Communications in Kinesiology

Review

Published by the Society for Transparency, Openness, and Replication in Kinesiology under the terms of the Creative Commons Attribution License, which permits unrestricted use, provided the original author and source are credited.

DOI:
10.51224/cik.2026.8043

Subject Areas:
Physical Activity, Health, and Disease

Keywords:
Attitude, Exercise, Health, Motivation, Psychology

Editor:
Leighton Jones

Approach-Avoidance Tendencies and Physical Activity Level: A Systematic Review and Meta-Analysis

François Jabouille[1,†,*], Ata Farajzadeh[1,†], and Matthieu P. Boisgontier[1,2]

[1]School of Rehabilitation Sciences, Faculty of Health Sciences, University of Ottawa, Ottawa, Canada
[2]Institut du Savoir Montfort, Hôpital Montfort, Ottawa, Ontario, Canada
[†]Contributed equally to this work.
[*]Correspondence: francois.jabouille@uottawa.ca

Purpose. To examine the relationship between approach-avoidance tendencies and physical activity as well as the factors that influence this relationship.

Methods. This systematic review with meta-analysis is reported in accordance with the PRISMA 2020 guidelines. Searches were conducted in MEDLINE, Web of Science, PsycINFO, SPORTDiscus, and CINAHL from inception to March 2026. We included observational studies assessing associations between approach-avoidance tendencies and physical activity. Pearson product-moment correlations were pooled from eligible studies using the generic inverse pooling and random-effects method. Subgroup meta-analyses were conducted to examine the effect of testing context, types of approach-avoidance tasks, types of physical activity measures, and stimulus type. Meta-regressions were conducted to examine the moderating effects of age, sex, and study quality score.

Results. The main meta-analysis included 22 estimates from 18 studies (n = 2,070 participants). Results showed a small positive correlation between approach-avoidance tendencies and physical activity (r = 0.11, 95% CI [0.04, 0.18], p = 0.004). However, the estimate from Rücker's limit meta-analysis, which models small-study effects, was no longer significant (r = 0.04, 95% CI [−0.08, 0.16], p = 0.488). Subgroup meta-analyses showed no evidence of differences according to physical activity measure, approach-avoidance task, or stimulus type, whereas differences were observed according to testing context ($Q(1)$ = 4.90, p = 0.039), with only in-person studies yielding a significant association (p = 0.0006). Meta-regressions showed no evidence of moderating effects of age, sex, or study quality score.

Conclusion. Our results suggest that the observed association between approach-avoidance tendencies and physical activity levels may be influenced by small-study effects and should therefore be interpreted cautiously. Substantial methodological variability, along with the lack of validity and reliability studies, currently limits robust conclusions regarding this relationship. Recommendations are provided for future studies to increase comparability.

Registration. The review was registered in PROSPERO (CRD420251034465).

Introduction

Since the seminal work on mental chronometry (Donders, 1969), reaction time has served as a tool for investigating psychological processes and underlying neural mechanisms. In particular, reaction-time paradigms have been instrumental in the study of automatic attitudes, defined as traces of cumulative past experiences that mediate favorable or unfavorable feeling, thought, or action toward a social object (Greenwald & Banaji, 1995). These automatic attitudes operate mostly outside of conscious awareness and influence behavior in ways that may not be accessible through introspective self-report (Conroy & Berry, 2017; Corneille & Hütter, 2020). In other words, an automatic attitude is an evaluative mental representation of a particular entity (Eagly & Chaiken, 2007) (e.g., physical activity) expressed in the form of dynamic mental operations (processes) that result in evaluative responses, which are observable manifestations (e.g., reaction time, self-report scores) captured through a variety of tests. This definition aligns with the classic threefold division of mental activities into knowing, feeling, and willing (Hilgard, 1980), which has led to differentiate cognitive, affective, and motivational automatic processes (Sheeran et al., 2013, 2016).

Physical activity is defined as any bodily movement produced by skeletal muscles that requires energy expenditure. It can be undertaken as part of sport, but also as part of active forms of recreation and art, work, or domestic tasks in various intensities (World Health Organization, 2018). Although insufficient physical activity has consequences for physical, mental, and social health (Bleich et al., 2018; Liu et al., 2017; Moore et al., 2016; Najar et al., 2019; Schuch et al., 2017; Wahid et al., 2016), resulting in $48 billion per year in healthcare costs (Santos et al., 2023), physical inactivity continues to increase worldwide (Strain et al., 2024). According to dual-process models, this trend may be partly explained by automatic processes, which interact with controlled processes (e.g., intentions) to influence behavior (Figure 1) (Cheval & Boisgontier, 2021; Conroy & Berry, 2017; Rebar et al., 2016).

The present work focused on automatic attitudes, which reflect a general and spontaneous orientation toward a given concept, such as physical activity. This construct is distinct from habits, which involve learned responses that are automatically triggered by recurring contextual cues and contribute to the maintenance of established behaviours (e.g., automatically initiating exercise in response to a familiar cue such as seeing one's running shoes) (Gardner, 2015; Gardner & Rebar, 2019). Automatic attitudes also differ from priming effects, which capture transient responses elicited by exposure to specific cues (Rebar et al., 2016; Tulving & Schacter, 1990). They further differ from momentary motivational states, such as urges and cravings, which can fluctuate throughout the day and across contexts (Stults-Kolehmainen et al., 2020, 2022). Focusing on automatic attitudes therefore provides a means of examining relatively general and spontaneous evaluations of physical activity, rather than context-specific behavioral responses, transient cue-induced effects, or momentary motivational states.

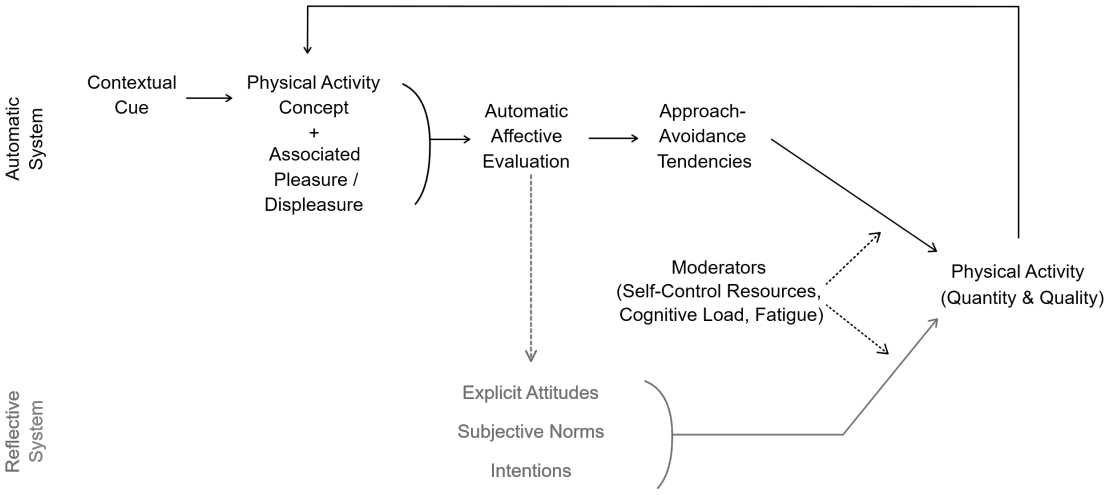


Figure 1: Conceptual dual-process model of physical activity (adapted from Conroy & Berry (2017)).

Commonly studied automatic processes relevant to the characterization of automatic attitudes include attentional bias (Berry et al., 2011; Calitri et al., 2009; Cheval, Radel, et al., 2018; Cheval et al., 2020; Quossi et al., 2025; Y.-B. Wang et al., 2024), automatic valuation (Cheval, Radel, et al., 2018; Chevance et al., 2019; Conroy & Berry, 2017; de Oliveira Araújo et al., 2024; Quossi et al., 2025; Y.-B. Wang, Yang, et al., 2023), and approach-avoidance tendencies (Berry, 2020; Cheval et al., 2014, 2015; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Sarrazin, Isoard-Gautheur, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh et al., 2023; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Goubran, Zammar, et al., 2025; Hannan et al., 2019; Locke & Berry, 2021; Moffitt et al., 2020; Oliver & Kemps, 2018; Preis et al., 2021; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025; Zenko & Ekkekakis, 2019). These processes are thought to operate at different stages of the pathway from cue exposure to behavioral engagement. Attentional bias reflects the early orienting of attention toward particular environmental cues (Cheval et al., 2020; Fadardi et al., 2016). Approach-avoidance tendencies are thought to be elicited by automatic valuation of a cue and to occur closer to behavior initiation (M. Chen & Bargh, 1999; Cheval & Boisgontier, 2021; Conroy & Berry, 2017; Friese et al., 2011). Whereas automatic affective attitudes reflect the association between target concepts (e.g., running and sedentary behavior) and attributes (positive and negative), approach-avoidance tendencies reflect the association between target concepts and action orientation (approaching or moving away). Consequently, approach-avoidance tendencies may provide a temporally more proximal measure of the motivational processes underlying physical activity engagement.

Therefore, we focused on approach-avoidance tendencies, defined as the automatic inclination to move toward or away from specific stimuli. These tendencies can be assessed through reaction-time paradigms that involve the physical (e.g., pulling or pushing a joystick) or symbolic (e.g., moving a virtual avatar) execution of approach or avoidance actions in response to visual stimuli (Krieglmeyer & Deutsch, 2010; Rougier et al., 2018). Reaction times are shorter when the stimulus is congruent with the direction of the action (e.g., pulling a positively valued stimulus, moving away from a negatively valued stimulus), suggesting a match between the stimulus' implicit valence and the executed action (M. Chen & Bargh, 1999; Solarz, 1960). This paradigm has been widely validated and applied in various domains, demonstrating that approach-avoidance tendencies measure is a robust indicator of automatic motivation (Friese et al., 2011; Sheeran et al., 2013), including in studies focusing on physical activity (Cheval et al., 2015).

Initial research on automatic attitudes toward physical activity behavior has predominantly focused on affective association (Bluemke et al., 2010; Conroy & Berry, 2017; Hyde et al., 2012) and attentional bias (Berry, 2006; Calitri et al., 2009; Cheval et al., 2020), with a meta-analysis showing a small positive correlation between automatic affective attitudes and physical activity ($r = 0.11$; 95% CI: 0.05, 0.17) (Chevance et al., 2019), but excluding studies examining approach-avoidance tendencies. However, over the past decade, a growing body of research has focused specifically on these tendencies (Cheval et al., 2014, 2015; Cheval, Tipura, et al., 2018; Farajzadeh et al., 2023; Farajzadeh, Jabouille, Benoit, et al., 2025; Goubran, Zammar, et al., 2025; Hannan et al., 2019; Oliver & Kemps, 2018; Preis et al., 2021; Quossi et al., 2025; C. Wang & Zhang, 2025). A subsequent meta-analysis reported a small positive correlation ($r = 0.16$; 95% CI: 0.11, 0.21) of approach-avoidance tendencies with physical activity and sedentary behaviors (Y.-B. Wang et al., 2024). Although this meta-analysis represents the first step toward improving our understanding of this relationship, some limitations should be noted. The analysis included only 12 estimates and combined physical activity and sedentary behavior, despite these being distinct constructs (Pearson et al., 2014; van der Ploeg & Hillsdon, 2017). Indeed, an individual may meet physical activity recommendations (Bull et al., 2020) (e.g., running 30 minutes per day), while also exhibiting high levels of sedentary behavior (e.g., sitting 8 hours per day at work). Moreover, the motivational mechanisms underlying physical activity and sedentary behavior differ (Biddle, 2011; Maltagliati et al., 2022). Because approach-avoidance biases toward physical activity and sedentary behavior are typically negatively correlated (Cheval et al., 2014; Farajzadeh et al., 2023), including both simultaneously required using the absolute values of the correlation coefficients to avoid mutual cancellation, which may have biased the overall estimate. Therefore, a systematic review of the literature addressing these limitations is needed to better understand the nature and strength of the relationship between automatic approach-avoidance tendencies and physical activity behavior.

Our objective was to systematically review the literature testing the relationship between automatic approach-avoidance tendencies toward physical activity-related stimuli and physical activity engagement.

In addition, we conducted a meta-analysis to estimate whether and to what extent these tendencies are associated with physical activity. Finally, we explored potential moderating factors to better understand the mechanisms underlying physical activity.

Methods

Search Strategy

This review is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). Potential studies were identified by searching the MEDLINE (via PubMed), PsycINFO, Web of Science, SPORTDiscus, and CINAHL databases. The search terms used to identify relevant studies were variants of approach-avoidance tendencies (i.e., approach avoidance, approach tendency, avoidance tendency, approach behavior, avoidance behavior, approach bias, avoidance bias, motivational orientation, automatic evaluation, implicit attitude, implicit motivation, affective response, automatic process, approach-avoidance Task, AAT, manikin task) and physical activity (i.e., exercise, physical activity) (Suppl. Material 1). Articles were searched from inception to March 18, 2026. A filter was used to limit the search to studies published in English. This systematic review was pre-registered in PROSPERO (CRD420251034465) (Farajzadeh, Jabouille, & Boisgontier, 2025) and approved by University of Ottawa's Research Ethics Boards (H-03-26-12753).

Eligibility Criteria and Study Selection

Inclusion Criteria

To be included in this systematic review, articles had to 1) be published in a peer-reviewed journal, 2) be written in English, 3) report original data collected from human participants, 4) include at least one measure of approach-avoidance tendencies toward physical activity, and 5) include at least one measure of physical activity. The measure of physical activity could be self-reported or device-based (e.g., accelerometry). Cohort studies, baseline data from clinical trials, and cross-sectional studies were included in this review.

Exclusion Criteria

Studies were excluded if they were 1) published as a book chapter, study protocol, review article, or conference abstract, or 2) based on laboratory-based measures of physical fitness (e.g., maximal muscle force, $\dot{V}O_2max$) and not on a measure of physical activity.

Study Selection

Articles were screened using the Covidence systematic review software (Veritas Health Innovation, Melbourne, Australia), a web-based collaborative software platform that streamlines the production of systematic reviews. After duplicates were removed, titles and abstracts were independently reviewed by two reviewers (FJ, MPB) according to the inclusion and exclusion criteria. If there was any doubt about the inclusion or exclusion of an article, the full text was not removed at this stage. Then, the full texts of the remaining articles were screened by two reviewers (AF, MPB). Inter-rater reliability between the two independent reviewers was assessed using Cohen's kappa (κ) for title and abstract screening as well as full-text screening. Any disagreements were resolved by consensus among the three reviewers (FJ, AF, MPB). Reference screening and forward citation tracking were performed on the included articles. All the articles citing these included articles were screened ("snowballing").

