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Using the EZ-Diffusion Model to Score a Single-Category Implicit Association Test of Physical Activity

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Abstract

Objective—The Single-Category Implicit Association Test (SC-IAT) has been used as a method for assessing automatic evaluations of physical activity, but measurement artifact or consciously-held attitudes could be confounding the outcome scores of these measures. The objective of these two studies was to address these measurement concerns by testing the validity of a novel SC-IAT scoring technique.

Design—Study 1 was a cross-sectional study, and study 2 was a prospective study.

Method—In study 1, undergraduate students ($N = 104$) completed SC-IATs for physical activity, flowers, and sedentary behavior. In study 2, undergraduate students ($N = 91$) completed a SC-IAT for physical activity, self-reported affective and instrumental attitudes toward physical activity, physical activity intentions, and wore an accelerometer for two weeks. The EZ-diffusion model was used to decompose the SC-IAT into three process component scores including the information processing efficiency score.

Results—In study 1, a series of structural equation model comparisons revealed that the information processing score did not share variability across distinct SC-IATs, suggesting it does not represent systematic measurement artifact. In study 2, the information processing efficiency score was shown to be unrelated to self-reported affective and instrumental attitudes toward physical activity, and positively related to physical activity behavior, above and beyond the traditional D-score of the SC-IAT.

Conclusions—The information processing efficiency score is a valid measure of automatic evaluations of physical activity.

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Keywords

automatic evaluations; response time measures; exercise; implicit attitudes

Research is emerging that physical activity is, in part, regulated by automatic evaluations (i.e., implicit attitudes) (Calitri, Lowe, Eves, & Bennett, 2009; Conroy, Hyde, Doerksen, & Ribeiro, 2010; Hyde, Elavsky, Doerksen, & Conroy, 2012). Given that people may not be aware of their automatic evaluations (Nosek, Greenwald, & Banaji, 2007), these evaluations have been commonly measured as scores based on response times of implicit tasks such as affective priming tasks (Klauer, Musch, Musch, & Klauer, 2003) or the Single Category Implicit Association Test (SC-IAT; Karpinski & Steinman, 2006). However, response times are not solely the result of automatic evaluations (Hahne & Friederici, 1999; Satpute & Lieberman, 2006; Schneider & Shiffrin, 1985). Response times may also be influenced by construct-irrelevant variability from measurement artifact (e.g., individual differences in reaction time or general cognitive ability) or consciously-held attitudes of physical activity (e.g., decisions made using deliberated information processing). To the extent that construct-irrelevant variability contaminates these scores, validity is reduced and incorrect inferences about these automatic processes could be made. A measure of automatic evaluations with stronger construct validity is necessary. These two studies tested the validity of a novel scoring technique of physical activity SC-IATs: the information processing efficiency score, calculated with the EZ-diffusion model (Wagenmakers, Van Der Maas, & Grasman, 2007).

Automatic Evaluations of Physical Activity

Within a fraction of a second of encountering a stimulus, a network of relevant concepts are automatically activated, including favorable or unfavorable evaluations toward the stimulus (Bargh, Chaiken, Raymond, & Hymes, 1996; Greenwald et al., 2002). Activation of favorable automatic evaluations leads to approach behavioral response tendencies, whereas activation of unfavorable automatic evaluations leads to avoidance behavioral response tendencies (Bargh, 1992; Chen & Bargh, 1999). Proposals are being put forth to account for the influence that automatic evaluations have on health behaviors such as physical activity (Lowe & Norman, 2013; Rothman, Sheeran, & Wood, 2009). One of the most common approaches to measuring these evaluations involves timed classification tasks that assess the strength of perceived compatibility between concepts (e.g., physical activity) and attributes (e.g., good), such as the Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998). The IAT is a measure of the relative valence of evaluations between two separate concepts (e.g., flowers as compared to insects). The SC-IAT (Karpinski & Steinman, 2006) is a variation of the IAT made to capture evaluations toward a single concept with no clear opposite, such as the concept of *physical activity*.

