subsequent intentions and actions, an argument recently highlighted in conceptual models of attitude (Granados Samayoa & Albarracín, 2025; Hamilton & Hagger, 2025).

A further advance of the current analysis is the testing of additional effects of theory constructs consistent with conceptual and empirical work focused on additional theory-implied hypotheses. Most prominent, is the direct effects of the attitude construct, particularly the affective attitude construct in the differentiated model, on behavior, independent of intentions. Our analysis provides robust evidence in support of this effect across the models tested. Consistent with predictions and empirical work stated elsewhere (e.g., Conner et al., 2015; Lawton et al., 2009), the direct effect effectively serves to incorporate an additional process relevant to behavioral engagement in the theory. Specifically, consistent with conceptual proposals of the direct effect, an emotion-driven route to action, which represents spontaneous uptake of the behavior as a direct result of individuals' evaluation of the behavior likely to elicit a positive affective response. Importantly, the effect is proposed to be independent of the intention-mediated effect, as it is proposed not to implicate reasoned, value-based decision making, and, rather, represents more rapid, impulsive processes leading to action. Such a proposal is consistent with dual process models of action, that specify a reasoned, deliberative route to action, as represented by the intention- mediated effects of beliefs, and a more impulsive, spontaneous route, as represented by the direct effect. Research has consistently supported the presence of this effect, particularly in behaviors likely to be rewarding or driven by impulsive processes, such as snacking or alcohol consumption.

Current findings extend this work to provide further robust, converging evidence that the direct effect is also relevant to physical activity. A likely explanation may be that, for some individuals, physical activity may be associated with a positive affective response (for example, phenomena such as "runner's high", may qualify in this regard) and, for these individuals, the direct route may apply. However, it is important to note the relatively small effect size for the direct effect, and the current findings indicate that both routes are relevant for this behavior, but the intention mediated effect larger and, therefore, likely more salient to physical activity behavior due to its relative complexity, necessitating greater reasoning to enact relative to simpler, most spontaneous behaviors (see Hagger et al., 2023). Adjunctly, it is important to note that even though the direct affective attitude-behavior effect observed in the differentiated construct model represents the most relevant test of this route, it was also noted that similar effects were found for the global, directly-measured construct in our other model's test, likely because these measures comprised items tapping affective responses alongside those tapping instrumental attitudes.

We also provided support for direct perceived behavioral control effects on behavior. This effect is proposed to represent situations where individuals' perceived control over performing physical activity in future closely mirrors their actual level of control (Ajzen, 1991). Our findings provide further robust evidence for the presence of this effect, as well as the intention-mediated route, across the included studies. It is clear that there is substantive variation in the extent to which individuals' perceived control may reflect actual control, even within a specific behavior such as physical activity. This is likely because individuals vary in the precision with which they are able to estimate their level of control, which is likely a function of factors such as prior behavioral experience and capacity for recall. However, it should be noted that the direct effect effectively serves to represent the theory-based proposal that effects of the attitude and subjective norms on intentions, and of intentions on behavior, is maximized when perceived control is high, that is absolute – which would be expected if individuals' control perceptions were aligned with actual control, hence the direct effect (see Ajzen, 1991). However, for many, control perceptions may not always be consistent with actual control – individuals often cite barriers that are perceived rather than actual. In which case, control perceptions would moderate the influence of the other beliefs on intentions, and of intentions on behavior, downwards. This pattern of effects has been identified empirically, consistent with the theory, including multi-behavior analyses (Hagger et al., 2022).

However, this was not possible in the current analysis as individual-level interaction effects were generally unavailable, so the direct effect test was the reasonable alternative. We look to a future where primary research data from studies testing theory effects in physical activity are openly accessible, which would provide capacity to provide important meta-analytic corroboration of the moderating perceived behavioral control effects across data in a physical activity context.

Moderator Analyses

An important contribution of the current analysis was the testing of salient conceptual moderators on theory effects across studies. A key innovation of our analysis is the examination of measurement correspondence as a moderator, which was shown to moderate indirect attitude and perceived behavioral control effects on behavior mediated by intentions. This provides some evidence to support the generalized conceptual perspective that belief-based determinants are context-tied and their effects maximized when there is good correspondence, in this case, with respect to intention and behavior measures. This effect aligns with the generalized notion of the need for specificity when it comes to behavioral prediction, an often-referenced example of which comes from observations that generalized attitudes tend not to be strongly related to behavior (e.g., Wicker, 1969). General, poorly-corresponding measures of beliefs tend to be poor behavioral predictors while prediction is maximized when specific belief measures with good correspondence with the behavior of interest are used. Our findings indicate that correspondence issues are salient and seem to signal the importance of adopting well-corresponding measures. That considered, we note the moderation effects were modest, and that the indirect rather than component direct effects were moderated. Further, generalized measurement correspondence of theory constructs and intentions and behavior did not moderate effects, the importance of measurement correspondence needs to be put into perspective, and measures with modest correspondence may lead to imprecision, but may not substantively alter patterns of effects in the theory applied in this behavioral context.