Data Extraction

Data extracted by two reviewers (FJ, MPB) from the selected articles included first author's name, article title, publication year, number of participants, proportion of women, mean age, health status, type of approach-avoidance task, stimulus type, type of approach-bias calculation, type of physical activity measure and outcome, component of physical activity, as well as statistical estimates and significance of the association between approach-avoidance tendencies and physical activity. The data extraction form was developed by the authors and was previously tested in three systematic reviews (Farajzadeh, Hébert, et al., 2026; Farajzadeh, Park, et al., 2026; Goubran, Farajzadeh, et al., 2025).

Bias Assessment

The included studies were assessed for methodological quality using questions from the Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies and the Quality Assessment of Controlled Intervention Studies questionnaires (National Heart, Lung, and Blood Institute, 2021). Two reviewers (FJ, MPB) independently answered these questions for each included study, with a third reviewer (AF) involved in case of disagreement. Details of the methodological quality assessment are freely available online (Jabouille & Boisgontier, 2026).

Meta-Analysis

All analyses were conducted in RStudio integrated development environment (IDE) (2025.09.0 Build 387, "Cucumberleaf Sunflower" release) running R 4.4.2 (R Core Team, 2024), using the 'meta' (Schwarzer, 2023), 'metasens' (Schwarzer et al., 2023), and 'metafor' (Viechtbauer, 2010, 2023) R packages.

Main Meta-Analysis

In the main meta-analysis, we pooled Pearson product-moment correlations from eligible studies to examine the relationship between approach-avoidance tendencies and physical activity. For two studies using a joystick-based approach-avoidance task (Preis et al., 2021; Zenko & Ekkekakis, 2019), we used the inverse correlation, as some authors have highlighted an interpretational ambiguity in the scoring of the task (Zenko & Ekkekakis, 2019): pulling the joystick is assumed to reflect an approach movement (e.g., via a zoom-in effect on the image), although the participant is physically moving away from the screen, and vice versa for pushing movements. Results based on the original correlations are reported as a sensitivity analysis.

When exact p-values were not reported in an article, but the sample size (n) and Pearson's correlation coefficient were available, the exact p-value was computed using an ad-hoc R code (Suppl. R Script 1) (Farajzadeh, Hébert, et al., 2026; Farajzadeh, Park, et al., 2026; Goubran, Farajzadeh, et al., 2025). Correlations were pooled using the generic inverse pooling method via the 'metacor' function in the R 'meta' package (Schwarzer, 2023). This function automatically performs a necessary Fisher's z-transformation on the original, untransformed correlations prior to pooling. The 'metacor' function reconverts the pooled association back to its original form for ease of interpretation.

When multiple correlations originated from the same study, we accounted for within-study dependence using two complementary approaches. First, we employed a three-level model implemented in the 'metafor' package (Viechtbauer, 2010, 2023) with random effects specified as ~ 1 | Author/Cluster. Second, we conducted a parallel meta-analysis using the 'meta' package (metacor, cluster = Author) with Knapp–Hartung adjustments to obtain cluster-robust confidence intervals (Knapp & Hartung, 2003). We anticipated considerable between-study heterogeneity and therefore used a random-effects model to pool correlations. The restricted maximum likelihood (REML) estimator (Viechtbauer, 2005) was used to calculate the heterogeneity variance τ^2. In addition to τ^2, to quantify between-study heterogeneity, we report the I^2 statistic, which provides the percentage of variability in the correlations that is not caused by sampling error (Higgins & Thompson, 2002). The I^2 statistic was interpreted as: 0-40%, may not be important; 30-60%, may represent moderate heterogeneity; 50-90%, may represent substantial heterogeneity; and 75-100%, may represent considerable heterogeneity. We also report the prediction interval, which provides a range within which we can expect the associations of future studies to fall based on the current evidence. If significant, the pooled correlation was interpreted using Cohen's conventions (Cohen, 1988): $r \approx 0.10$ (small), $r \approx 0.30$ (moderate), and $r \approx 0.50$ (large).

Publication Bias Assessment

Publication bias refers to the fact that studies with positive or significant results are more likely to be published compared to studies with negative or non-significant results, affecting the validity and generalization of conclusions of a meta-analysis (Lin & Chu, 2018). Methods used to assess publication bias are limited in that their results may arise from factors other than publication bias (e.g., methodological differences, chance, or heterogeneity) (Page et al., 2021; Sterne et al., 2011). Accordingly, we considered multiple complementary approaches and interpreted them in combination to account for the limitations of individual methods and reduce the risk of misinterpretation. We first assessed

publication bias using a funnel plot, which is a scatter plot of the studies' effect size expressed as the Fisher's z-transformed correlation on the x-axis against a measure of their standard error (which is indicative of precision of the study's effect size) on the y-axis. We also used Egger's regression to formally test funnel plot's asymmetry (Egger et al., 1997). Because the probability of obtaining significant results rises with a larger sample size, publication bias will disproportionately affect small studies. Rücker's limit meta-analysis method explicitly accounts for the publication bias due to small studies and includes heterogeneity variance in the model (Rücker et al., 2011) (Suppl. Material 2), so we used it to compute a bias-corrected estimate of the true effect size.

Publication bias was also assessed using p-curve analysis (Simonsohn et al., 2014). When the null hypothesis is true (i.e., there is no true effect), p-values are assumed to follow a uniform distribution: Highly significant effects (e.g., $p = 0.010$) are as likely as barely significant effects (e.g., $p = 0.049$). However, when the null hypothesis is false (i.e., there is a true effect in our data), p-values are assumed to follow a right-skewed distribution: Highly significant effects are more likely than barely significant effects. A left-skewed distribution would suggest that some studies used statistical tests to find significant results in ways that may not be reproducible or generalizable (i.e., p-hacking). For the p-curve analysis, we followed the recommendation to include one critical test per study (Simonsohn et al., 2014). When multiple correlations were available, we selected the effect size corresponding to (a) the most objective physical activity measure (device-based measures preferred to self-reported measures) and (b) the largest available subsample.

Because the primary meta-analysis accounted for dependent effect sizes using a three-level model, Egger's test and Rücker's limit meta-analysis could not be applied directly, as these methods are not implemented for three-level models. We therefore retained the three-level model as the primary analysis and conducted a separate two-level sensitivity analysis for publication bias assessment. For the aggregated study-level sensitivity analyses, the sample size assigned to each aggregated effect corresponded to the largest sample size among effect sizes from the same study cluster, as these effects were based on overlapping samples.

Secondary Meta-Analysis

A secondary meta-analysis was conducted based on Spearman's rho values, to further test the relationship between approach-avoidance tendencies and physical activity. We chose not to compare r and rho values in the same meta-analysis because they do not reflect the same property of the data. Since only two independent studies reported rho values, the secondary meta-analysis was done only with the 'metacor' function described in Main Meta-Analysis.

Subgroup Meta-Analyses and Meta-Regressions

Subgroup meta-analyses were conducted to examine differences in correlations between studies using different testing contexts (in-person vs. online), types of approach-avoidance tasks (Manikin task vs. modified Manikin task vs. Visual Approach-Avoidance by the Self Task (VAAST) vs. Implicit Association Test-Recoding Free (IAT-RF) vs. joystick-based approach-avoidance task), stimulus type (pictograms vs. images vs. words), and types of physical activity measures (self-reported vs. device-based).

Meta-regressions were conducted to examine if the average age of participants, the proportion of women, and the quality score of a study predicted the reported correlation between approach-avoidance tendencies and physical activity.

Results

Literature Search

The primary search identified 2,267 potentially relevant articles from the five databases (Figure 2) and 3 potential articles from citation searching (Cheval, Sarrazin, Isoard-Gautheur, et al., 2016; Farajzadeh, Jabouille, Benoit, et al., 2025; Goubran, Zammar, et al., 2025), including 1,023 duplicates. Of the 1,247 articles screened, 1,218 were unrelated to approach-avoidance tendencies or physical activity, leaving 29 articles that met the criteria for further investigation and potential inclusion. We emailed the corresponding authors of 7 articles that did not formally test the association between approach-avoidance tendencies and physical activity to request the correlation estimate or raw data so we could

compute this estimate ourselves (Cheval et al., 2014; Cheval, Sarrazin, Pelletier, et al., 2016; Locke & Berry, 2021; Preis et al., 2021; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025). All authors replied: four authors provided raw data of five articles (Cheval et al., 2014; Cheval, Sarrazin, Pelletier, et al., 2016; Locke & Berry, 2021; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025) and two provided required estimates (Preis et al., 2021; C. Wang & Zhang, 2025). Detailed reasons for exclusion at each stage are provided in the PRISMA flow diagram (Figure 2). The inter-rater reliability for the decisions between the two reviewers was high both for title and abstract screening ($\kappa = 0.83$; observed agreement = 99.4%) and full-text screening ($\kappa = 0.69$; observed agreement = 88.5%). Ultimately, 22 articles met the eligibility criteria. Three articles from our group using overlapping datasets were treated as a single study (Farajzadeh et al., 2023; Farajzadeh, Jabouille, Benoit, et al., 2025; Goubran, Zammar, et al., 2025). One article included two studies (Moffitt et al., 2020). Because Cheval et al. (2015) and Cheval, Sarrazin, Isoard-Gautheur, et al. (2016) analyzed the same dataset, with the latter constituting a secondary analysis of the former, only the primary analysis (Cheval et al., 2015) was retained. Therefore, the final sample resulted in 19 articles representing 20 independent studies with 24 estimates (k = 24), including 22 Pearson r estimates from 18 studies and 2 Spearman rho estimates from 2 studies.

Descriptive Results

Participants

The 20 studies identified by the systematic review included a total of 2,347 participants (1,531 females, 816 males), with a weighted mean age of 30.4 years. Studies conducted in the general population contributed 22 estimates (k = 22) (Berry, 2020; Cheval et al., 2014, 2015; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Hannan et al., 2019; Locke & Berry, 2021; Moffitt et al., 2020; Oliver & Kemps, 2018; Preis et al., 2021; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025; Zenko & Ekkekakis, 2019), whereas the study involving individuals with cardiovascular disease contributed 2 estimates (k = 2) (Fessler et al., 2024) (Table 1). Participants were assessed in person (k = 16) (Berry, 2020; Cheval et al., 2014, 2015; Cheval, Tipura, et al., 2018; Daou et al., 2017; Fessler et al., 2024; Hannan et al., 2019; Oliver & Kemps, 2018; Preis et al., 2021; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023; Zenko & Ekkekakis, 2019) or online (k = 8) (Cheval, Sarrazin, Pelletier, et al., 2016; Farajzadeh, Jabouille, Benoit, et al., 2025; Locke & Berry, 2021; Moffitt et al., 2020; Quossi et al., 2025; Terashima et al., 2025; Woodman, 2025).

Approach-avoidance tendencies

In twelve of the twenty included studies, approach-avoidance tendencies were assessed using the Manikin task (k = 12) (Berry, 2020; Cheval et al., 2014, 2015; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Locke & Berry, 2021; Oliver & Kemps, 2018; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023), in which participants moved an onscreen manikin upward or downward using keyboard keys to approach or avoid a visual stimulus (e.g., images depicting physical activity). One study used a modified version of the Manikin task (k = 1), in which participants had to approach or avoid the shape surrounding the visual stimuli (i.e., circle or square) rather than the stimulus itself (Cheval, Sarrazin, Pelletier, et al., 2016). Two studies used the VAAST (k = 5), in which the visual environment zooms in or out to simulate an approach or avoidance movement, respectively (Fessler et al., 2024; Woodman, 2025). Two studies employed the IAT-RF (k = 2) (Hannan et al., 2019; Moffitt et al., 2020), and one study used a Modified IAT (k = 1) (Moffitt et al., 2020), both assessing automatic associations between words representing attribute categories (approach vs. avoid) and action-related concepts (physical activity or sedentary behavior). Two studies used a joystick-based approach-avoidance task (k = 3), where participants physically pull or push a joystick to indicate approach or avoidance movements (Preis et al., 2021; Zenko & Ekkekakis, 2019). In total, twelve studies used pictograms (k = 15) (Cheval et al., 2014, 2015; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Oliver & Kemps, 2018; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023), four used words (k = 4) (Hannan et al., 2019; Moffitt et al., 2020; Woodman, 2025), and four used image stimuli (k = 5) (Berry, 2020; Locke & Berry, 2021; Preis et al., 2021; Zenko & Ekkekakis, 2019).

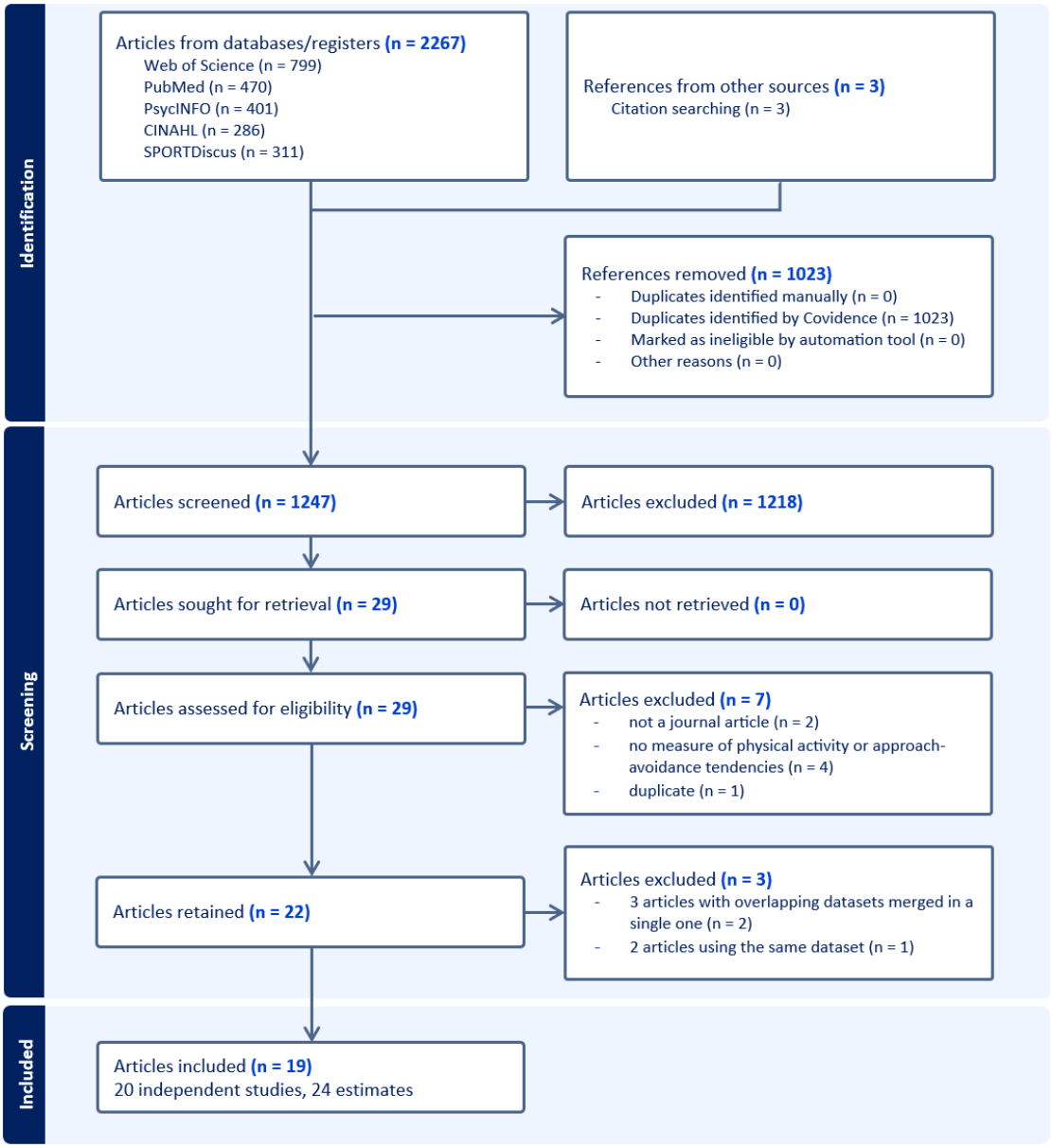


Figure 2: PRISMA flow diagram of study selection process

Approach bias score values were reported directly in the manuscripts (k = 8) (Berry, 2020; Cheval et al., 2015; Hannan et al., 2019; Moffitt et al., 2020; Oliver & Kemps, 2018; Terashima et al., 2025; Zenko & Ekkekakis, 2019), retrieved from raw data (k = 13) (Cheval et al., 2014; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Locke & Berry, 2021; Quossi et al., 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025), or provided by the authors upon request (k = 3) (Preis et al., 2021; C. Wang & Zhang, 2025). Six different methods were used to calculate approach bias scores (Table 1).