The SC-IAT involves categorizing stimuli into two categories. Stimuli are exemplars of the targeted concept and attributes (e.g., *walking*, *desire*, and *thief* are exemplars of the concept *physical activity* and the attributes *good* and *bad*, respectively). One response category on the SC-IAT includes both an attribute and a concept and the other response category involves just an attribute. For example, during one test block, respondents may select between the categories *physical activity/good* vs. *bad* and in the other test block, respondents

would select between the categories *good* vs. *physical activity/bad*. The rationale underlying the test is that people with favorable evaluations of physical activity will perceive the concept (*physical activity*) as being more compatible with *good* than *bad* attributes and this will result in observable SC-IAT response biases (De Houwer, 2001; Mierke & Klauer, 2001; Steffens & Plewe, 2001).

Using the SC-IAT, research has shown that people with more favorable automatic evaluations toward physical activity are more physically active than people with less favorable automatic evaluations (Conroy et al., 2010), and when these automatic evaluations become more favorable, physical activity levels increase (Hyde et al., 2012). Additionally, research has shown that SC-IAT measured automatic evaluations of physical activity are independent of consciously-held affective attitudes toward physical activity (Hyde, Doerksen, Ribeiro, & Conroy, 2010).

The D-score

Traditionally, SC-IATs are scored using the D-score (Greenwald et al., 1998; Greenwald, Nosek, & Banaji, 2003), calculated as $(MRT_1 - MRT_2) / SDRT_{1,2}$, where MRT_1 represents the mean response time of one test block, MRT_2 represents the mean response time of the other block, and $SDRT_{1,2}$ represents the pooled standard deviation across both blocks (i.e., the entire test). The D-score has been shown to relate to prospective behavior (Greenwald et al., 2003; Greenwald, Poehlman, Uhlmann, & Banaji, 2009); however the D-score is limited in that it may include construct-irrelevant variability.

A control for between-person differences in speed of responding is built into the D-score (by controlling for pooled response time standard deviation); however previous studies have shown that the D-score shares variability across IATs of distinct concepts (Back, Schmukle, & Egloff, 2005; Cai, Sriram, Greenwald, & McFarland, 2004). This suggests that there may be other forms of measurement artifact confounding the D-score. There is also a risk that SC-IAT scores may include construct-irrelevant variability stemming from consciously-held attitudes. Performance on button-pressing tasks, such as SC-IATs, is the result of non-conscious (quick, automatic) and consciously-held (slow, deliberate) processes (Hahne & Friederici, 1999; Satpute & Lieberman, 2006; Schneider & Shiffrin, 1985). A valid measure of automatic evaluations will distinguish between automatic evaluations and construct-irrelevant variability such as measurement artifact or consciously-held attitudes. Whereas no association would be expected between measurement artifact and a valid measure of automatic evaluations, associations between automatic evaluations and consciously-held attitudes of physical activity are conceptually plausible (Gawronski & Bodenhausen, 2006).

Process Component Scores

One promising method for separating construct-irrelevant variability from the true underlying construct of automatic evaluations is to decompose SC-IAT response data using process models. Process models have been utilized to separate choice response time behavior into *process component* scores that represent different processes used to complete the task (Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005; Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007; van Ravenzwaaij, van der Maas, & Wagenmakers, 2011). One

process model that has been previously used to decompose IAT-evoked response times into process component scores is the Ratcliff diffusion model (Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998).

The Ratcliff diffusion model proposes that the amount of time taken to respond on a two-choice response time task depends on several factors including information processing efficiency (i.e., speed and accuracy of processing of stimuli), response conservativeness (i.e., speed-accuracy tradeoff), and non-decision processing time (i.e., translating evaluation into response behavior) (Ratcliff, 1978). Klauer et al. (2007) used the Ratcliff diffusion model to decompose IAT performance and found that these three scores reflected IAT effects. That is, information processing, response conservativeness, and non-decision time estimates were longer during the incompatible than then compatible test block. A limitation of using the Ratcliff diffusion model to score an IAT is that it requires estimating distributions of response times for errors. People rarely make sufficient errors on IATs to permit accurate estimations of these distributions. Wagenmakers and colleagues (2007) suggested that accurate estimation would require about 200 trials per test block (as opposed to the typical 72 in the SC-IAT) given a 5% error rate (typical error rates of SC-IATs are oftentimes even lower).