We also identified some other noteworthy moderating effects, unique to the current analysis. For example, the larger direct and indirect effects of key theory constructs, namely attitude on behavior in studies targeting structured physical activities, may be attributable to the relative stability of the context in which these types of activity are typically performed. For example, structured activities have a clear purpose and also tend to be conducted in highly specific contexts or have very clearly-defined conditions of performance. For example, attending an exercise class is usually focused on attaining salient outcomes, like losing weight or improving fitness, and also necessitates attending a particular gym or center, enrolling in the class, and at a particular time. This means that individuals' beliefs in the utility of the behavior in producing outcomes, as summarized in their attitudes, will be highly relevant to their intentions and less likely to be affected by contextual factors that might introduce uncertainty to performing the behavior. This may manifest as larger attitude-intention effects, and indirect intention-mediated effects of attitude on behavior, in studies in these contexts. By contrast, unstructured activities can be those that do not service specific, salient goals and may also be performed in contexts that are less clearly defined and may be subject to extraneous factors that can potentially alter plans or interfere with intention enactment. Beliefs in the utility of the behavior to produce salient outcomes may be, by comparison, less relevant for such behaviors, accounting for the smaller attitude effects.

We also observed larger effects in studies employing self-report behavior measures, a finding consistent with other meta-analyses of the theory, which corroborates findings observed in a prior meta-analysis of the theory for physical activity behaviors (McEachan et al., 2011). This effect is consistent with the generalized notion that self-report measures tend to be associated with greater error variance in measures, which have been shown to both inflate and diminish effect sizes in studies adopting such methods (Donaldson & Grant-Vallone, 2002). Another conceptual issue in this case is that self-report measures share a common method with those used to tap beliefs, which will tend to advantage associations due to the influence of common method variance (McDermott & Sharma, 2017). We note that the limited number of studies employing non-self-report measures reflects a generalized trend in the research literature testing the theory and hence recommend that more data employing such measures may enable greater precision in effects.

Finally, we observed larger effects of study constructs on intentions and behavior in studies adopting a proximal time lag, a finding also observed in other meta-analyses of the theory (e.g., McEachan et al., 2011). This provides further convergence of findings across studies applying the theory, and is an important conceptual issue outlined by Ajzen (1985, 1991) in the original conceptualization of the theory. Measurement of study constructs and behavior in close proximity means lower opportunity for extraneous factors to affect individuals' beliefs (e.g., new information or context change) and, therefore, undermine predictive effect due to greater variance in the predictor. This is largely a function of the single follow-up correlational study designs typically employed to test theory effects (Hagger & Hamilton, 2025). Better prediction may be advantaged in studies that adopt multiple behavior follow-up or even highly intensive behavior assessment within the time specified by the theory measured, such as data from repeated measures or experience sampling studies. Such studies allow researchers to better model change in theory constructs and may attenuate the moderating effects of measurement lag (for a more detailed discussion, see Hagger & Hamilton, 2024).

Strengths, Limitations, and Future Research Directions

Here we note the strengths of the current meta-analysis of applications of the theory of planned behavior in physical activity contexts, summarize its unique contributions to knowledge beyond currently available meta-analyses, and identify some key limitations and caveats to the findings in light of which our findings should be interpreted. Notable strengths include: a sound conceptual basis with proposals to test unique hypotheses relating to key theory effects and theory-implied hypotheses previously untested meta-analytically; adoption of a comprehensive and exhaustive approach to identifying studies for inclusion; development of innovative means to code key moderators such as assessment of measurement correspondence; and adoption of state-of-the- art analytic techniques to test theory effects that mirror those used in primary studies. With respect to contribution, beyond providing robust, large sample estimates of the unique effects of theory constructs in applications in physical activity and expected variance estimates that corroborate those observed in similar prior meta-analyses, the current analysis provides tests of three versions of the theory representing its basic and elaborated forms. Specifically, it provides the first test of an elaborated version of the theory encompassing indirect effects of indirectly-measured theory constructs on behavior, tests of additional theory-implied effects such as the direct attitude- behavior effect, and tests of unique conceptually-salient moderators such as measurement correspondence and physical activity behavior type. The current analysis contributes guideline effect size and variability estimates for previously tested, and unique, theory effects in physical activity behavior, which could serve as priors for future applications of the theory in physical activity contexts. It also contributes to an evidence base of theory constructs that could be candidates for targeting in messaging interventions purposed to change physical activity behavior through belief change.

It would be remiss, not to consider the potential for some salient limitations and caveats to our analysis that should be accounted for when interpreting current findings. These included an absence of available data to tests the effects of some additional salient moderators of theory, the likelihood of theory effects to vary due to effects of other, untested moderators, and an exclusive reliance on correlational data. We summarize these limitations and their implications, next.