Physical Activity

Eighteen studies assessed physical activity using a self-reported measure (Table 1). Fifteen of these studies used the short form of the International Physical Activity Questionnaire (IPAQ-SF) (k = 16) (Cheval et al., 2014; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Hannan et al., 2019; Moffitt et al., 2020; Preis et al., 2021; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025;

Woodman, 2025; Zenko & Ekkekakis, 2019), which consists of 6 items assessing time spent in light (i.e., walking), moderate (e.g., carrying light loads, cycling at moderate speed, doubles tennis), and vigorous physical activity (e.g., digging, fast cycling, heavy lifting, aerobics) over the last 7 days (Maddison et al., 2007). The other questionnaire used to assess physical activity was the Godin Leisure-Time Exercise Questionnaire (GLTEQ) (k = 3) (Berry, 2020; Locke & Berry, 2021; Y.-B. Wang, Sun, et al., 2023), a three-item questionnaire asking to self-report the number of activity bouts performed in the past 7 days at three different intensity levels: mild, moderate, and vigorous (Godin & Shephard, 1985).

Physical activity was also assessed with devices such as accelerometers measuring accelerations in three dimensions (k = 2) (Cheval et al., 2015; Fessler et al., 2024) and pedometers measuring the number of steps (k = 2) (Oliver & Kemps, 2018; Preis et al., 2021) (Table 1). These devices were worn at the hip (k = 3) (Cheval et al., 2015; Oliver & Kemps, 2018; Preis et al., 2021), and one study did not report where the device was worn (Fessler et al., 2024). Studies based on accelerometer-derived measures used an ActiGraph GT3X+ device (ActiGraph, LLC, Pensacola, FL, USA) (Cheval et al., 2015; Fessler et al., 2024). The pedometers used were the Omron Walking Style 2.1 Model HJ321-E (Omron Healthcare, Kyoto, Japan) (Preis et al., 2021), and an unspecified commercial G-sensor (Oliver & Kemps, 2018). Two studies used both self-reported and device-based measures (Fessler et al., 2024; Preis et al., 2021).

To assess physical activity, the studies used the following outcomes: min/week (Cheval et al., 2014, 2015; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Hannan et al., 2019; Moffitt et al., 2020; Preis et al., 2021; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Woodman, 2025; Zenko & Ekkekakis, 2019), MET score (Berry, 2020; Locke & Berry, 2021; Y.-B. Wang, Sun, et al., 2023), steps per day (Oliver & Kemps, 2018; Preis et al., 2021), and min/day (Fessler et al., 2024).

Association Between Approach-Avoidance Tendencies and Physical Activity

Among the 20 studies included in the systematic review, eight reported correlation coefficients of the association between physical activity and approach-avoidance tendencies. Of those, six reported a Pearson's r correlation coefficient (Berry, 2020; Cheval et al., 2015; Hannan et al., 2019; Oliver & Kemps, 2018; Terashima et al., 2025; Zenko & Ekkekakis, 2019) and two reported a Spearman's rho (Moffitt et al., 2020). We computed one or several Pearson's r values in ten studies (Cheval et al., 2014; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Locke & Berry, 2021; Quossi et al., 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025). We obtained 3 additional Pearson's r values through email correspondence (Preis et al., 2021; C. Wang & Zhang, 2025). In total, 22 Pearson's r and 2 Spearman's rho values were used in the meta-analyses (Table 1).

Table 1: Sample Characteristics of Studies Included in the Systematic Review

						Approach-Avoidance Tendencies			Physical Activity					
Study	*n*	% of Women	Mean Age	Population	Testing Context	Tool	Stimuli	Approach-Bias Calculation	Tool	Component (Mean)	Study Design	Quality Score	Corr.	*p*
Cheval et al., 2014	91	84%	18.9	General population	In-person	Manikin	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (251)	Cross-sectional	5	0.06	0.56
Cheval et al., 2015[b]	97	53%	38.3	General population	In-person	Manikin	Pictograms	RT avoid PA - RT approach PA	Accelerometer	MVPA in min/week (53)	Interventional	9	0.27	0.008
Cheval, Sarrazin, Pelletier, et al., 2016	114	57%	19.6	General population	Online	Modified Manikin	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (356)	Cross-sectional	9	−0.06	0.52
Daou et al., 2017	116	70%	20.6	General population	In-person	Manikin	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (511)	Cross-sectional	7	−0.02	0.81
Cheval, Tipura, et al., 2018	29	55%	22.8	General population	In-person	Manikin	Pictograms	(RT avoid PA - RT avoid neutral) - (RT approach PA - RT approach neutral)[a]	IPAQ-SF	MVPA in min/week (216)	Cross-sectional	5	0.26	0.17
Oliver & Kemps, 2018	103	69%	26.5	General population	In-person	Manikin	Pictograms	RT approach SED - RT approach PA	Pedometer	Total incidental PA in steps/day (6073)	Cross-sectional	4	0.03	0.76
Hannan et al., 2019	104	72%	28.1	General population	In-person	IAT-RF	Words	(RT avoid PA - RT approach PA)/participant's SD	IPAQ-SF	MVPA in min/week (235)	Cross-sectional	5	0.25	0.01
Zenko & Ekkekakis, 2019	92	61%	24.8	General population	In-person	Joystick-based AAT	Images	(RT avoid PA - RT approach PA) - (RT avoid neutral - RT approach neutral)	IPAQ-SF	MVPA in min/week (227)	Cross-sectional	6	0.32[d]	0.002
Berry, 2020	149	67%	19.4	General population	In-person	Manikin	Images	(RT avoid PA - RT approach PA)/participant's SD	GLTEQ	MVPA in MET score (36)	Cross-sectional	4	0.19	0.02
Moffitt et al., 2020 (1)	189	77%	22.7	General population	Online	Modified IAT	Words	RT avoid PA - RT approach PA	IPAQ-SF	MVPA in min/week (148)	Cross-sectional	4	−0.12	0.18

Study	*n*	% of Women	Mean Age	Population	Testing Context	Approach-Avoidance Tendencies			Physical Activity		Study Design	Quality Score	Corr.	*p*
						Tool	Stimuli	Approach-Bias Calculation	Tool	Component (Mean)				
Moffitt et al., 2020 (2)	88	67%	32.7	General population	Online	IAT-RF	Words	RT avoid PA - RT approach PA	IPAQ-SF	MVPA in min/week (55)	Interventional	6	0.01	0.91
Preis et al., 2021	36	89%	22.4	General population	In-person	Joystick-based AAT	Images	(RT avoid PA + RT approach SED) - (RT approach PA + RT avoid SED)	Pedometer	Total PA in steps/day (6611)	Interventional	8	−0.02[d]	0.89
	36	89%	22.4	General population	In-person	Joystick-based AAT	Images	(RT avoid PA + RT approach SED) - (RT approach PA + RT avoid SED)	IPAQ-SF	MVPA in min/week (253)	Interventional	8	−0.08[d]	0.64
Locke & Berry, 2021	132	43%	29	General population	Online	Manikin	Images	(RT avoid PA - RT approach PA)/participant's SD[a]	GLTEQ	MVPA in MET score (51)	Cross-sectional	6	0.03	0.70
Y.-B. Wang, Sun, et al., 2023	31	52%	19.4	General population	In-person	Manikin	Pictograms	RT avoid PA - RT approach PA[a]	GLTEQ	Running MVPA in MET score (14)	Cross-sectional	6	0.27	0.14
Farajzadeh, Jabouille, Benoit, et al., 2025[c]	364	60%	53.7	General population	Online	Manikin	Pictograms	(RT avoid PA - RT approach PA) - (RT avoid neutral - RT approach neutral)[a]	IPAQ-SF	MVPA in min/week (398)	Cross-sectional	6	−0.04	0.46
Fessler et al., 2024	42	52%	58.4	General population	In-person	VAAST	Pictograms	RT avoid PA - RT approach PA[a]	Accelerometer	MVPA in min/week (284)	Cross-sectional	7	0.04	0.78
	13	31%	61.7	Cardiovascular disease	In-person	VAAST	Pictograms	RT avoid PA - RT approach PA[a]	Accelerometer	MVPA in min/week (326)	Cross-sectional	7	0.42	0.15
	45	58%	58	General population	In-person	VAAST	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (561)	Cross-sectional	7	0.12	0.42
	16	31%	60.7	Cardiovascular disease	In-person	VAAST	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (333)	Cross-sectional	7	−0.24	0.38
Terashima et al., 2025	226	62%	23.7	General population	Online	Manikin	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	Total PA in min/week (495)	Cross-sectional	6	0.15	0.02

Study	*n*	% of Women	Mean Age	Population	Testing Context	Approach-Avoidance Tendencies			Physical Activity		Study Design	Quality Score	Corr.	*p*
						Tool	Stimuli	Approach-Bias Calculation	Tool	Component (Mean)				
Quossi et al., 2025	201	74%	24.7	General population	Online	Manikin	Pictograms	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (385)	Cross-sectional	6	0.03	0.70
C. Wang & Zhang, 2025	34	68%	20.9	General population	In-person	Manikin	Pictograms	RT avoid PA - RT approach PA	IPAQ-SF	MVPA in min/week (242)	Cross-sectional	6	0.58	0.0003
Woodman, 2025	90	76%	36.3	General population	Online	VAAST	Words	RT avoid PA - RT approach PA[a]	IPAQ-SF	MVPA in min/week (257)	Cross-sectional	3	0.07	0.54

Note. N = Number of participants; RT = Reaction Time; Corr. = Correlation; PA = Physical Activity; SED = Sedentary; SD = Standard Deviation; GLTEQ = Godin Leisure-Time Exercise Questionnaire; IPAQ-SF = International Physical Activity Questionnaire – Short Form; IAT = Implicit Association Test; IAT-RF = Recoding-Free Implicit Association Test; MVPA = Moderate-to-Vigorous Physical Activity; MET = Metabolic Equivalent of Task; AAT = Approach-Avoidance Task; VAAST = Visual Approach-Avoidance by the Self Task. [a]Approach-bias was computed from the raw data as follows: (median RT avoid PA - median RT approach PA) - (median RT avoid neutral - median RT approach neutral) when possible. If not, it was computed as (median RT avoid PA) – (median RT approach PA). [b]The dataset used for the analysis encompasses data from two studies (Cheval et al., 2015, 2016). [c]The dataset used for the analysis encompasses data from three studies (Farajzadeh et al., 2023; Farajzadeh, Jabouille, Benoit, et al., 2025; Goubran, Zammar, et al., 2025). [d]This corresponds to the opposite correlation to that reported in the original studies, according to the interpretational ambiguity of the scoring system of joystick-based approach-avoidance tasks pointed out by Zenko & Ekkekakis (2019).

Meta-Analysis

Main meta-analysis

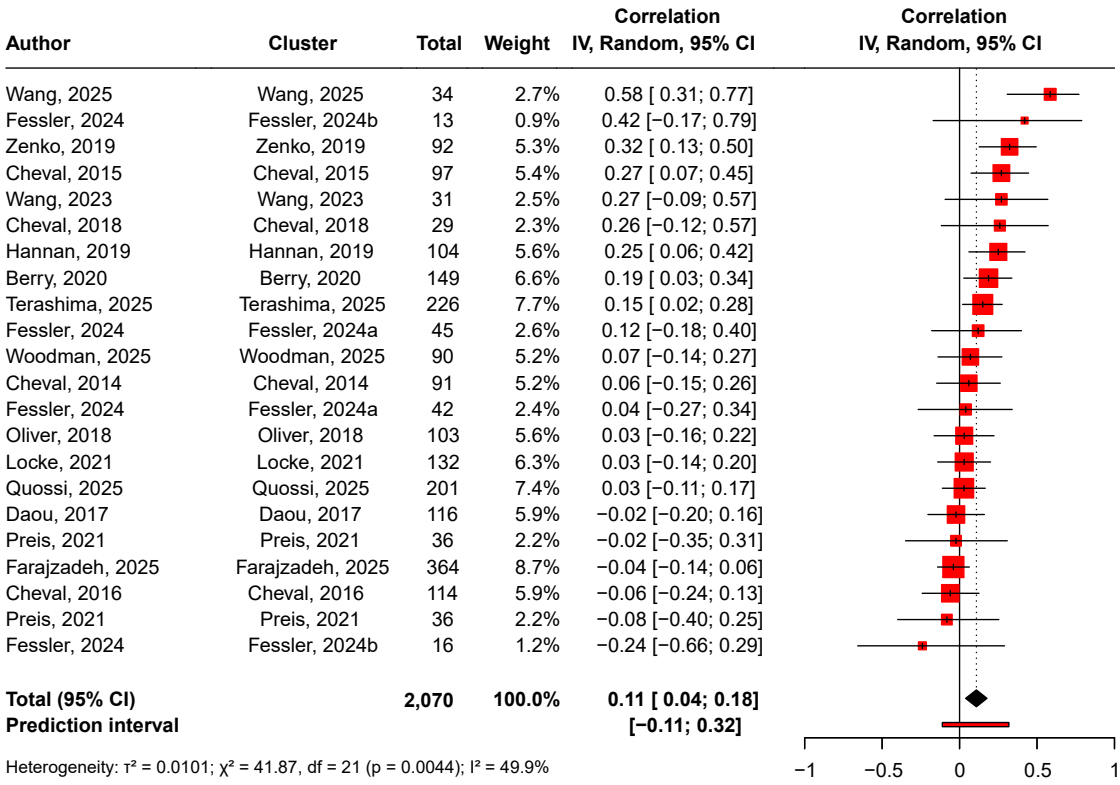


Figure 3: Main meta-analysis forest plot. Correlation between approach-avoidance tendencies and physical activity based on Pearson's r-values (k = 22, n = 2,070). CI = Confidence interval. Studies are labeled by first author and year; ambiguous labels correspond to: Cheval, 2016 (Cheval, Sarrazin, Pelletier, et al., 2016); Cheval, 2018 (Cheval, Tipura, et al., 2018); Wang, 2023 (Y.-B. Wang, Sun, et al., 2023); Wang, 2025 (C. Wang & Zhang, 2025); Farajzadeh, 2025 (Farajzadeh, Jabouille, Benoit, et al., 2025). Fessler, 2024a and Fessler, 2024b are the general-population and cardiovascular-disease samples, respectively, of Fessler et al. (2024).