Wagenmakers and colleagues (2007) created a simplified version of the Ratcliff diffusion model that calculates these three parameters without error rate distributions. The EZ-diffusion model requires the input of mean response time, variance of response times, percentage of correct responses, and the scaling parameter (s ; set to 0.1). It yields person-level parameters for information processing efficiency, response conservativeness, and non-decision processing time. The equations used to calculate the scores are provided in the Appendix, and an explanation of the equations, a demonstration of their use, and R code for applying the equations are available in Wagenmakers et al. (2007). In general terms, a high information processing efficiency score reflects low variability of response times and a high percentage of accuracy, a high response conservativeness score reflects high variability of response times and a high percentage of accuracy, and a high non-decision processing time score represents a long mean response time left unaccounted for by information processing efficiency and response conservativeness.

It may be that the difference in information processing efficiency between blocks of an SC-IAT is a valid measure of automatic evaluations. Favorable automatic evaluations manifest as preexisting associations to the concept with *good* attributes, and this bias should lead to more efficient information processing during the block when the concept is paired with good attributes and less efficient processing during the block when the concept is paired with bad attributes (Greenwald et al., 1998). Unfavorable automatic evaluations are preexisting biases to associate the concept with *bad* attributes so should lead to more efficient information processing during the block when the concept is paired with bad attributes and less efficient information processing during the block when the concept is paired with good attributes. Indeed, previous research has shown that significant differences exist in information processing efficiency between test blocks of IATs (Klauer et al., 2007; van Ravenzwaaij et al., 2011). It was found that people have less efficient information processing during the

block with conceptually incompatible categories (e.g., categories *flower/bad* vs. *insect/good*).

The other two EZ-diffusion model process component scores (response conservativeness and non-decision processing time) are less likely to represent automatic evaluations. Klauer and colleagues (2007) found that between-block differences in response conservativeness on a political attitudes IAT related to the same score on two unrelated IATs, suggesting response conservativeness may represent measurement artifact. Non-decision processing time represents the response time left after accounting for evaluative processes, presumably a representation of preparatory time required for translating evaluations into button-pressing behavior (Klauer et al., 2007). Between-block differences in response conservativeness and non-decision processing time may capture consciously-held attitudes toward the concept or measurement artifact, but it is not expected that these scores will reflect automatic evaluations.

The Present Studies

There is a risk that construct validity of the traditional SC-IAT D-score is reduced by construct-irrelevant variability from measurement artifact or consciously-held attitudes toward the concept. Two studies were designed to investigate construct validity of the information processing efficiency score of the SC-IAT as a measure of automatic evaluations of physical activity. Study 1 tested whether the information processing efficiency score shared variability across three distinct SC-IATs. The construct of automatic evaluations of physical activity is conceptually distinct from automatic evaluations of other behaviors (e.g., sedentary behavior) and objects (e.g., flowers); therefore construct validity of the information processing efficiency score would be supported if the score was found to not share significant variability across the distinct SC-IATs. Study 2 tested whether the information processing efficiency score of a physical activity SC-IAT was independent from consciously-held attitudes toward physical activity and convergent with prospective physical activity. Physical activity intentions were included as a covariate in this model because previous research suggests that automatic evaluations of physical activity relate to physical activity behavior after accounting for behavioral intentions (Conroy et al., 2010). Construct validity of automatic evaluations of physical activity would be supported if the score was shown to be independent from consciously-held attitudes toward physical activity, but related to objectively-measured physical activity.