First, we were unable to test interactive effects of perceived behavioral control on theory effects across studies, a key hypothesis of the theory, as proposed in its original conceptualization (Ajzen, 1991). We were, however, able to provide a robust test of direct perceived behavioral control effects on physical activity, a notable, but largely unsatisfactory, proxy for perceived behavioral control moderating effects (Hagger et al., 2023). Until studies routinely provide participant-level data such that interaction terms representing the moderating effects can be calculated, such effects will not be able to be tested meta-analytically. We look to a future where researchers make their data openly available by default for this test to be realized.

Second, while we were able to test effects of key moderators on proposed theory effects in the current analysis, we also note the potential for theory effects to be affected by other candidate moderators. For example, our physical activity behavior type moderator was relatively crude insofar as we classified behaviors along meaningful but higher-order categories, namely structured and unstructured forms. This precluded an analysis focused on specific subgroups of these behavior types such as active transport, specific types of exercise (e.g., cardiovascular or strength activities). Again, the expanding database of research studies applying the theory in this context may permit more fine-grained analysis of the effects of physical activity type on theory effects. Similarly, we were unable to test for the effects of broader sample-level characteristics, such as individual differences on trait-level psychological characteristics (e.g., personality factors, trait self-control). Such constructs have been shown to predict and moderate theory effects (e.g., Conner et al., 2023; Hagger et al., 2019), and there may be potential to examine effects of these constructs as predictors or moderators in subsequent meta-analyses as research in the field incorporating such measures alongside theory constructs proliferates.

Finally, the vast majority of studies adopted correlational designs, either cross-sectional or longitudinal, with a relative sparseness of experimental or intervention designs involving manipulations or intervention techniques purposed to change theory constructs and tests of its effects on other theory constructs or physical activity behavior. All data in the current study, therefore, were treated as correlational, placing restrictions on the extent to which we were able to infer causal or directional effects from our theory tests.

Conclusion

In the current meta-analysis we tested predictions of the theory of planned behavior in applications of the theory in physical activity across models representing the basic theory, and elaborated versions specifying differentiated constructs and encompassing directly- and indirectly- measured forms of its component constructs. In addition, the analysis allowed for robust tests of additional theory effect and additional theory-implied effects and effects of moderators on theory effects representing key conditions on which theory effects are proposed to depend such as correspondence in theory construct measures and intentions and behavior and types of physical activity. Results indicate robust support for the predicted theory effects, including the hypothesized mediation of core and differentiated theory constructs mediated by intention, of indirectly-measured constructs on physical activity behavior mediated by directly-measured constructs and intention, and direct effects of affective attitude and self-efficacy in the differentiated model.

Results also identified notable systematic differences in indirect effects of theory constructs on behavior according to our moderator variables such as larger indirect effects of attitude and perceived behavioral control on behavior in studies reporting high intention-behavior measurement correspondence, and larger attitude-intention and indirect attitude-behavior effects in studies targeting structured forms of physical activity.

The value of the current analysis lies in the provision of robust estimates of theory effects consistent with theory, and associated variability estimates, which represent the size, pattern and variability in effects that researchers may anticipate in applications of the theory in physical activity contexts. The research also offers a first meta-analytic tests of versions of the theory testing predictions not tested in previous meta-analyses including a differentiated construct approach and a comprehensive model encompassing both directly and indirectly-measured theory constructs. Our analysis also provides the opportunity to test additional effects that represent salient additional processes by which theory determinants relate to behavior conceptually consisted with theory specification and have received prior support in primary studies, but have not been tested meta-analytically, such as the direct attitude-behavior effects, particularly for affective attitudes in the differentiated version of the theory, which provides information on an impulse-related route to action. We also note that our adoption of a meta-analytic structural equation modeling analysis to test each model represents an important innovation insofar as prior analyses have adopted suboptimal ‘univariate’ or path analytic approaches (Jak & Cheung, 2024). Beyond providing robust support for these predictions and additional processes in the theory, findings highlight methodological imperatives for future research relating to measurement, such as the need to consider measurement correspondence issues and inclusion of belief-based constructs, and contexts where more data are needed, such as specific types of physical activity behaviors. Our findings also set an agenda for research needed to progress knowledge of the current theory, including studies that adopt longitudinal and randomized experimental or intervention designs to permit better inference of directional and causal effects.

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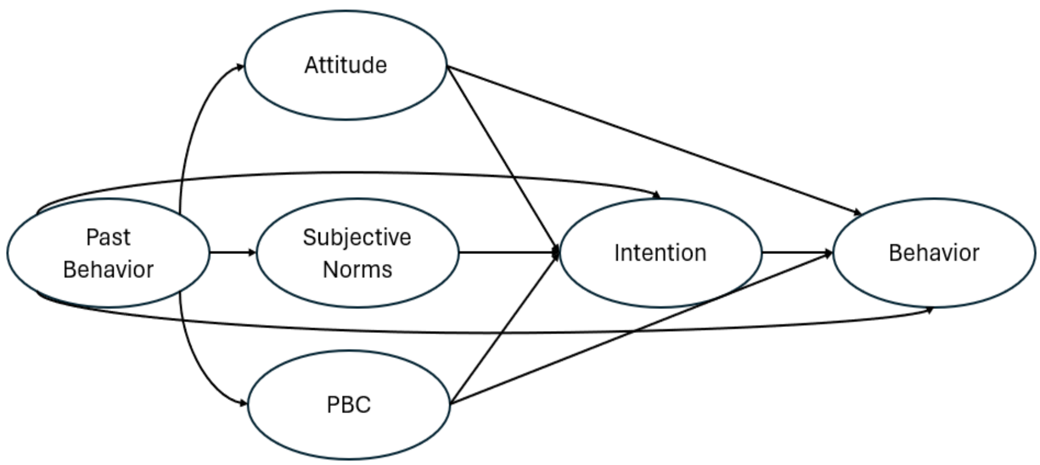
Appendices