Our meta-analysis of 18 studies (Berry, 2020; Cheval et al., 2014, 2015; Cheval, Sarrazin, Pelletier, et al., 2016; Cheval, Tipura, et al., 2018; Daou et al., 2017; Farajzadeh, Jabouille, Benoit, et al., 2025; Fessler et al., 2024; Hannan et al., 2019; Locke & Berry, 2021; Oliver & Kemps, 2018; Preis et al., 2021; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025; Zenko & Ekkekakis, 2019) (k = 22; n = 2,070) based on Pearson's r values showed a small positive correlation between approach-avoidance tendencies and physical activity (r = 0.11; 95% confidence interval [95% CI]: 0.04, 0.18; p = 0.004; Table 2; Figure 3). Sensitivity analysis showed that the correlation remained significant (r = 0.08; 95% CI: 0.00, 0.16; p = 0.047) with the original r correlation directions of joystick-based approach-avoidance tasks.

Heterogeneity analyses showed that most of the variability arose from differences between studies ($\tau^2_{\text{between}} = 0.0101$; $\tau_{\text{between}} = 0.1006$), while variation within studies was almost nonexistent ($\tau^2_{\text{within}} < 0.0001$). These results suggest that effect sizes differed primarily across studies rather than within studies. Overall heterogeneity was moderate to substantial ($I^2 = 49.9\%$, 95% CI: 18.0%, 69.3%; $Q(21) = 41.87$, $p = 0.004$), suggesting that factors like measurement methods or participant characteristics likely influenced the size of the observed effects.

The prediction interval, ranging from r = −0.11 to 0.32, further indicated that although the average effect was positive, future research may still observe stronger, weaker, null, or even negative associations depending on the context.

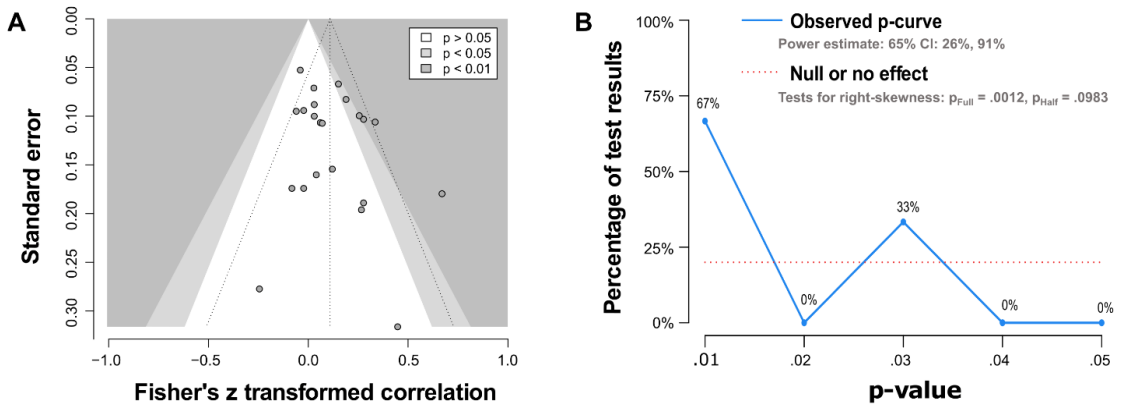


Figure 4: Publication bias assessment: (**A**) contour-enhanced funnel plot of the main meta-analysis and (**B**) p-curve analysis. *Notes: (A) The vertical dashed line represents the average effect size. The two other dashed lines represent the idealized funnel-shape that studies are expected to follow. When there is no publication bias, the data points in a funnel plot should form a roughly symmetrical, upside-down funnel. Studies in the top part of the plot, which have lower standard errors, are expected to lie closely together, and not far away from the pooled effect size. In the lower part of the plot, studies have higher standard errors, the funnel "opens up," and effect sizes are expected to scatter more heavily to the left and right of the pooled effect. (B) The solid blue line indicates the distribution of the analyzed p-values. The red dotted line illustrates a uniform distribution of the p-values, indicating the absence of a true effect.*

Publication Bias Assessment

The funnel plot did not visually show an asymmetrical pattern (Figure 4A). Egger's regression test further showed no statistical evidence of asymmetry (b = 1.63, 95% CI: −0.07, 3.33, p = 0.077). However, the estimated effect from Rücker's limit meta-analysis was no longer statistically significant after adjustment for small-study effects (r = 0.04, 95% CI: −0.08, 0.16, p = 0.488). The test for small-study effects was statistically significant ($Q - Q' = 6.63$, p = 0.010), suggesting the presence of such effects. Residual heterogeneity remained significant after adjustment ($Q' = 31.74$, p = 0.016), indicating that small-study effects alone do not fully account for the observed variability. These results may be consistent with publication bias, but small-study effects can also arise from other factors, such as differences in study procedures and between-study heterogeneity.

The 20 studies reporting a total of 24 correlation values (Pearson or Spearman) were considered for the p-curve analysis (Figure 4B). Of these, 6 studies (25.0%) reported statistically significant results ($p < 0.05$), all of which had $p < 0.025$ and were therefore eligible for inclusion in the p-curve. The remaining results were excluded because their p-values exceeded 0.05. The p-curve showed significant right-skewness, indicating that the effect of our meta-analysis is true and suggesting that the observed association is unlikely to be solely attributable to selective reporting or publication bias. This was supported by the test for right-skewness for the full curve (p = 0.001), whereas the half-curve test was not statistically significant (p = 0.098). In addition, tests for flatness were non-significant (all ps $\geq$ 0.888), suggesting that the significant results were unlikely to reflect only bias or selective reporting. Overall, these results are consistent with the presence of a genuine underlying effect.

The estimated statistical power of the included studies was 65% (95% CI: 26%, 91%), indicating moderate replicability. However, this estimate should be interpreted with caution given the relatively small number of significant results (k = 6) included in the analysis.

Secondary Meta-Analysis

The secondary analysis using Spearman's rho (Moffitt et al., 2020) (k = 2, n = 277) showed no evidence of a correlation (r = −0.08, 95% CI: −0.69, 0.60, p = 0.414) (Table 2). Given the small number of studies, this estimate should be interpreted cautiously, as shown by the wide prediction interval (−0.69 to 0.60).

Subgroup Meta-Analyses

A subgroup meta-analysis was conducted to examine whether the association between approach-avoidance tendencies and physical activity differed by testing context (in-person vs. online). Results indicated that testing context moderated the association ($Q(1) = 4.90$, $p = 0.039$), with a small positive association in in-person studies ($r = 0.16$, 95% CI: 0.08, 0.24, $p = 0.0006$), but no evidence of an association in online studies ($r = 0.03$, 95% CI: −0.06, 0.12, $p = 0.522$) (Figure 5; Table 2).

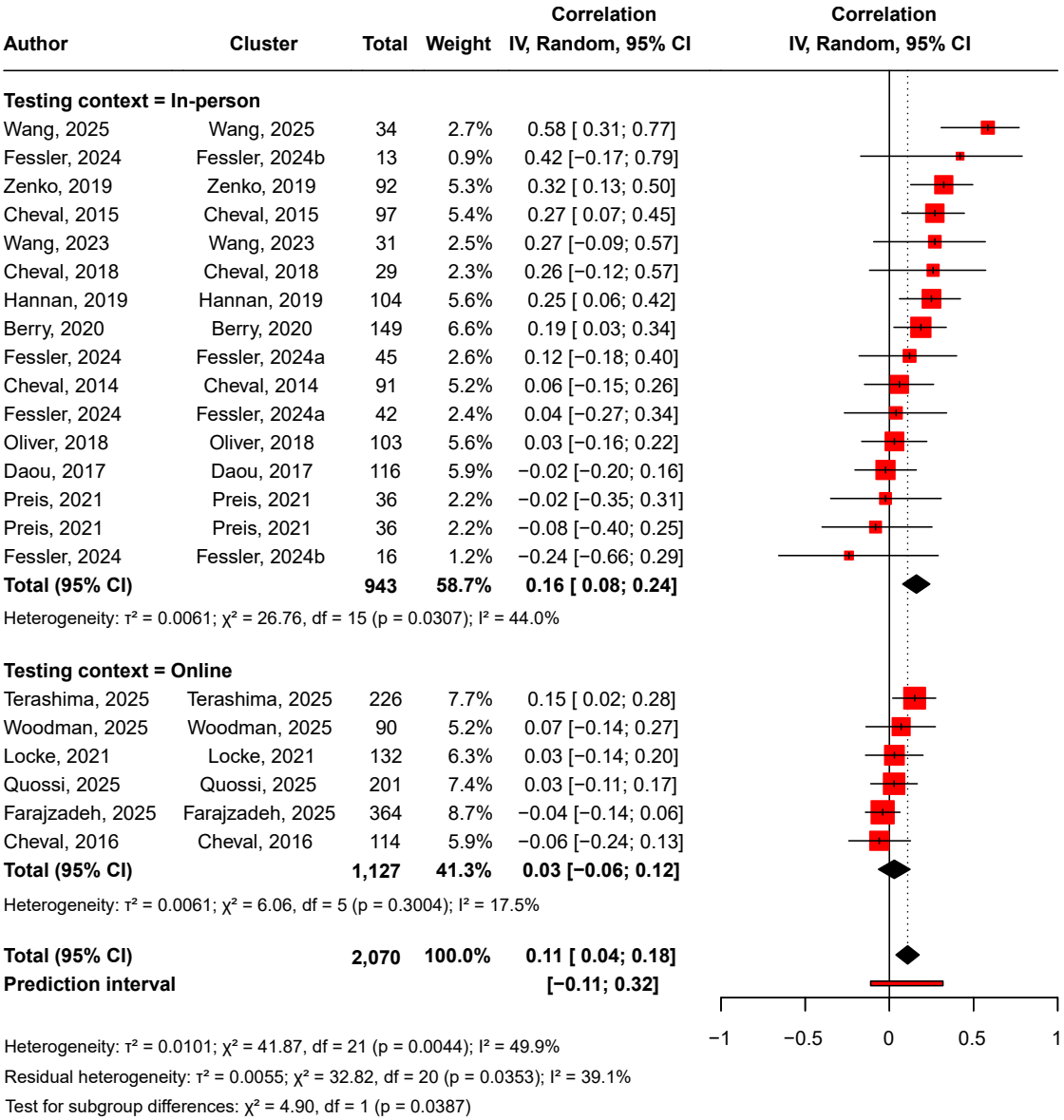


Figure 5: Forest plot of subgroup analysis by testing context. Correlation between approach-avoidance tendencies and physical activity based on Pearson's r-values in in-person ($k = 16$, $n = 943$) and online studies ($k = 6$, $n = 1{,}127$). CI = Confidence interval. Study labels as in Figure 3.

A subgroup analysis examined whether the association differed in self-reported ($k = 17$) and device-based measures of physical activity ($k = 5$). Results showed no evidence of a moderating effect ($Q(1) = 0.07$, $p = 0.795$).

A subgroup analysis examined whether the association differed across different approach-avoidance tasks: Manikin task (k = 12), modified Manikin task (k = 1), IAT-RF (k = 1), joystick-based approach-avoidance tasks (k = 3), and VAAST (k = 5). Results showed no evidence of a moderating effect (Q(4) = 0.67, p = 0.621).

A subgroup analysis examined whether the association differed across stimulus types: pictograms (k = 15), words (k = 2), and images (k = 5). Results showed no evidence of a moderating effect (Q(2) = 0.25, p = 0.779).

Meta-Regressions

Results showed no evidence of a moderating effect of age (b = −0.002, 95% CI: −0.008, 0.003, t(20) = −0.86, p = 0.402), sex (b = −0.13, 95% CI: −0.72, 0.47, t(20) = −0.45, p = 0.661), and study quality score (b = -0.01, 95% CI: −0.06, 0.03, t(20) = -0.61, p = 0.551) on the association between approach-avoidance tendencies and physical activity (k = 22).

Table 2: Results of the main, secondary, and subgroup meta-analyses

Characteristics	k	n	Corr.	95% CI	I^2 (%)	*p*-value
Main: Pearson r	22	2,070	0.11	0.04, 0.18	49.9	**0.004**
Main: Rücker's limit meta-analysis	22	2,070	0.04	−0.08, 0.16	53.1	0.488
Secondary: Spearman rho	2	277	−0.08	−0.69, 0.60	0	0.414
Subgroup: Testing context						**0.039**
In-person	16	943	0.16	0.08, 0.24	44.0	**0.001**
Online	6	1,127	0.03	−0.06, 0.12	17.5	0.522
Subgroup: Physical activity measures						0.795
Subgroup: Approach-avoidance tasks						0.621
Subgroup: Stimulus type						0.779

Note. k = Number of estimates; n = Number of participants; Corr = Correlation estimates; CI = Confidence interval; I^2 = Percentage of variability in the correlations that is not caused by sampling error. Significant p-values are shown in bold.

Discussion

Our meta-analysis revealed a significant small positive correlation of r = 0.11 (95% CI: 0.04, 0.18; p = 0.004) between approach-avoidance tendencies and physical activity. However, the result should be interpreted with caution, as the estimate from Rücker's limit meta-analysis, which models small-study effects, was no longer statistically significant (r = 0.04, 95% CI: −0.08, 0.16, p = 0.488).