Study 1

Methods

Participants and procedure—The data used for the analyses were from a broader research project of university students whom agreed to permit their data from a class project to be used for research purposes ($N = 104$; 54 female; $M_{\text{age}} = 21$ years; 90% Caucasian). During an hour-long laboratory visit, participants completed a physical activity SC-IAT and a sedentary behavior SC-IAT. Additionally, most participants completed a flower SC-IAT ($N = 79$). During that time, the rest of the participants completed a computer-based task for a separate research project. Whether a participant completed the flower SC-IAT or the

unrelated task was determined based on randomization of study condition; therefore the missing flower SC-IAT data can be considered missing completely at random. Data were collected using MediaLab® and DirectRT® software (Empirisoft Corp., New York, NY) on Windows-based computers with a DirectIN High-Efficiency Button Box (Empirisoft Corp., New York, NY).

Measures

Physical Activity Single-Category Implicit Association Test—The SC-IAT (Karpinski & Steinman, 2006) was used to measure automatic evaluations of physical activity. The test consisted of two randomly presented blocks, each consisting of 24 practice trials and 72 test trials. Participants were asked to sort three types of words (physical activity, good, bad) into two categories with overlap: *physical activity/good* vs. *bad* (one block) or *good* vs. *physical activity/bad* (other block). Categories were presented in green on the upper-left and upper-right corners of the black screen and the stimuli (words) appeared in random order on the center of the screen in white. Physical activity words (*walk, jog, bike, move, stand, lift, carry, pull, stretch, play, jump, and throw*) were selected to cover a broad range of intensities and to cover lifestyle and leisure activities. The 12 good (e.g., *cozy, passion, and brave*), and 12 bad stimuli (e.g., *inferior, deformed, and danger*) were selected from the Affective Norms for English Words based on word length and valence ratings (Bradley & Lang, 1999). Participants categorized the stimuli by pressing one of two buttons. Following an incorrect selection, a red X would appear above the stimulus until the selection was corrected. In previous research, the D-score from this SC-IAT has been shown to positively relate to physical activity (Conroy et al., 2010; Hyde et al., 2012).

Sedentary and Flower Single-Category Implicit Association Tests—The same procedures and scoring methods used for the physical activity SC-IAT was used for these tests. The good and bad stimuli were the same as those in the physical activity SC-IAT. The sedentary stimuli were *sit, sofa, recline, computer, driving, chair, couch, and reading*. The flower stimuli (e.g., *rose, orchid, iris*) were the same as those used in seminal implicit association test studies (e.g., Greenwald et al., 1998).

Data preparation

Data reduction—Before the SC-IATs were scored, response times shorter than 100 ms and individuals' outliers based on Tukey's outlier criterion (Weisstein, 1999) were discarded. For each block, individuals' interquartile ranges were calculated. Response times longer than the individual's third quartile plus 1.5 times their interquartile range in that block or shorter than their first quartile minus 1.5 times the interquartile range were discarded. Less than 1% of trials (49 of 14,976) were removed. This individualized outlier treatment has been used previously in research on the application of the diffusion model to IAT data (Klauer et al., 2007).

D-scores—The SC-IAT data were scored using the established D-score algorithm (Greenwald et al., 2003). As in previous research utilizing the D-score on SC-IAT data, a split-half reliability with a Spearman-Brown correction was estimated. Reliability was .84,

higher than that reported in previous SC-IAT research (Hyde et al., 2010: $\alpha = .73$; Karpinski & Steinman, 2006: $\alpha = .69$).