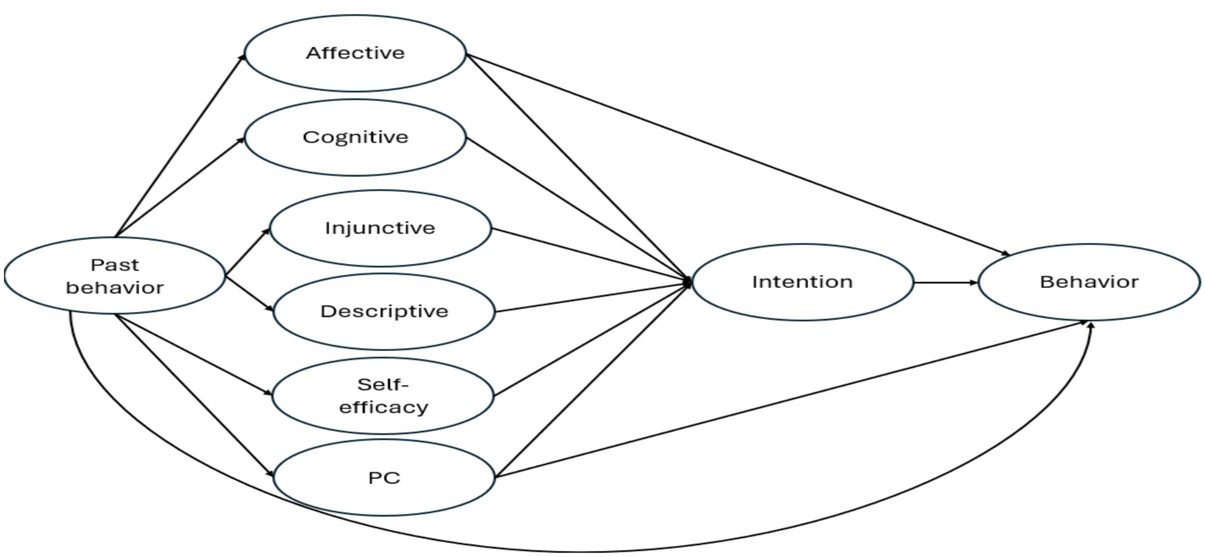
Figure 1. Diagrammatic Representation of Models of the Theory of Planned Behavior (TPB) for Physical Activity Behavior.

Note. Panel A Represents a Model Specifying Hypothesized Relations Among Core, Directly-Measured Theory Constructs with Control for Past Behavior Effects. Panel B Represents a Model Specifying Relations Among Differentiated Versions of Theory Constructs. Panel C Represents a Model of an Elaborated Versions of the Theory Specifying Relations Among Directly- and Indirectly-Measured Theory Constructs.

Panel A



Panel B



Panel C

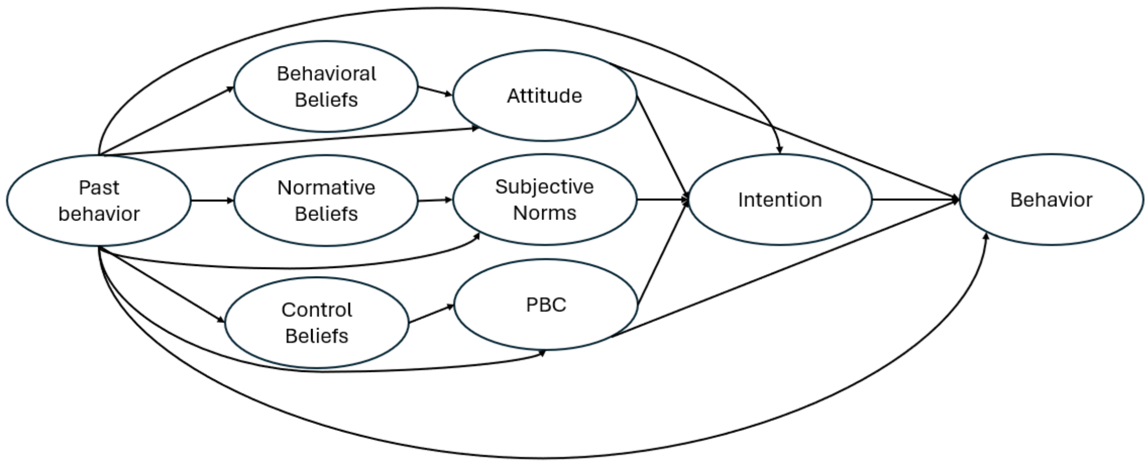

Behavioral Beliefs
Attitude
Past behavior
Normative Beliefs
Subjective Norms
Intention
Behavior
Control Beliefs
PBC