The magnitude of the uncorrected estimate is comparable to the uncorrected one reported in a previous meta-analysis examining the association between automatic valuation and physical activity, but excluding approach-avoidance tendencies (r = 0.11) (Chevance et al., 2019). Similarly, another meta-analysis examining the association between approach-avoidance tendencies and both physical activity and sedentary behaviors reported an uncorrected correlation of r = 0.16 (Y.-B. Wang et al., 2024). These results are consistent with the dominant theoretical framework proposing that these constructs are related, with automatic valuation typically preceding and shaping approach-avoidance tendencies, which in turn influence physical activity behavior (M. Chen & Bargh, 1999; Cheval & Boisgontier, 2021; Conroy & Berry, 2017).

Implications

Awareness campaigns that primarily target controlled processes such as intentions have shown limited effectiveness in producing meaningful behavioral changes among physically inactive individuals (Abioye et al., 2013; den Braver et al., 2022). Having the intention to be physically active is not sufficient: nearly half of people who intend to be physically active fail to translate their intentions into action, a phenomenon commonly referred to as the "intention-behavior gap" (Feil et al., 2023). Automatic processes, including approach-avoidance tendencies, have therefore been proposed as potential complementary mechanisms that may help explain physical activity behavior. However, our meta-analysis suggests that the current evidence is insufficient to determine whether approach-avoidance tendencies represent a meaningful determinant of physical activity. Rather, two interpretations of the available evidence should be considered.

First, the observed association may be influenced by small-study effects and methodological limitations, raising uncertainty about whether it reflects a robust underlying relationship. This interpretation is supported by the persistent significant heterogeneity after adjustment for small-study effects. Smaller studies may produce more variable estimates due to reporting biases, sampling variability, methodological differences, and limitations in study design or measurement (Sterne et al., 2011). This possibility is particularly relevant given the important heterogeneity in approach-avoidance tasks and physical activity measurement. Thus, if measurement error and analytical flexibility substantially contribute to the observed effects, the pooled estimate may not correctly represent the underlying relationship.

A second possibility is that the observed association reflects a true but small relationship between approach-avoidance tendencies and physical activity. Under this interpretation, automatic approach-avoidance processes may represent one of several independent factors that contribute to physical activity behavior, rather than a major determinant of behavior. This interpretation is consistent with evidence suggesting that automatic processes are modestly associated with physical activity (Chevance et al., 2019; Y.-B. Wang et al., 2024).

These two interpretations point to two priorities for future studies. First, resolving methodological and psychometric limitations through standardized task procedures and rigorous evaluation of their reliability and validity. Second, determining whether any robust association is sufficiently meaningful to warrant intervention. If the observed relationship is primarily driven by measurement limitations or small-study effects, targeting approach-avoidance tendencies in behavioral interventions would be premature. By contrast, if a small but robust association is established, future research should determine the feasibility of an intervention (Fessler et al., 2026; Jabouille et al., 2026) and whether modifying these tendencies can meaningfully change physical activity behavior.

Methodological Heterogeneity as a Limiting Factor

Reaction-Time Assessment Requires a Controlled Environment

The persistence of significant residual heterogeneity after adjusting for small-study effects suggests that publication bias alone does not account for the variability across studies. Additional methodological differences may also have contributed. In support of this interpretation, subgroup analyses identified testing context as a potential moderator, with the subgroup comparison test indicating a significant difference between in-person and online studies. Specifically, the association was stronger in in-person studies than in online studies. Although online experiments may facilitate recruitment and reduce research costs, they provide less experimental control. However, this result should be interpreted with caution given the slight overlap in confidence intervals between the two subgroup estimates and the relatively small number of studies. Further studies are needed to determine whether this moderating effect can be replicated with greater statistical power.

Approach-Avoidance Tasks: The Garden of Forking Paths

From measurement to processing, approach-avoidance tendencies were characterized by substantial methodological heterogeneity across the analytical pipeline. First, they were measured using six different tasks. Evidence from affective and food-related domains suggests that different approach-avoidance tasks are often weakly correlated (Fricke et al., 2023; Wittekind et al., 2021; Zech et al., 2023) and may not capture the same underlying processes, reducing the comparability across studies. Second, the tasks

varied in device type, operationalization of approach-avoidance responses, number and randomization of conditions and trials, data-processing criteria, score computation, and the number and type of stimuli. This is consistent with the broader approach-avoidance literature, where a wide range of scoring and preprocessing methods has been observed across studies (Kahveci et al., 2024). However, this lack of consensus leaves researchers with multiple analytical decisions that may affect the reliability and validity of measures of individual differences (Kahveci et al., 2024). This analytical freedom creates multiple plausible pathways for preprocessing and scoring the same underlying data, making it difficult to determine whether different results reflect genuine differences in psychological processes or instead arise from analytical choices.

Among those decisions, the approach-avoidance score is of major importance because it ultimately determines what a test measures. One study (Oliver & Kemps, 2018) used a score based on a between-category difference within a single response direction. This approach may conflate approach-avoidance tendencies with category-specific differences in stimulus familiarity, visual characteristics, perceptual processing, or ambiguity. Conversely, many studies (Berry, 2020; Cheval et al., 2014, 2015; Cheval, Sarrazin, Pelletier, et al., 2016; Daou et al., 2017; Fessler et al., 2024; Hannan et al., 2019; Locke & Berry, 2021; Moffitt et al., 2020; Quossi et al., 2025; Terashima et al., 2025; C. Wang & Zhang, 2025; Y.-B. Wang, Sun, et al., 2023; Woodman, 2025) calculated a simple difference between avoidance and approach reaction times for a single stimulus category. Although intuitive, this score may capture general differences in the ease or speed of performing approach versus avoidance movements, such as anatomy, posture, motor execution, or device setup. For example, if avoidance movements are mechanically easier than approach movements, an approach-avoidance difference may reflect motor asymmetry rather than motivational bias. Finally, other studies (Cheval, Tipura, et al., 2018; Farajzadeh et al., 2023; Farajzadeh, Jabouille, Benoit, et al., 2025; Goubran, Farajzadeh, et al., 2025; Preis et al., 2021; Zenko & Ekkekakis, 2019) used a double-difference score, comparing the approach-avoidance contrast for the target category relative to a reference category (e.g., neutral stimuli). This approach more directly isolates a relative approach-avoidance bias, but remains susceptible to other stimulus-response compatibility effects. That is, certain stimulus-response combinations (e.g., approaching physical activity stimuli) may elicit faster responses due to the affective or semantic value of the image. Such association may be shaped by past experiences (e.g., family vacation activities) or by promotional campaigns portraying physical activity positively. In such cases, it may reflect learned associations rather than a genuine approach-avoidance tendency toward the effort or energy expenditure characterizing physical activity and sedentary behaviors. To remove this bias, future studies could consider using neutral images previously conditioned to represent high and low levels of physical effort (Boisgontier, 2019). Nevertheless, it has been shown that double-difference scores remain less subject to being biased with unrelated sources of variance, and are more reliable and valid than category-specific differences (Kahveci et al., 2024).

Another important consideration is the meaning carried by the approach-avoidance score. While most of the studies used neutral stimuli like geometric shapes as a reference in their double-difference score, one study (Preis et al., 2021) used sedentary stimuli. In such cases, a positive or negative score indicates that one category is approached or avoided more strongly relative to the other category, but it does not establish that the individual has an absolute automatic approach tendency toward one or the other category. In other words, if the reference is not considered as neutral, it reflects a relative preference between categories but not a construct-specific automatic tendency.

Action Interpretation as a Trigger of Approach-Avoidance Tendencies

Task implementation and instructions may influence approach-avoidance tendencies by creating ambiguity regarding the meaning of the required action. For example, joystick-based approach-avoidance tasks involve a physical movement moving away from the stimulus (i.e., pulling) paired with a visual enlargement of the stimulus. Although we reversed the scoring of these tasks to better align with a self-related frame of reference, this mismatch between the physical movement and its conceptual interpretation may still have influenced how participants interpreted the action and could potentially contribute to the low reliability reported for this task in another field ($r = 0.35$) (Reinecke et al., 2010) and to findings suggesting that the manikin task is more sensitive and valid (Krieglmeyer & Deutsch, 2010).

Participants may interpret the responses simply as pushing or pulling the joystick, or as making the stimulus grow or shrink in case of stimulus enlargement, rather than as genuine approach-avoidance

actions. Indeed, participants are often instructed to "push" or "pull" the joystick rather than being explicitly instructed to "approach" or "avoid" the stimulus or being provided with a contextual framing (Preis et al., 2021; Zenko & Ekkekakis, 2019). However, accumulating evidence suggests that approach and avoidance are not intrinsically tied to a specific movement direction or frame of reference (Eder & Rothermund, 2008; Phaf et al., 2014; Seibt et al., 2008). Rather, contextual framing and task instructions appear to shape how an action is interpreted and, in turn, condition the resulting approach-avoidance response. Identical motor responses can produce different evaluative effects depending on how their meaning is framed (Z. Chen et al., 2025; Z. Chen & Van Dessel, 2024; Laham et al., 2014; Van Dessel et al., 2018). For instance, push-pull responses influenced stimulus evaluation when they were explicitly framed as collecting or discarding, whereas the same movements produced no effect when not accompanied by elaborated framing, even in the presence of stimulus zooming (Laham et al., 2014). Similarly, identical responses produced different evaluative consequences when they were described as approach/avoidance rather than simply upward/downward movements, or when their interpretation was manipulated while motor execution remained unchanged (Z. Chen et al., 2025; Z. Chen & Van Dessel, 2024; Van Dessel et al., 2018). Thus, although visual feedback, response devices, and movement characteristics may facilitate particular interpretations, arm flexion and extension do not appear to carry fixed motivational meanings in themselves. Rather, the mental representation and contextual interpretation of the response appear to play a central role in determining the meaning and consequences of the interaction with the stimulus.

Physical Activity: A Landscape of Methodological Choices

The subgroup analysis by physical activity measures did not show a significant effect. However, the small number of estimates based on accelerometers ($k = 3$) and pedometers ($k = 2$), combined with device-specific preprocessing and data processing procedures, did not allow for a reliable subgroup analysis. Additional studies are needed to draw firm conclusions about this subgroup analysis and the specific relationship between approach-avoidance tendencies and accelerometer- or pedometer-based physical activity. Of note, 79% of physical activity level estimates were based on self-reported questionnaires, which have demonstrated limited reliability and validity as they tend to overestimate activity levels due to biases such as social desirability and recall bias (Helmerhorst et al., 2012; Lee et al., 2011). Therefore, although self-report instruments provide an easy and inexpensive way to assess physical activity, we do not recommend their use as a primary research outcome. This is consistent with the World Health Organization's current direction toward wearable device-based assessment, which offers more precise and harmonizable estimates of real-world physical activity (World Health Organization, 2025, 2026).

The increased precision of accelerometers to measure physical activity comes at the cost of greater methodological complexity. Notably, device-based studies substantially differed in data-processing decisions, such as valid wear-time criteria, data processing procedures, cut-offs for activity intensity, and intensity adjustment. As these methodological choices can substantially influence estimated physical activity levels, they likely reduced comparability across studies and contributed to heterogeneity in effect sizes. Recent consensus and reporting guidelines emphasize the need for transparent and standardized accelerometry protocols and provide recommendations to improve comparability across studies (Clevenger et al., 2022; Migueles et al., 2017, 2022).

The type and intensity of physical activity need to be considered, as they directly influence physical activity level estimates and the resulting correlation. However, they were measured inconsistently across studies. Five different assessment tools were used and outcomes were operationalized as total physical activity, moderate-to-vigorous leisure-time physical activity or during running only, or incidental physical activity excluding exercise. We did not conduct a subgroup analysis because only one estimate per group would have resulted in very low statistical power. However, we repeated the main meta-analysis after excluding the two studies with conceptually distinct physical activity components, namely running-specific volume (Y.-B. Wang, Sun, et al., 2023) and incidental physical activity only (Oliver & Kemps, 2018). The pooled estimate remained almost unchanged ($r = 0.11$, 95% CI: 0.03, 0.18, $p = 0.007$). While this suggests that these methodological differences did not meaningfully influence the overall result, this may be explained by the small weight of these two studies in the meta-analysis.

Another consideration is how physical activity intensity is accounted for. Most studies expressed physical activity levels in minutes per week. This time-based unit does not fully capture differences in the underlying volume and intensity distribution of physical activity. For example, two individuals may both accumulate 100 minutes of total physical activity per week while displaying markedly different

intensity profiles. Although movement at any intensity confers health benefits (Liu et al., 2017; Tarp et al., 2024), the magnitude of these effects may vary as a function of intensity (Biswas et al., 2025). Traditionally, intensity has often been characterized using count-based methods (Migueles et al., 2017). However, these are device-dependent and require raw acceleration signals to be filtered and aggregated into counts, resulting in loss of information. Their interpretation commonly relies on cut-points derived from specific calibration protocols, which impose thresholds on continuous movement data and classify it into discrete intensity bands. More recent analytical approaches implemented in open-source tools such as GGIR enable direct processing of raw acceleration data and the computation of cut-point-free metrics, including average acceleration reflecting overall activity volume and intensity gradient reflecting the distribution of activity across the intensity spectrum (Migueles et al., 2019; Rowlands et al., 2018). Machine-learning approaches also offer promising alternatives by extracting detailed information on activity type and intensity directly from raw acceleration signals, although challenges regarding validation, generalizability, and standardization remain (Zi et al., 2026).

Need for a Standardized and Psychometrically Sound Measurement

Although no statistically significant differences in effect size were found across the five approach-avoidance tasks included in the subgroup analysis of our main meta-analysis, this result should be interpreted cautiously. The limited number of estimates in four of the five categories (k = 1–5) restricted the statistical power to detect reliable between-task differences. Additionally, the variability in measurement approaches described above makes it difficult to draw clear conclusions about approach-avoidance tendencies in the context of physical activity.

These concerns are supported by the limited evidence regarding the reliability and validity of approach-avoidance measures and scoring procedures in the physical activity domain (Zech et al., 2023). To date, the tasks included in this meta-analysis have not been adequately tested for validity or reliability, leaving uncertainty as to whether they consistently and accurately capture the intended construct. Measurement error associated with insufficiently reliable measures may attenuate observed associations and therefore contribute to an underestimation of the true relationship between approach-avoidance tendencies and physical activity. A previous meta-analysis of automatic processes and physical activity found that task reliability moderated the magnitude of observed associations (Y.-B. Wang et al., 2024). In the absence of reliability studies, it is therefore difficult to determine the extent to which between-study heterogeneity reflects genuine variability in approach-avoidance tendencies rather than differences in measurement precision.