Process component scores—To estimate the process component scores, including the information processing efficiency score, Wagenmaker's (2007) EZ-diffusion model algorithms were calculated for each test block. The EZ-diffusion model requires a non-zero percentage of error responses, but 23 participants (22%) had no errors in one or the other test block. Rather than omitting these participants from analyses, their proportion of correct responses of 1.0 was substituted with 0.995 (equivalent to having half of one error response). A similar technique was used to account for 1.0 accuracy rates in another two-choice response time task (Becker, Goldinger, & Stone, 2006). The scores were calculated as the difference of the process components of the SC-IAT test blocks with positive numbers indicating more efficient information processing, less response-conservativeness, and less non-decision time processing during the block with the categories *physical activity/good* vs. *bad*. Difference scores can inflate scaling if there is not multivariate normality. Shapiro-Francia Multivariate Normality tests (Delmair, 2009) showed that information processing efficiency ($W = 0.99$; $p = .41$), but neither response conservativeness ($W = 0.84$, $p < .01$), nor non-decision processing time ($W = 0.88$, $p < .01$) had multivariate normality.

The EZ-diffusion model process component estimates have been shown to strongly, positively relate to the estimates of the full diffusion model, but to ensure the most accurate estimation, there are three testable assumptions of the EZ-diffusion model (Wagenmakers et al., 2007). The three assumptions of the EZ-diffusion model were tested on a subsample of participants ($n = 64$) for which the SC-IAT was reprogrammed so that time to error and correct responses were available. First, as assumed by the EZ-diffusion model, the SC-IAT response time data were positively skewed and the skew was greater in the block that most people took longer to respond and made more mistakes (skew in block with categories *physical activity/good* vs. *bad* = 0.77; skew in block with categories *good* vs. *physical activity/bad* = 0.86). Second, error response times were not significantly faster than correct responses, $t(61) = 0.54$, $d = .14$; $p = .59$, so the EZ-diffusion model assumption that errors occur at the same speed as correct responses was met. To test if there were a priori biases in attractiveness of the categories, the relative speed of correct and error responses of the different categories were compared. There were no a priori biases in the attractiveness of the categories in the SC-IAT block with categories *good* vs. *physical activity/bad*: $t(22) = 1.08$, $d = .44$; $p = .29$; however there were a priori biases in the attractiveness of the categories in the block of the SC-IAT with categories *physical activity/good* vs. *bad*: $t(13) = -2.54$, $d = -1.31$; $p = .02$. People were biased to respond to *physical activity/good*, as represented by their tendency to have smaller error response time ratios of *physical activity/good* responses than of *bad* responses. The assumption of no a priori biases was not fully met. As a result of this unmet assumption, the process components, in particular information processing efficiency, may be systematically underestimated.

Data analyses—The measurement models were compared using OpenMx (Boker et al., 2011) in R version 2.14.1 (R Core Team, 2013), which utilizes full information maximum likelihood estimation. Full-information maximum likelihood estimation has been shown to

be a robust modelling strategy, even with non-normal data (Enders & Bandalos, 2001; Enders, 2001). For each model, -2 log-likelihood, Bayesian Information Criterion (BIC), and χ^2 were calculated. The BIC and -2 log-likelihood value ratio tests were used to compare model fit (Fox, Byrnes, Boker, & Neale, 2012). A smaller BIC and -2 log-likelihood represent a better fitting model; however adding parameters will always improve model fit. The -2 log-likelihood value ratio test is an objective criterion for determining if the additional estimated parameters significantly improve model fit.

In the first set of model comparisons, the base model held that there were no latent factors (i.e., scores do not share variability). Fit of alternative models were compared to fit of the base model to test if any of the process component scores shared variability across distinct SC-IATs. Alternative models were tested with the information processing efficiency score from each test loaded onto a latent factor (Figure 1, Panel a), the response conservativeness score from each test loaded onto a latent factor (Figure 1, Panel b), and the non-decision processing scores from each test loaded onto a latent factor (Figure 1, Panel c). To determine if all the scores shared variability, an alternative model that held all nine scores loading onto a single latent factor was also tested (Figure 1, Panel d). Additionally, a model with three orthogonal latent factors representing the distinct SC-IATs (i.e., the process component scores of the physical activity SC-IAT loading onto one factor, the scores of the sedentary SC-IAT loading onto a second factor, and the scores of the flower SC-IAT loading onto a third factor) was tested (Figure 1, Panel e).