Table 1

Standardized Parameter Estimates and 95% Confidence Intervals for Multilevel Meta-Analytic Structural Equation Model of the Basic Direct Measures Version of the Theory of Planned Behavior (Model 1) in the Full Sample of Studies Unadjusted and Adjusted for Covariates and Excluding and Including Past Behavior Effect

	Unadjusted for covariates						Adjusted for covariates[a]					
	Past behavior excluded			Past behavior included			Past behavior excluded			Past behavior included		
	β	95% CI		B	95% CI		β	95% CI		β	95% CI	
		LL	UL		LL	UL		LL	UL		LL	UL
Direct effects												
PB→Att	–	–	–	.287	.266	.309	–	–	–	.262	.241	.284
Int→Beh	0.357[b]	0.329	0.385	.216[b]	.182	.249	.337[b]	.310	.364	.210[b]	.183	.237
PB→Beh	–	–	–	.384	.345	.423	–	–	–	.356	.317	.395
PBC→Beh	0.120[b]	0.092	0.147	.058[b]	.028	.088	.113	.087	.139	.099	.075	.123
Att→Int	0.292[b]	0.274	0.309	.248[b]	.229	.267	.282	.265	.299	.304	.285	.323
PB→Int	–	–	–	.223	.200	.245	–	–	–	.270	.248	.293
PBC→Int	0.346[b]	0.329	0.364	.301[b]	.282	.321	.336[b]	.319	.353	.070[b]	.050	.090
SN→Int	0.154	0.136	0.171	.133	.115	.152	.148	.131	.165	.165	.146	.183
PB→PBC	–	–	–	.329	.308	.350	–	–	–	.309	.288	.330
PB→SN	–	–	–	.196	.174	.218	–	–	–	.172	.150	.194
Indirect effects												
Att→Int→Beh	0.104[b]	0.094	0.115	.053[b]	.044	.063	.095[b]	.085	.105	.064[b]	.054	.073
SN→Int→Beh	0.055[b]	0.047	0.063	.029[b]	.023	.035	.050[b]	.043	.057	.035[b]	.029	.041
PBC→Int→Beh	0.124[b]	0.111	0.136	.065[b]	.054	.076	.113[b]	.102	.125	.015[b]	.010	.019
Total effects												
PBC→Beh[c]	0.243[b]	0.221	0.265	.123[b]	.097	.148	.226[b]	.205	.248	.113[b]	.090	.137
Correlations												
Att↔PBC	0.387[b]	0.369	0.404	.294[b]	.278	.309	.357[b]	.340	.375	.287[b]	.271	.302
SN↔PBC	0.285[b]	0.266	0.303	.221[b]	.205	.238	.255[b]	.237	.273	.212[b]	.196	.228
Att↔SN	0.311[b]	0.292	0.329	.267[b]	.251	.283	.282	.263	.300	.258	.242	.274

Note. All model effects non-zero ($p < .001$). [a]Model parameters adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study design, and study quality. [b]Parameter estimates statistically significantly different ($p < .05$) across models excluding and including past behavior using Schenker and Gentleman's (2001) 'standard method' based on confidence intervals. [c]Total effect of perceived behavioral control on behavior comprising indirect effect mediated by intention and direct effect. β = Standardized path coefficient; 95% CI = 95% confidence interval of parameter estimate; LL = Lower limit of 95% CI; PB = Past behavior; Att = Attitude; SN = Subjective norm; PBC = Perceived behavioral control; Int = Intention; Beh = Behavior.

Table 2

Standardized Parameter Estimates and 95% Confidence Intervals for Multilevel Meta-Analytic Structural Equation Model of the Basic Direct Measures Version of the Theory of Planned Behavior (Model 1) in the Full Sample of Studies Unadjusted and Adjusted for Covariates and Excluding and Including the Direct Attitude-Behavior Effect