Task standardization and dedicated psychometric evaluation should thus be a priority, especially for reaction-time-based measures, which can be sensitive to several aspects of the task, from its design (e.g., number of trials, operationalization of the approach-avoidance movement, instructions) to its analysis (e.g., outliers' removal, preprocessing decisions, scoring algorithms). Future research should first resolve current methodological uncertainties (e.g., comparing alternative scoring procedures, establishing the number of trials required to obtain reliable estimates, harmonizing preprocessing decisions by testing the robustness of different scores under them) by developing standardized, evidence-based assessment procedures. They should then establish their reliability as well as their construct, convergent, discriminant, and predictive validity (Lim, 2024). This would help clarify the practical relevance of approach-avoidance tendencies for physical activity engagement and whether they have potential utility as intervention targets.

Assessment Recommendations for Future Research

To strengthen the literature on approach-avoidance tendencies in physical activity, future research should prioritize greater methodological rigor and standardization. Based on the present findings, several recommendations emerge: (i) further validation of remotely administered tasks is needed, and controlled in-person studies may currently offer greater experimental consistency; (ii) physical activity and sedentary behavior should be treated as distinct constructs; (iii) the rationale for selecting tasks other than the Manikin task should be clearly justified; (iv) physical activity should be assessed using device-based measures with transparent reporting methods (Migueles et al., 2017); (v) outcomes should capture the full spectrum of physical activity, including light-intensity behaviors that confer health benefits (Amagasa et al., 2018; Rezende et al., 2024), and (vi) analyses should be adjusted for activity

intensity, given the dose-response relationship between physical activity and health outcomes (Biswas et al., 2025).

For data preprocessing, it has been recommended to (vii) fully exclude error trials and (viii) apply absolute reaction-time cut-offs in combination with an adaptive outlier-removal procedure, excluding reaction times that fall more than ±3 standard deviations from the participant's mean (Kahveci et al., 2024). This approach is intended to improve reliability and validity while reducing the risk of Type I errors. For the absolute cut-offs, we recommend a lower reaction time threshold of 150 ms, as this value has been proposed for reaction-time analyses because it is close to the estimated physiological lower bound for a simple response to a visual stimulus (Miller, 2023). Simple reaction times are generally slower than this threshold (Boisgontier et al., 2014; Woods et al., 2015). For the upper threshold, relatively wide cut-offs have been recommended so that only clearly implausible responses are removed (Miller, 2023). We therefore recommend an upper cut-off of 3,000 ms, which has previously been used in a sample ranging from 21 to 77 years of age to accommodate the slower responses that may occur in older adults (Farajzadeh et al., 2023). We recommend (ix) removing the earliest trials at the start of each block as familiarization trials. Reaction times tend to be longer during the first few trials of a block, with this initial transient typically resolving within fewer than 10 trials (Harris et al., 2014). This effect is particularly pronounced on the first trial and may partly reflect a restart cost (Poljac et al., 2009), that is, the extra effort needed to reactivate the relevant task representation in memory after a cue or interruption (Altmann, 2002). Nosek et al. (2014) found that including the first four trials of the Brief Implicit Association Test reduced the task's reliability and validity. However, the optimal trade-off in approach-avoidance tasks between excluding potentially unstable early trials and retaining as much information as possible remains to be established.

Regarding bias-score computation, a multiverse analysis has shown that (x) using the double-difference D-score, calculated by dividing a participant's double mean difference score by the standard deviation of their reaction times, consistently showed the highest reliability and validity and the lowest variability across both simulated and empirical datasets compared with mean-, median-, and multilevel-based alternatives (Kahveci et al., 2024). We recommend that (xi) approach-avoidance bias scores account for general response tendencies, for example by controlling for responses to neutral stimuli (Cheval, Tipura, et al., 2018).

Limitations

The results of this study should be considered in light of several limitations. (i) Only articles published in English were included. Inclusion of articles published in other languages may have influenced the results. (ii) Due to the correlational nature of the meta-analyzed results, we cannot conclude a causal relationship between approach-avoidance tendencies and physical activity, nor can we exclude the possibility that this relationship is indirect, i.e., mediated by other factors. (iii) Secondary meta-analysis and several subgroup estimates are based on very small samples, compromising their interpretation. (iv) Publication bias assessment using Egger's test and Rücker's limit meta-analysis did not account for the dependency between effect estimates, as these methods are not currently implemented for three-level meta-analytic models.

Conclusion

Our findings indicate a small positive association between approach-avoidance tendencies and physical activity in the primary analyses. However, this association was attenuated and no longer statistically significant in the analysis accounting for small-study effects, suggesting that the evidence should be interpreted cautiously. Although these processes may represent a promising avenue for research aimed at promoting physical activity, confidence in the current literature is limited by substantial methodological heterogeneity, limited comparability across measures, and insufficient validity and reliability data for the tasks used in this field. Accordingly, firmer conclusions will require more rigorous and standardized future research.

Additional Information

Data Accessibility

The supplemental material, dataset, and scripts (R and R Markdown) are freely available in Zenodo at https://doi.org/10.5281/zenodo.19686794 (Jabouille & Boisgontier, 2026).

Author Contributions

Based on the Contributor Roles Taxonomy (CRediT), individual author contributions to this work are as follows:

- François Jabouille: Methodology; Investigation; Formal Analysis; Data Curation; Visualization; Writing – Original Draft; Writing – Review and Editing.
- Ata Farajzadeh: Methodology (systematic review); Investigation; Writing – Review and Editing.
- Matthieu P. Boisgontier: Conceptualization; Methodology; Investigation; Formal Analysis; Data Curation; Visualization; Writing – Original Draft; Writing – Review and Editing; Supervision (FJ, AF); Project Administration; Funding Acquisition.

Conflict of Interest

Matthieu P. Boisgontier serves as Chair of Publications for the Society of Transparency, Openness, and Replication in Kinesiology (STORK), which publishes Communications in Kinesiology, SportRχiv, and Kinesiology Books. François Jabouille is the Treasurer of STORK. Neither author was involved in the editorial handling, peer-review process, or publication decision for the current article. The authors declare no financial conflicts of interest related to the content of this article.

Funding

Matthieu P. Boisgontier is supported by Natural Sciences and Engineering Research Council of Canada (NSERC; RGPIN-2021-03153), the Canada Foundation for Innovation (CFI 43661), and Mitacs. Ata Farajzadeh and François Jabouille are both supported by an Admission Scholarship, a Doctoral International Scholarship, a Special Merit Scholarship from the University of Ottawa, and a BMO Graduate Scholarship.

Artificial Intelligence

ChatGPT (GPT-5; OpenAI) was used to review the manuscript throughout to ensure grammatical correctness and clarity of wording, and to assist in extracting, organizing, and deriving the physical activity scores, approach-avoidance scores, and estimates from raw data reported in articles that did not test the association of interest. Artificial intelligence was not used for the code for the meta-analyses (meta_approach_avoidance_PA.Rmd) or for creating any figures. The authors understand all analyses conducted in the study, have reviewed the entire manuscript, and take full responsibility for its content.

Preprint

The pre-publication version of this manuscript can be found on SportRxiv (DOI: 10.51224/SportRxiv.839).

References

Abioye, A. I., Hajifathalian, K., & Danaei, G. (2013). Do mass media campaigns improve physical activity? A systematic review and meta-analysis. *Archives of Public Health*, *71*(1), 20. https://doi.org/10.1186/0778-7367-71-20

Altmann, E. M. (2002). Functional decay of memory for tasks. *Psychological Research*, *66*(4), 287–297. https://doi.org/10.1007/s00426-002-0102-9

Amagasa, S., Machida, M., Fukushima, N., Kikuchi, H., Takamiya, T., Odagiri, Y., & Inoue, S. (2018). Is objectively measured light-intensity physical activity associated with health outcomes after adjustment for moderate-to-vigorous physical activity in adults? A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *15*(1), 65. https://doi.org/10.1186/s12966-018-0695-z

Berry, T. R. (2006). Who's even interested in the exercise message? Attentional bias for exercise and sedentary-lifestyle related words. *Journal of Sport and Exercise Psychology*, *28*(1), 4–17. https://doi.org/10.1123/jsep.28.1.4

Berry, T. R. (2020). You do (not?) have to go to the gym: Effects of negations in exercise messages. *Sport, Exercise, and Performance Psychology*, *9*(3), 437–449. https://doi.org/10.1037/spy0000185

Berry, T. R., Spence, J. C., & Stolp, S. M. (2011). Attentional bias for exercise-related images. *Research Quarterly for Exercise and Sport*, *82*(2), 302–309. https://doi.org/10.1080/02701367.2011.10599758

Biddle, S. J. H. (2011). Fit or sit? Is there a psychology of sedentary behaviour? *Sport and Exercise Psychology Review*, *7*(2), 5–10. https://doi.org/10.53841/bpssepr.2011.7.2.5

Biswas, R. K., Ahmadi, M. N., Bauman, A., Milton, K., Koemel, N. A., & Stamatakis, E. (2025). Wearable device-based health equivalence of different physical activity intensities against mortality, cardiometabolic disease, and cancer. *Nature Communications*, *16*(1), 8315. https://doi.org/10.1038/s41467-025-63475-2

Bleich, S. N., Vercammen, K. A., Zatz, L. Y., Frelier, J. M., Ebbeling, C. B., & Peeters, A. (2018). Interventions to prevent global childhood overweight and obesity: A systematic review. *The Lancet Diabetes & Endocrinology*, *6*(4), 332–346. https://doi.org/10.1016/S2213-8587(17)30358-3

Bluemke, M., Brand, R., Schweizer, G., & Kahlert, D. (2010). Exercise might be good for me, but I don't feel good about it: Do automatic associations predict exercise behavior? *Journal of Sport and Exercise Psychology*, *32*(2), 137–153. https://doi.org/10.1123/jsep.32.2.137

Boisgontier, M. P. (2019). *Solving the exercise paradox: A neuro-behavioral approach* [Habilitation à diriger des recherches, Université Grenoble Alpes]. HAL. https://theses.hal.science/tel-05144080

Boisgontier, M. P., Wittenberg, G. F., Fujiyama, H., Levin, O., & Swinnen, S. P. (2014). Complexity of central processing in simple and choice multilimb reaction-time tasks. *PLoS ONE*, *9*(2), e90457. https://doi.org/10.1371/journal.pone.0090457

Bull, F. C., Al-Ansari, S. S., Biddle, S., Borodulin, K., Buman, M. P., Cardon, G., Carty, C., Chaput, J.-P., Chastin, S., Chou, R., Dempsey, P. C., DiPietro, L., Ekelund, U., Firth, J., Friedenreich, C. M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P. T., … Willumsen, J. F. (2020). World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *British Journal of Sports Medicine*, *54*(24), 1451–1462. https://doi.org/10.1136/bjsports-2020-102955

Calitri, R., Lowe, R., Eves, F. F., & Bennett, P. (2009). Associations between visual attention, implicit and explicit attitude and behaviour for physical activity. *Psychology and Health*, *24*(9), 1105–1123. https://doi.org/10.1080/08870440802245306

Chen, M., & Bargh, J. A. (1999). Consequences of automatic evaluation: Immediate behavioral predispositions to approach or avoid the stimulus. *Personality and Social Psychology Bulletin*, *25*(2), 215–224. https://doi.org/10.1177/0146167299025002007

Chen, Z., & Van Dessel, P. (2024). Action interpretation determines the effects of go/no-go and approach/avoidance actions on stimulus evaluation. *Open Mind*, *8*, 898–923. https://doi.org/10.1162/opmi_a_00151

Chen, Z., Van Dessel, P., Serverius, J., Zhu, D., & Figner, B. (2025). Action interpretation determines the effects of go/no-go and approach/avoidance actions on food choice. *Journal of Cognition*, *8*(1), 26. https://doi.org/10.5334/joc.436

Cheval, B., & Boisgontier, M. P. (2021). The theory of effort minimization in physical activity. *Exercise and Sport Sciences Reviews*, *49*(3), 168–178. https://doi.org/10.1249/JES.0000000000000252

Cheval, B., Miller, M. W., Orsholits, D., Berry, T., Sander, D., & Boisgontier, M. P. (2020). Physically active individuals look for more: An eye-tracking study of attentional bias. *Psychophysiology*, *57*(6), e13582. https://doi.org/10.1111/psyp.13582

Cheval, B., Radel, R., Neva, J. L., Boyd, L. A., Swinnen, S. P., Sander, D., & Boisgontier, M. P. (2018). Behavioral and neural evidence of the rewarding value of exercise behaviors: A systematic review. *Sports Medicine*, *48*(6), 1389–1404. https://doi.org/10.1007/s40279-018-0898-0

Cheval, B., Sarrazin, P., Isoard-Gautheur, S., Radel, R., & Friese, M. (2015). Reflective and impulsive processes explain (in)effectiveness of messages promoting physical activity: A randomized controlled trial. *Health Psychology*, *34*(1), 10–19. https://doi.org/10.1037/hea0000102

Cheval, B., Sarrazin, P., Isoard-Gautheur, S., Radel, R., & Friese, M. (2016). How impulsivity shapes the interplay of impulsive and reflective processes involved in objective physical activity. *Personality and Individual Differences*, *96*, 132–137. https://doi.org/10.1016/j.paid.2016.02.067

Cheval, B., Sarrazin, P., & Pelletier, L. (2014). Impulsive approach tendencies towards physical activity and sedentary behaviors, but not reflective intentions, prospectively predict non-exercise activity thermogenesis. *PLoS ONE*, *9*(12), e115238. https://doi.org/10.1371/journal.pone.0115238

Cheval, B., Sarrazin, P., Pelletier, L., & Friese, M. (2016). Effect of retraining approach-avoidance tendencies on an exercise task: A randomized controlled trial. *Journal of Physical Activity and Health*, *13*(12), 1396–1403. https://doi.org/10.1123/jpah.2015-0597

Cheval, B., Tipura, E., Burra, N., Frossard, J., Chanal, J., Orsholits, D., Radel, R., & Boisgontier, M. P. (2018). Avoiding sedentary behaviors requires more cortical resources than avoiding physical activity: An EEG study. *Neuropsychologia*, *119*, 68–80. https://doi.org/10.1016/j.neuropsychologia.2018.07.029

Chevance, G., Bernard, P., Chamberland, P. É., & Rebar, A. L. (2019). The association between implicit attitudes toward physical activity and physical activity behaviour: A systematic review and correlational meta-analysis. *Health Psychology Review*, *13*(3), 248–276. https://doi.org/10.1080/17437199.2019.1618726

Clevenger, K. A., Montoye, A. H. K., Van Camp, C. A., Strath, S. J., & Pfeiffer, K. A. (2022). Methods for estimating physical activity and energy expenditure using raw accelerometry data or novel analytical approaches: A repository, framework, and reporting guidelines. *Physiological Measurement*, *43*(9), 09NT01. https://doi.org/10.1088/1361-6579/ac89c9