Effect	Unadjusted for covariates						Adjusted for covariates[a]					
	Excl. direct Att-Beh effect			Incl. direct Att-Beh effect			Excl. direct Att-Beh effect			Incl. direct Att-Beh effect		
	B	95% CI		B	95% CI		β	95% CI		β	95% CI	
		LL	UL		LL	UL		LL	UL		LL	UL
Direct effects												
PB→Att	.287***	.266	.309	.279***	.257	.301	.262***	.241	.284	.258***	.236	.280
Att→Beh	–	–	–	.037**	.009	.064	–	–	–	.019	-.009	.047
Int→Beh	.216***	.182	.249	.195***	.159	.232	.210***	.183	.237	.199***	.168	.230
PB→Beh	.384***	.345	.423	.379***	.340	.418	.356***	.317	.395	.356***	.317	.395
PBC→Beh	.058***	.028	.088	.052***	.022	.082	.099***	.075	.123	.093***	.067	.118
Att→Int	.248***	.229	.267	.247***	.228	.266	.304***	.285	.323	.303***	.285	.322
PB→Int	.223***	.200	.245	.228***	.205	.251	.270***	.248	.293	.273***	.251	.296
PBC→Int	.301***	.282	.321	.301***	.281	.320	.070***	.050	.090	.070***	.050	.090
SN→Int	.133***	.115	.152	.133***	.114	.151	.165***	.146	.183	.164***	.146	.183
PB→PBC	.329***	.308	.350	.330***	.309	.351	.309***	.288	.330	.310***	.288	.331
PB→SN	.196***	.174	.218	.195***	.173	.217	.172***	.150	.194	.172***	.150	.194
Indirect effects												
Att→Int→Beh	.053***	.044	.063	.048***	.038	.058	.064***	.054	.073	.060***	.050	.071
SN→Int→Beh	.029***	.023	.035	.026***	.020	.032	.035***	.029	.041	.033***	.026	.039
PBC→Int→Beh	.065***	.054	.076	.059***	.047	.071	.015***	.010	.019	.014***	.009	.018
Total effects[b]												
Att→Beh	–	–	–	.111***	.084	.138	–	–	–	.107***	.081	.133
PBC→Beh	.123***	.097	.148	.085***	.060	.110	.113***	.090	.137	.080***	.055	.104
Correlations												
Att↔PBC	.294***	.278	.309	.296***	.280	.311	.287***	.271	.302	.287***	.272	.303
SN↔PBC	.221***	.205	.238	.222***	.205	.238	.212***	.196	.228	.212***	.196	.228
Att↔SN	.267***	.251	.283	.269***	.254	.285	.258***	.242	.274	.259***	.243	.275

Note. None of the parameter estimates were significantly different across models that excluded or included the direct attitude-behavior effect. [a]Model parameters adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study design, and study quality. [b]Total effect of attitude/perceived behavioral control on behavior comprising indirect effect mediated by intention and direct effect. β =

Standardized path coefficient; 95% CI = 95% confidence interval of parameter estimate; LL = Lower limit of 95% CI; PB = Past behavior; Att = Attitude; SN = Subjective norm; PBC = Perceived behavioral control; Int = Intention; Beh = Behavior. $^{**}p < .001$ $^{**}p < .01$ $^{*}p < .05$

Table 3

Standardized Parameter Estimates and 95% Confidence Intervals for Multilevel Meta-Analytic Structural Equation Model of the Reasoned Action Approach (Model 2) in the Full Sample of Studies Unadjusted and Adjusted for Covariates and Excluding and Including the Direct Affective Attitude-Behavior Effect

Effect	Unadjusted for covariates						Adjusted for covariates[a]					
	Excl. direct AA-Beh effect			Incl. direct AA-Beh effect			Excl. direct AA-Beh effect			Incl. direct AA-Beh effect		
	β	95% CI		β	95% CI		β	95% CI		β	95% CI	
		LL	UL		LL	UL		LL	UL		LL	UL
Direct effects												
PB→AA	.316***	.270	.362	.281***	.232	.331	.309***	.263	.355	.276***	.226	.325
AA→Beh	–	–	–	.119***	.057	.181	–	–	–	.116***	.055	.178
Int→Beh	.236***	.194	.278	.204***	.159	.249	.235***	.194	.276	.204***	.160	.249
PB→Beh	.397***	.357	.437	.394***	.352	.436	.393***	.353	.432	.390***	.348	.431
PC→Beh	.003	-.074	.080	-.067	-.152	.018	.002	-.074	.078	-.066	-.150	.019
PB→DN	.212***	.159	.265	.211***	.158	.264	.204***	.151	.257	.203***	.150	.256
PB→IA	.206***	.159	.254	.201***	.153	.248	.200***	.152	.247	.194***	.147	.242
AA→Int	.235***	.176	.294	.228***	.170	.286	.234***	.175	.292	.226***	.169	.283
DN→Int	.116***	.060	.172	.113***	.058	.169	.116***	.060	.171	.113***	.058	.169
IA→Int	.093**	.029	.158	.095**	.030	.160	.093**	.029	.156	.094**	.030	.158
PB→Int	.171***	.135	.207	.182***	.147	.217	.170***	.134	.205	.181***	.146	.215
PC→Int	.050	-.058	.159	.058	-.049	.164	.052	-.055	.159	.059	-.046	.164
SE→Int	.270***	.197	.342	.262***	.191	.334	.269***	.197	.340	.262***	.192	.332
SN→Int	.080***	.043	.116	.079***	.043	.115	.080***	.045	.116	.080***	.045	.115
PB→PC	.270***	.181	.359	.295***	.205	.384	.263***	.175	.352	.288***	.198	.377
PB→SE	.379***	.340	.418	.384***	.345	.424	.374***	.335	.413	.379***	.340	.419
PB→SN	.192***	.169	.215	.191***	.167	.214	.184***	.161	.207	.183***	.160	.206
Indirect effects												
AA→Int→Beh	.055***	.038	.073	.046***	.032	.061	.055***	.038	.072	.046***	.032	.061
IA→Int→Beh	.022**	.006	.038	.019**	.006	.033	.022**	.007	.037	.019**	.006	.033
SN→Int→Beh	.019***	.010	.028	.016***	.008	.024	.019***	.010	.028	.016***	.008	.024
DN→Int→Beh	.027***	.013	.041	.023***	.010	.036	.027***	.013	.041	.023***	.011	.036
PC→Int→Beh	.012	-.014	.038	.012	-.011	.034	.012	-.013	.038	.012	-.010	.034
SE→Int→Beh	.064***	.043	.084	.054***	.035	.072	.063***	.043	.083	.053***	.035	.072
Sum of indirect effects[b]												
AA/IA→Int→Beh	.077***	.057	.098	.066***	.048	.084	.077***	.057	.097	.066***	.048	.083