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587

Conroy, D. E., & Berry, T. R. (2017). Automatic affective evaluations of physical activity. *Exercise and Sport Sciences Reviews*, *45*(4), 230–237. https://doi.org/10.1249/JES.0000000000000120

Corneille, O., & Hütter, M. (2020). Implicit? What do you mean? A comprehensive review of the delusive implicitness construct in attitude research. *Personality and Social Psychology Review*, *24*(3), 212–232. https://doi.org/10.1177/1088868320911325

Daou, M., Lohse, K., & Miller, M. (2017). To take the stairs or not to take the stairs? Employing the reflective–impulsive model to predict spontaneous physical activity. *Sports*, *5*(4), 75. https://doi.org/10.3390/sports5040075

de Oliveira Araújo, A., Oliveira, G. T. A., de Oliveira Matos, F., Lopes, F. A., Browne, R. A. V., & Elsangedy, H. M. (2024). Automatic processes moderate the association between reflective processes and movement behavior: A cross-sectional study. *Psychology of Sport and Exercise*, *70*, 102554. https://doi.org/10.1016/j.psychsport.2023.102554

den Braver, N. R., Garcia Bengoechea, E., Messing, S., Kelly, L., Schoonmade, L. J., Volf, K., Zukowska, J., Gelius, P., Forberger, S., Woods, C. B., & Lakerveld, J. (2022). The impact of mass-media campaigns on physical activity: A review of reviews through a policy lens. *European Journal of Public Health*, *32*(Suppl. 4), iv71–iv83. https://doi.org/10.1093/eurpub/ckac085

Donders, F. C. (1969). On the speed of mental processes. *Acta Psychologica*, *30*, 412–431. https://doi.org/10.1016/0001-6918(69)90065-1

Eagly, A. H., & Chaiken, S. (2007). The advantages of an inclusive definition of attitude. *Social Cognition*, *25*(5), 582–602. https://doi.org/10.1521/soco.2007.25.5.582

Eder, A. B., & Rothermund, K. (2008). When do motor behaviors (mis)match affective stimuli? An evaluative coding view of approach and avoidance reactions. *Journal of Experimental Psychology: General*, *137*(2), 262–281. https://doi.org/10.1037/0096-3445.137.2.262

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ*, *315*(7109), 629–634. https://doi.org/10.1136/bmj.315.7109.629

Fadardi, J. S., Cox, W. M., & Rahmani, A. (2016). Neuroscience of attentional processes for addiction medicine: From brain mechanisms to practical considerations. *Progress in Brain Research*, *223*, 77–89. https://doi.org/10.1016/bs.pbr.2015.08.002

Farajzadeh, A., Goubran, M., Beehler, A., Cherkaoui, N., Morrison, P., de Chanaleilles, M., Maltagliati, S., Cheval, B., Miller, M. W., Sheehy, L., Bilodeau, M., Orsholits, D., & Boisgontier, M. P. (2023). Automatic approach-avoidance tendency toward physical activity, sedentary, and neutral stimuli as a function of age, explicit affective attitude, and intention to be active. *Peer Community Journal*, *3*, e21. https://doi.org/10.24072/pcjournal.246

Farajzadeh, A., Hébert, A., Lahart, I. M., Bilodeau, M., & Boisgontier, M. P. (2026). Apathy and physical activity: A systematic review and meta-analysis. *Physiotherapy Canada*, *78*(3), 389–405. https://doi.org/10.3138/ptc-2024-0050

Farajzadeh, A., Jabouille, F., Benoit, N., Bezeau, O., Bourgie, T., Gerro, B., Ouimet, J., & Boisgontier, M. P. (2025). Apathy, intentions, explicit attitudes, and approach-avoidance tendencies in physical activity behavior. *Communications in Kinesiology*, *1*(6). https://doi.org/10.51224/cik.2024.68

Farajzadeh, A., Jabouille, F., & Boisgontier, M. P. (2025). *Systematic review and meta-analysis of the association between approach/avoidance tendencies and physical activity engagement (PROSPERO CRD420251034465)*. https://www.crd.york.ac.uk/PROSPERO/view/CRD420251034465

Farajzadeh, A., Park, K., Lahart, I. M., Carlsen, A. N., & Boisgontier, M. P. (2026). *Habitual physical activity and motor cortical neurophysiology: A systematic review with meta-analyses of transcranial magnetic stimulation measures*. SportRxiv. https://doi.org/10.51224/SportRxiv.815

Feil, K., Fritsch, J., & Rhodes, R. E. (2023). The intention–behaviour gap in physical activity: A systematic review and meta-analysis of the action control framework. *British Journal of Sports Medicine*, *57*(19), 1265–1271. https://doi.org/10.1136/bjsports-2022-106640

Fessler, L., Maltagliati, S., Meyer, P., Finckh, A., Cullati, S., Sander, D., Friese, M., Wiers, R. W., Farajzadeh, A., Luthy, C., Sarrazin, P., & Cheval, B. (2026). Anatomy of a failure: A retrospective evaluation of a cognitive bias modification intervention to promote physical activity in cardiac rehabilitation. *BMJ Open*, *16*(4), e101558. https://doi.org/10.1136/bmjopen-2025-101558

Fessler, L., Tessitore, E., Craviari, C., Sarrazin, P., Meyer, P., Luthy, C., Hanna-Deschamps, E., & Cheval, B. (2024). Motivational and emotional correlates of physical activity and sedentary behavior after cardiac rehabilitation: An observational study. *BMC Sports Science, Medicine and Rehabilitation*, *16*(1), 209. https://doi.org/10.1186/s13102-024-00997-0

Fricke, K., Alexander, N., Jacobsen, T., & Vogel, S. (2023). Comparison of two reaction-time-based and one foraging-based behavioral approach-avoidance tasks in relation to interindividual differences and their reliability. *Scientific Reports*, *13*(1), 22376. https://doi.org/10.1038/s41598-023-49864-x

Friese, M., Hofmann, W., & Wiers, R. W. (2011). On taming horses and strengthening riders: Recent developments in research on interventions to improve self-control in health behaviors. *Self and Identity*, *10*(3), 336–351. https://doi.org/10.1080/15298868.2010.536417

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

Gardner, B., & Rebar, A. L. (2019). Habit formation and behavior change. In *Oxford research encyclopedia of psychology*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190236557.013.129

Godin, G., & Shephard, R. J. (1985). A simple method to assess exercise behavior in the community. *Canadian Journal of Applied Sport Sciences*, *10*(3), 141–146.

Goubran, M., Farajzadeh, A., Lahart, I. M., Bilodeau, M., & Boisgontier, M. P. (2025). Relationship between fear of movement and physical activity in patients with cardiac, rheumatologic, neurologic, pulmonary, or pain conditions: A systematic review and meta-analysis. *Physical Therapy*, *105*(6), pzaf050. https://doi.org/10.1093/ptj/pzaf050

Goubran, M., Zammar, C., Tellez Alvarez, S., Héran, É., Proulx, S., Bilodeau, M., & Boisgontier, M. P. (2025). Approach-avoidance tendencies moderate the relationship between fear of movement and physical activity in osteoarthritis. *Physiotherapy Canada*. https://doi.org/10.3138/ptc-2025-0011

Greenwald, A. G., & Banaji, M. R. (1995). Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, *102*(1), 4–27. https://doi.org/10.1037/0033-295X.102.1.4

Hannan, T. E., Moffitt, R. L., Neumann, D. L., & Kemps, E. (2019). Implicit approach–avoidance associations predict leisure-time exercise independently of explicit exercise motivation. *Sport, Exercise, and Performance Psychology*, *8*(2), 210–222. https://doi.org/10.1037/spy0000145

Harris, C. M., Waddington, J., Biscione, V., & Manzi, S. (2014). Manual choice reaction times in the rate-domain. *Frontiers in Human Neuroscience*, *8*, 418. https://doi.org/10.3389/fnhum.2014.00418

Helmerhorst, H. H. J., Brage, S., Warren, J., Besson, H., & Ekelund, U. (2012). A systematic review of reliability and objective criterion-related validity of physical activity questionnaires. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 103. https://doi.org/10.1186/1479-5868-9-103

Higgins, J. P. T., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in Medicine*, *21*(11), 1539–1558. https://doi.org/10.1002/sim.1186

Hilgard, E. R. (1980). The trilogy of mind: Cognition, affection, and conation. *Journal of the History of the Behavioral Sciences*, *16*(2), 107–117. https://doi.org/10.1002/1520-6696(198004)16:2%3C107::AID-JHBS2300160202%3E3.0.CO;2-Y

Hyde, A. L., Elavsky, S., Doerksen, S. E., & Conroy, D. E. (2012). The stability of automatic evaluations of physical activity and their relations with physical activity. *Journal of Sport and Exercise Psychology*, *34*(6), 715–736. https://doi.org/10.1123/jsep.34.6.715

Jabouille, F., & Boisgontier, M. P. (2026). *Approach-avoidance tendencies and physical activity level: A systematic review and meta-analysis; Data, code, and material* [Data set]. Zenodo. https://doi.org/10.5281/zenodo.19686794

Jabouille, F., Dumas, T., Boisgontier, M. P., & Park, K. (2026). *Robot-based cognitive bias modification to improve physical activity engagement in older adults: A pilot study*. SportRxiv. https://doi.org/10.51224/SportRxiv.811

Kahveci, S., Rinck, M., van Alebeek, H., & Blechert, J. (2024). How pre-processing decisions affect the reliability and validity of the approach–avoidance task: Evidence from simulations and multiverse analyses with six datasets. *Behavior Research Methods*, *56*(3), 1551–1582. https://doi.org/10.3758/s13428-023-02109-1

Knapp, G., & Hartung, J. (2003). Improved tests for a random effects meta-regression with a single covariate. *Statistics in Medicine*, *22*(17), 2693–2710. https://doi.org/10.1002/sim.1482

Krieglmeyer, R., & Deutsch, R. (2010). Comparing measures of approach–avoidance behaviour: The manikin task vs. two versions of the joystick task. *Cognition and Emotion*, *24*(5), 810–828. https://doi.org/10.1080/02699930903047298

Laham, S. M., Kashima, Y., Dix, J., Wheeler, M., & Levis, B. (2014). Elaborated contextual framing is necessary for action-based attitude acquisition. *Cognition and Emotion*, *28*(6), 1119–1126. https://doi.org/10.1080/02699931.2013.867833

Lee, P. H., Macfarlane, D. J., Lam, T., & Stewart, S. M. (2011). Validity of the international physical activity questionnaire short form (IPAQ-SF): A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *8*(1), 115. https://doi.org/10.1186/1479-5868-8-115

Lim, W. M. (2024). A typology of validity: Content, face, convergent, discriminant, nomological and predictive validity. *Journal of Trade Science*, *12*(3), 155–179. https://doi.org/10.1108/JTS-03-2024-0016

Lin, L., & Chu, H. (2018). Quantifying publication bias in meta-analysis. *Biometrics*, *74*(3), 785–794. https://doi.org/10.1111/biom.12817

Liu, X., Zhang, D., Liu, Y., Sun, X., Han, C., Wang, B., Ren, Y., Zhou, J., Zhao, Y., Shi, Y., Hu, D., & Zhang, M. (2017). Dose–response association between physical activity and incident hypertension: A systematic review and meta-analysis of cohort studies. *Hypertension*, *69*(5), 813–820. https://doi.org/10.1161/HYPERTENSIONAHA.116.08994

Locke, S. R., & Berry, T. R. (2021). Examining the relationship between exercise-related cognitive errors, exercise schema, and implicit associations. *Journal of Sport and Exercise Psychology*, *43*(4), 345–352. https://doi.org/10.1123/jsep.2021-0031

Maddison, R., Ni Mhurchu, C., Jiang, Y., Vander Hoorn, S., Rodgers, A., Lawes, C. M., & Rush, E. (2007). International Physical Activity Questionnaire (IPAQ) and New Zealand Physical Activity Questionnaire (NZPAQ): A doubly labelled water validation. *International Journal of Behavioral Nutrition and Physical Activity*, *4*(1), 62. https://doi.org/10.1186/1479-5868-4-62

Maltagliati, S., Sarrazin, P., Isoard-Gautheur, S., Rhodes, R. E., Boisgontier, M. P., & Cheval, B. (2022). I sit but I don't know why: Investigating the multiple precursors of leisure-time sedentary behaviors. *Research Quarterly for Exercise and Sport*, *93*(3), 548–563. https://doi.org/10.1080/02701367.2021.1877246

Migueles, J. H., Aadland, E., Andersen, L. B., Brønd, J. C., Chastin, S. F., Hansen, B. H., Konstabel, K., Kvalheim, O. M., McGregor, D. E., Rowlands, A. V., Sabia, S., van Hees, V. T., Walmsley, R.,

Ortega, F. B., & External Review Group. (2022). GRANADA consensus on analytical approaches to assess associations with accelerometer-determined physical behaviours (physical activity, sedentary behaviour and sleep) in epidemiological studies. *British Journal of Sports Medicine*, *56*(7), 376–384. https://doi.org/10.1136/bjsports-2020-103604

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., Labayen, I., Ruiz, J. R., & Ortega, F. B. (2017). Accelerometer data collection and processing criteria to assess physical activity and other outcomes: A systematic review and practical considerations. *Sports Medicine*, *47*(9), 1821–1845. https://doi.org/10.1007/s40279-017-0716-0

Migueles, J. H., Rowlands, A. V., Huber, F., Sabia, S., & van Hees, V. T. (2019). GGIR: A research community–driven open source R package for generating physical activity and sleep outcomes from multi-day raw accelerometer data. *Journal for the Measurement of Physical Behaviour*, *2*(3), 188–196. https://doi.org/10.1123/jmpb.2018-0063

Miller, J. (2023). Outlier exclusion procedures for reaction time analysis: The cures are generally worse than the disease. *Journal of Experimental Psychology: General*, *152*(11), 3189–3217. https://doi.org/10.1037/xge0001450

Moffitt, R. L., Kemps, E., Hannan, T. E., Neumann, D. L., Stopar, S. P., & Anderson, C. J. (2020). Implicit approach biases for physically active lifestyle cues. *International Journal of Sport and Exercise Psychology*, *18*(6), 833–849. https://doi.org/10.1080/1612197X.2019.1581829

Moore, S. C., Lee, I.-M., Weiderpass, E., Campbell, P. T., Sampson, J. N., Kitahara, C. M., Keadle, S. K., Arem, H., Berrington de Gonzalez, A., Hartge, P., Adami, H.-O., Blair, C. K., Borch, K. B., Boyd, E., Check, D. P., Fournier, A., Freedman, N. D., Gunter, M., Johannson, M., … Patel, A. V. (2016). Association of leisure-time physical activity with risk of 26 types of cancer in 1.44 million adults. *JAMA Internal Medicine*, *176*(6), 816–825. https://doi.org/10.1001/jamainternmed.2016.1548