SN/DN→Int→Beh	.046***	.032	.060	.039***	.026	.052	.046***	.032	.060	.039***	.026	.053
PC/SE→Int→Beh	.076***	.053	.098	.065***	.042	.088	.075***	.053	.098	.065***	.043	.088
Total effects												
AA/IA→Beh	–	–	–	.185***	.125	.244	–	–	–	.182***	.123	.240
PC/SE→Beh	.079*	.012	.145	-.001	-.082	.080	.078*	.011	.144	.000	-.081	.080
RAA→B	.202***	.147	.258	.222***	.165	.280	.200***	.145	.256	.221***	.164	.278
Correlations												
AA↔DN	.170***	.104	.236	.184***	.117	.250	.167***	.102	.233	.180***	.114	.246
IA↔DN	.110**	.045	.175	.112**	.047	.177	.106**	.041	.171	.108**	.043	.173
SN↔DN	.310***	.268	.352	.311***	.269	.353	.306***	.264	.349	.307***	.265	.350
AA↔IA	.419***	.381	.456	.430***	.392	.467	.416***	.378	.453	.426***	.388	.463
AA↔PC	.282***	.193	.371	.283***	.200	.365	.279***	.191	.368	.280***	.198	.363
DN↔PC	.140***	.060	.220	.132**	.053	.211	.137**	.057	.217	.130**	.051	.209
IA↔PC	.351***	.267	.436	.351***	.269	.434	.348***	.264	.432	.348***	.265	.431
SN↔PC	.193***	.129	.257	.191***	.129	.254	.189***	.125	.253	.188***	.126	.251
AA↔SE	.196***	.118	.273	.215***	.137	.293	.193***	.116	.271	.212***	.135	.290
DN↔SE	.124***	.057	.190	.124***	.057	.191	.121***	.055	.188	.122***	.055	.188
IA↔SE	.240***	.165	.315	.242***	.167	.317	.236***	.162	.311	.239***	.164	.314
PC↔SE	.431***	.360	.501	.418***	.346	.490	.428***	.357	.498	.415***	.343	.487
SN↔SE	.184***	.143	.226	.184***	.143	.225	.182***	.141	.223	.182***	.140	.223
AA↔SN	.223***	.187	.259	.231***	.195	.267	.220***	.185	.256	.227***	.192	.263
IA↔SN	.327***	.290	.364	.330***	.294	.367	.323***	.286	.360	.326***	.290	.363

Note. [a]Model parameters adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study design, and study quality. [b]Sum of indirect effects of each set of RAA components together on behavior mediated by intention. [c]Total effect of all RAA components on behavior comprising the sum of indirect effects of each component mediated by intention and the direct effect of perceived control on behavior. β = Standardized path coefficient; 95% CI = 95% confidence interval of parameter estimate; LL = Lower limit of 95% CI; PB = Past behavior; AA = Affective attitude; IA = Instrumental attitude; SN = Subjective (injunctive) norm; DN = Descriptive norm; PC = Perceived control; SE = Self-efficacy; Int = Intention; Beh = Behavior; RAA = Reasoned action approach.

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

Table 4

Standardized Parameter Estimates and 95% Confidence Intervals for Multilevel Meta-Analytic Structural Equation Model of the Direct and Indirect Measures Version of the Theory of Planned Behavior (Model 3) in the Full Sample of Studies Unadjusted and Adjusted for Covariates and Excluding and Including the Direct Attitude-Behavior Effect

Effect	Unadjusted for covariates						Adjusted for covariates[a]					
	Excl. direct Att-Beh effect			Incl. direct Att-Beh effect			Excl. direct Att-Beh effect			Incl. direct AAtt-Beh effect		
	β	95% CI		β	95% CI		β	95% CI		β	95% CI	
		LL	UL		LL	UL		LL	UL		LL	UL
Direct effects												
BB→Att	.448***	.402	.495	.451***	.405	.498	.430***	.383	.476	.433***	.386	.479
PB→Att	.164***	.132	.196	.157***	.124	.189	.154***	.123	.185	.147***	.116	.179
PB→BB	.283***	.233	.333	.279***	.229	.330	.262***	.211	.313	.259***	.208	.310
Att→Beh	–	–	–	.034*	.006	.061	–	–	–	.032*	.006	.059
Int→Beh	.209***	.176	.243	.190***	.153	.228	.204***	.172	.236	.186***	.151	.222
PB→Beh	.391***	.352	.430	.386***	.347	.425	.378***	.340	.416	.373***	.335	.412
PBC→Beh	.063***	.033	.093	.059***	.029	.089	.062***	.034	.091	.058***	.029	.087
PB→CB	.365***	.306	.425	.366***	.307	.425	.346***	.286	.406	.347***	.287	.407
Att→Int	.249***	.230	.268	.248***	.229	.267	.245***	.227	.263	.244***	.226	.263
PB→Int	.225***	.202	.248	.230***	.207	.253	.222***	.199	.244	.226***	.204	.249
PBC→Int	.302***	.283	.322	.302***	.282	.321	.297***	.278	.315	.296***	.277	.315
SN→Int	.135***	.116	.153	.134***	.116	.153	.133***	.115	.151	.133***	.115	.151
PB→NB	.269***	.203	.335	.269***	.202	.335	.248***	.180	.315	.247***	.180	.315
CB→PBC	.494***	.435	.553	.493***	.434	.552	.474***	.415	.533	.474***	.415	.532
PB→PBC	.150***	.108	.192	.151***	.109	.193	.143***	.103	.183	.144***	.104	.184
NB→SN	.514***	.445	.583	.514***	.445	.583	.494***	.425	.563	.495***	.426	.564
PB→SN	.059*	.014	.104	.059*	.014	.104	.050*	.007	.093	.050*	.007	.093
Indirect effects												
BB→Att→Int	.112***	.097	.127	.112***	.097	.127	.105***	.091	.120	.106***	.091	.120
NB→SN→Int	.069***	.056	.083	.069***	.055	.083	.066***	.053	.079	.066***	.053	.079
CB→PBC→Int	.149***	.129	.170	.149***	.128	.169	.141***	.121	.161	.140***	.120	.160
BB→Att→Int→Beh[b]	.023***	.018	.028	.036***	.024	.049	.021***	.017	.026	.034***	.022	.045
NB→SN→Int→Beh	.014***	.011	.018	.013***	.009	.017	.013***	.010	.017	.012***	.009	.016
CB→PBC→Int→Beh[c]	.062***	.047	.078	.057***	.042	.073	.058***	.044	.073	.054***	.039	.068
Att→Int→Beh	.052***	.043	.062	.047***	.037	.057	.050***	.041	.059	.045***	.036	.055
SN→Int→Beh	.028***	.022	.034	.026***	.019	.032	.027***	.021	.033	.025***	.019	.031

PBC→Int→Beh	.063***	.052	.074	.057***	.045	.070	.061***	.050	.071	.055***	.044	.066
Total effects												
Att→Beh[d]	–	–	–	.081***	.056	.106	–	–	–	.078***	.053	.102
PBC→Beh[e]	.127***	.101	.152	.116***	.089	.143	.123***	.098	.148	.113***	.087	.139
Correlations												
BB↔CB	.326***	.273	.378	.328***	.276	.381	.313***	.259	.366	.315***	.262	.368
NB↔CB	.244***	.178	.310	.244***	.178	.310	.231***	.165	.298	.232***	.165	.298
BB↔NB	.395***	.335	.456	.397***	.337	.458	.382***	.321	.443	.384***	.323	.445
Att↔PBC	.221***	.198	.243	.222***	.199	.244	.220***	.199	.242	.221***	.199	.243
SN↔PBC	.161***	.136	.185	.161***	.136	.185	.157***	.133	.180	.157***	.134	.181
Att↔SN	.176***	.152	.201	.177***	.153	.202	.174***	.151	.197	.175***	.151	.198

Note. None of the parameter estimates were significantly different across models that excluded or included the direct attitude-behavior effect. [a]Model parameters adjusted for the following covariates: age, sex, sample type (student vs. non-student), sample type (clinical vs. non-clinical), study design, and study quality. [b]Effect also includes indirect effect of behavioral beliefs on behavior mediated by attitude only for the version of the model that includes the direct attitude-behavior effect. [c]Effect also includes the indirect effect of control beliefs on behavior mediated by perceived behavioral control only. [d]Total effect of attitude on behavior comprising indirect effect mediated by intention and direct effect for the version of the model that includes the direct attitude-behavior effect. [e]Total effect of perceived behavioral control on behavior comprising indirect effect mediated by intention and direct effect. β = Standardized path coefficient; 95% CI = 95% confidence interval of parameter estimate; LL = Lower limit of 95% CI; PB = Past behavior; BB = Behavioral beliefs; NB = Normative beliefs; CB = Control beliefs; Att = Attitude; SN = Subjective norm; PBC = Perceived behavioral control; Int = Intention; Beh = Behavior. $^{**}p <$ .001 $^{**}p < .01$ $^{*}p < .05$. $^{***}p < .001$ $^{**}p < .01$ $^{*}p < .05$