Najar, J., Östling, S., Gudmundsson, P., Sundh, V., Johansson, L., Kern, S., Guo, X., Hällström, T., & Skoog, I. (2019). Cognitive and physical activity and dementia: A 44-year longitudinal population study of women. *Neurology*, *92*(12), e1322–e1330. https://doi.org/10.1212/WNL.0000000000007021

National Heart, Lung, and Blood Institute. (2021). *Study quality assessment tools*. https://www.nhlbi.nih.gov/health-topics/study-quality-assessment-tools

Nosek, B. A., Bar-Anan, Y., Sriram, N., Axt, J. R., & Greenwald, A. G. (2014). Understanding and using the Brief Implicit Association Test: Recommended scoring procedures. *PLoS ONE*, *9*(12), e110938. https://doi.org/10.1371/journal.pone.0110938

Oliver, S., & Kemps, E. (2018). Motivational and implicit processes contribute to incidental physical activity. *British Journal of Health Psychology*, *23*(4), 820–842. https://doi.org/10.1111/bjhp.12318

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ*, *372*, n160. https://doi.org/10.1136/bmj.n160

Pearson, N., Braithwaite, R. E., Biddle, S. J. H., van Sluijs, E. M. F., & Atkin, A. J. (2014). Associations between sedentary behaviour and physical activity in children and adolescents: A meta-analysis. *Obesity Reviews*, *15*(8), 666–675. https://doi.org/10.1111/obr.12188

Phaf, R. H., Mohr, S. E., Rotteveel, M., & Wicherts, J. M. (2014). Approach, avoidance, and affect: A meta-analysis of approach-avoidance tendencies in manual reaction time tasks. *Frontiers in Psychology*, *5*, 378. https://doi.org/10.3389/fpsyg.2014.00378

Poljac, E., Koch, I., & Bekkering, H. (2009). Dissociating restart cost and mixing cost in task switching. *Psychological Research*, *73*(3), 407–416. https://doi.org/10.1007/s00426-008-0151-9

Preis, M. A., Zellerhoff, M., & Brockmeyer, T. (2021). Approach bias modification training to increase physical activity: A pilot randomized controlled trial in healthy volunteers. *Journal of Health Psychology*, *26*(13), 2470–2486. https://doi.org/10.1177/1359105320913936

Quossi, A., Fessler, L., Maltagliati, S., Gardner, B., Miller, M. W., Sander, D., Rebar, A. L., Szabo, A., & Cheval, B. (2025). Can automatic reactions mirror exercise dependence? *International Journal of Sport and Exercise Psychology*, *23*(7), 1207–1233. https://doi.org/10.1080/1612197X.2024.2387698

R Core Team. (2024). *R: A language and environment for statistical computing* (Version 4.4.2) [Computer software]. R Foundation for Statistical Computing. https://doi.org/10.32614/R.manuals

Rebar, A. L., Dimmock, J. A., Jackson, B., Rhodes, R. E., Kates, A., Starling, J., & Vandelanotte, C. (2016). A systematic review of the effects of non-conscious regulatory processes in physical activity. *Health Psychology Review*, *10*(4), 395–407. https://doi.org/10.1080/17437199.2016.1183505

Reinecke, A., Becker, E. S., & Rinck, M. (2010). Three indirect tasks assessing implicit threat associations and behavioral response tendencies: Test-retest reliability and validity. *Journal of Psychology*, *218*(1), 4–11. https://doi.org/10.1027/0044-3409/a000002

Rezende, L. F. M., Ahmadi, M., Ferrari, G., del Pozo Cruz, B., Lee, I.-M., Ekelund, U., & Stamatakis, E. (2024). Device-measured sedentary time and intensity-specific physical activity in relation to all-cause and cardiovascular disease mortality: The UK Biobank cohort study. *International Journal of Behavioral Nutrition and Physical Activity*, *21*(1), 68. https://doi.org/10.1186/s12966-024-01615-5

Rougier, M., Muller, D., Ric, F., Alexopoulos, T., Batailler, C., Smeding, A., & Aubé, B. (2018). A new look at sensorimotor aspects in approach/avoidance tendencies: The role of visual whole-body movement information. *Journal of Experimental Social Psychology*, *76*, 42–53. https://doi.org/10.1016/j.jesp.2017.12.004

Rowlands, A. V., Edwardson, C. L., Davies, M. J., Khunti, K., Harrington, D. M., & Yates, T. (2018). Beyond cut points: Accelerometer metrics that capture the physical activity profile. *Medicine and Science in Sports and Exercise*, *50*(6), 1323–1332. https://doi.org/10.1249/MSS.0000000000001561

Rücker, G., Schwarzer, G., Carpenter, J. R., Binder, H., & Schumacher, M. (2011). Treatment-effect estimates adjusted for small-study effects via a limit meta-analysis. *Biostatistics*, *12*(1), 122–142. https://doi.org/10.1093/biostatistics/kxq046

Santos, A. C., Willumsen, J., Meheus, F., Ilbawi, A., & Bull, F. C. (2023). The cost of inaction on physical inactivity to public health-care systems: A population-attributable fraction analysis. *The Lancet Global Health*, *11*(1), e32–e39. https://doi.org/10.1016/S2214-109X(22)00464-8

Schuch, F., Vancampfort, D., Firth, J., Rosenbaum, S., Ward, P. B., Reichert, T., Bagatini, N. C., Bgeginski, R., & Stubbs, B. (2017). Physical activity and sedentary behavior in people with major depressive disorder: A systematic review and meta-analysis. *Journal of Affective Disorders*, *210*, 139–150. https://doi.org/10.1016/j.jad.2016.10.050

Schwarzer, G. (2023). *meta: General package for meta-analysis* [R package]. https://doi.org/10.32614/CRAN.package.meta

Schwarzer, G., Carpenter, J. R., & Rücker, G. (2023). *metasens: Advanced statistical methods to model and adjust for bias in meta-analysis* [R package]. https://doi.org/10.32614/CRAN.package.metasens

Seibt, B., Neumann, R., Nussinson, R., & Strack, F. (2008). Movement direction or change in distance? Self- and object-related approach–avoidance motions. *Journal of Experimental Social Psychology*, *44*(3), 713–720. https://doi.org/10.1016/j.jesp.2007.04.013

Sheeran, P., Bosch, J. A., Crombez, G., Hall, P. A., Harris, J. L., Papies, E. K., & Wiers, R. W. (2016). Implicit processes in health psychology: Diversity and promise. *Health Psychology*, *35*(8), 761–766. https://doi.org/10.1037/hea0000409

Sheeran, P., Gollwitzer, P. M., & Bargh, J. A. (2013). Nonconscious processes and health. *Health Psychology*, *32*(5), 460–473. https://doi.org/10.1037/a0029203

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2014). P-curve: A key to the file-drawer. *Journal of Experimental Psychology: General*, *143*(2), 534–547. https://doi.org/10.1037/a0033242

Solarz, A. K. (1960). Latency of instrumental responses as a function of compatibility with the meaning of eliciting verbal signs. *Journal of Experimental Psychology*, *59*(4), 239–245. https://doi.org/10.1037/h0047274

Sterne, J. A. C., Sutton, A. J., Ioannidis, J. P. A., Terrin, N., Jones, D. R., Lau, J., Carpenter, J., Rücker, G., Harbord, R. M., Schmid, C. H., Tetzlaff, J., Deeks, J. J., Peters, J., Macaskill, P., Schwarzer, G., Duval, S., Altman, D. G., Moher, D., & Higgins, J. P. T. (2011). Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ*, *343*, d4002. https://doi.org/10.1136/bmj.d4002

Strain, T., Flaxman, S., Guthold, R., Semenova, E., Cowan, M., Riley, L. M., Bull, F. C., Stevens, G. A., & Country Data Author Group. (2024). National, regional, and global trends in insufficient physical activity among adults from 2000 to 2022: A pooled analysis of 507 population-based surveys with 5.7 million participants. *The Lancet Global Health*, *12*(8), e1232–e1243. https://doi.org/10.1016/S2214-109X(24)00150-5

Stults-Kolehmainen, M. A., Blacutt, M., Bartholomew, J. B., Boullosa, D., Janata, P., Koo, B. B., McKee, P. C., Casper, R., Budnick, C. J., Gilson, T. A., Blakemore, R. L., Filgueiras, A., Williamson, S. L., SantaBarbara, N., Barker, J. L., Bueno, F. A., Heldring, J., & Ash, G. I. (2022). Urges to move and other motivation states for physical activity in clinical and healthy populations: A scoping review protocol. *Frontiers in Psychology*, *13*, 901272. https://doi.org/10.3389/fpsyg.2022.901272

Stults-Kolehmainen, M. A., Blacutt, M., Bartholomew, J. B., Gilson, T. A., Ash, G. I., McKee, P. C., & Sinha, R. (2020). Motivation states for physical activity and sedentary behavior: Desire, urge, wanting, and craving. *Frontiers in Psychology*, *11*, 568390. https://doi.org/10.3389/fpsyg.2020.568390

Tarp, J., Dalene, K. E., Fagerland, M. W., Steene-Johannesen, J., Hansen, B. H., Anderssen, S. A., Hagströmer, M., Dohrn, I.-M., Dempsey, P. C., Wijndaele, K., Brage, S., Nordström, A., Nordström, P., Diaz, K. M., Howard, V. J., Hooker, S. P., Morseth, B., Hopstock, L. A., Sagelv, E. H., … Ekelund, U. (2024). Physical activity volume, intensity, and mortality: Harmonized meta-analysis of prospective cohort studies. *American Journal of Preventive Medicine*, *67*(6), 887–896. https://doi.org/10.1016/j.amepre.2024.07.022

Terashima, M., Rebar, A. L., Naredi, H., Khafi, N., Maltagliati, S., de Chanaleilles, M., Zenko, Z., Cheval, B., & Gardner, B. (2025). Active without thinking? Distinguishing between automatic responses as predictors of physical activity. *Peer Community Journal*, *5*, e62. https://doi.org/10.24072/pcjournal.569

Tulving, E., & Schacter, D. L. (1990). Priming and human memory systems. *Science*, *247*(4940), 301–306. https://doi.org/10.1126/science.2296719

van der Ploeg, H. P., & Hillsdon, M. (2017). Is sedentary behaviour just physical inactivity by another name? *International Journal of Behavioral Nutrition and Physical Activity*, *14*(1), 142. https://doi.org/10.1186/s12966-017-0601-0

Van Dessel, P., Eder, A. B., & Hughes, S. (2018). Mechanisms underlying effects of approach-avoidance training on stimulus evaluation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(8), 1224–1241. https://doi.org/10.1037/xlm0000514

Viechtbauer, W. (2005). Bias and efficiency of meta-analytic variance estimators in the random-effects model. *Journal of Educational and Behavioral Statistics*, *30*(3), 261–293. https://doi.org/10.3102/10769986030003261

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*(3), 1–48. https://doi.org/10.18637/jss.v036.i03

Viechtbauer, W. (2023). *metafor: Meta-analysis package for R* [R package]. https://doi.org/10.32614/CRAN.package.metafor

Wahid, A., Manek, N., Nichols, M., Kelly, P., Foster, C., Webster, P., Kaur, A., Smith, C. F., Wilkins, E., Rayner, M., Roberts, N., & Scarborough, P. (2016). Quantifying the association between physical activity and cardiovascular disease and diabetes: A systematic review and meta-analysis. *Journal of the American Heart Association*, *5*(9), e002495. https://doi.org/10.1161/JAHA.115.002495

Wang, C., & Zhang, G. (2025). Examination of the consistency effect between physical activity levels and approach-avoidance behaviors. *Psychology of Sport and Exercise*, *79*, 102825. https://doi.org/10.1016/j.psychsport.2025.102825

Wang, Y.-B., Sun, X. T., & Mao, Z.-X. (2023). Is approaching sedentary behaviour or physical activity a reward? An EEG study. *Behavioural Brain Research*, *445*, 114364. https://doi.org/10.1016/j.bbr.2023.114364

Wang, Y.-B., Yang, L., & Mao, Z.-X. (2023). To run or not to run? Differences in implicit attitudes towards running: An EEG study. *Behavioural Brain Research*, *454*, 114637. https://doi.org/10.1016/j.bbr.2023.114637

Wang, Y.-B., Zhang, Z., & Mao, Z.-X. (2024). You don't know why you (don't) exercise: The relationship between automatic processes and physical activity (or sedentary behavior): A meta-analysis. *Scandinavian Journal of Psychology*, *65*(3), 501–510. https://doi.org/10.1111/sjop.12991

Wittekind, C. E., Blechert, J., Schiebel, T., Lender, A., Kahveci, S., & Kühn, S. (2021). Comparison of different response devices to assess behavioral tendencies toward chocolate in the approach-avoidance task. *Appetite*, *165*, 105294. https://doi.org/10.1016/j.appet.2021.105294

Woodman, J. (2025). Approach bias toward physical activities using the VAAST. *North American Journal of Psychology*, *27*(2), 279–288.

Woods, D. L., Wyma, J. M., Yund, E. W., Herron, T. J., & Reed, B. (2015). Factors influencing the latency of simple reaction time. *Frontiers in Human Neuroscience*, *9*, 131. https://doi.org/10.3389/fnhum.2015.00131

World Health Organization. (2018). *Global action plan on physical activity 2018–2030: More active people for a healthier world*. https://iris.who.int/handle/10665/272722

World Health Organization. (2025). *Measuring physical activity in adults using wearable technologies: Report of a scientific meeting, 10–12 June 2025, Montreal, Canada*. World Health Organization. https://www.who.int/publications/i/item/9789240116696

World Health Organization. (2026). *Integrating wearable technology into population health monitoring systems for physical activity measurement: Meeting report, Utrecht, Kingdom of the Netherlands, 25–27 November 2025*. World Health Organization. https://doi.org/10.2471/B09745

Zech, H. G., Gable, P., van Dijk, W. W., & van Dillen, L. F. (2023). Test-retest reliability of a smartphone-based approach-avoidance task: Effects of retest period, stimulus type, and demographics. *Behavior Research Methods*, *55*(5), 2652–2668. https://doi.org/10.3758/s13428-022-01920-6

Zenko, Z., & Ekkekakis, P. (2019). Internal consistency and validity of measures of automatic exercise associations. *Psychology of Sport and Exercise*, *43*, 4–15. https://doi.org/10.1016/j.psychsport.2018.12.005

Zi, Y., van de Ven, S. R. B., de Geus, E. J. C., & Chen, P. (2026). Machine and deep learning for detection of moderate-to-vigorous physical activity from accelerometer data: Systematic scoping review. *Interactive Journal of Medical Research*, *15*, e76601. https://doi.org/10.2196/76601