Given that the process component scores are calculated from the same response data, it is likely that they have common variability. A second set of model comparisons was conducted to test the hypotheses while accounting for this. The base model held that the process component scores from each distinct SC-IAT loaded onto a latent factor, resulting in three latent factors (Figure 1, Panel e). To test if the latent factors were related across tests, an alternative oblique three latent factor model was tested. Additionally, alternative models with an additional latent factor loaded with a process component score from the three distinct SC-IATs were tested. As an example, the alternative model with the information processing efficiency latent factor is presented in Figure 1, Panel f.

Results and Discussion

Table 1 presents descriptive statistics of the D-score and the process component scores. According to the sample means of the D-scores, people responded faster during the block when the construct was paired with *good* as a category than in the block when it was paired with *bad*. The positive values for process component score sample means also revealed that people were generally more efficient in information processing, less conservative in their responses, and spent less time in non-decision processing when the concept was paired with *good* than when it was paired with *bad*. As seen in Table 2, correlations were estimated between process component scores within and between SC-IATs assessing distinct evaluations. Within tests, the D-score was positively related to the information processing efficiency and response conservativeness scores, but not the non-decision processing time score. Across tests, the process component scores were unrelated.

The model with no latent factors ($-2LL = -4374.76$, $BIC = 72.49$, $\chi^2 = 240.03$, $p < .05$) fit better than any of the alternative models with a process component score from the distinct SC-IATs loading onto a latent factor ($BIC = 79.24 - 86.18$; $-2LL = 0.27 - 3.44$, p 's $> .05$). The alternative model with all scores loading onto a latent factor fit significantly better than the base model with no latent factors ($BIC = 70.72$; $-2LL = 43.65$, $p < .05$), suggesting that there is shared variability between all the scores. The model with the scores of each SC-IAT loading onto three separate latent factors fit even better, suggesting the shared variability is test-specific ($BIC = -59.80$; $-2LL = 174.17$, $p < .05$).

The best fitting model of the first set of model comparisons served as the base for the second set of model comparisons. This model ($-2LL = -4548.93$, $BIC = -59.80$, $\chi^2 = 65.85$, $p < .05$) had better fit than the oblique three-factor model ($BIC = -47.50$; $-2LL = 1.66$, $p > .05$), suggesting the three latent factors were not significantly related. The alternative models with the additional information processing efficiency score ($BIC = -51.91$; $-2LL = 6.07$, $p > .05$) and the non-decision processing time score latent factors ($BIC = -51.27$; $-2LL = 5.43$, $p > .05$) did not fit significantly better than the base model. These results suggest that these scores do not share variability across distinct SC-IATs after accounting for the shared test-specific variability. The alternative model with the additional response conservativeness score latent factor is shown in Figure 2. This model ($-2LL = -4561.19$, $BIC = -58.10$, $\chi^2 = 53.59$, $p < .05$) fit significantly better than the base model ($BIC = -58.10$; $-2LL = 12.26$, $p < .05$), suggesting that, after accounting for the shared test-specific variability, the response conservativeness score shared variability across distinct SC-IATs.

Overall, these results show that the information processing efficiency score does not share variability across distinct SC-IATs. Additionally, it was revealed that response conservativeness scores share variability across distinct SC-IATs. Given that the D-score was significantly, positively related to both the information processing efficiency and the response conservativeness score, there is a risk that the D-score is confounded with measurement artifact. It may be that the information processing efficiency score reflects less construct-irrelevant variability than the D-score. Study 2 was designed to further investigate construct validity the information processing efficiency score.

Study 2

Methods

Participants and procedure—The data used for the analyses are from a separate sample of university students whom agreed to permit their data from a class project to be used for research purposes ($N = 91$; 38 female; $M_{\text{age}} = 20$ years; 88% Caucasian). During an initial laboratory visit, participants completed a physical activity SC-IAT, self-reported their instrumental and affective attitudes toward physical activity, physical activity intentions, and were provided with an ActiGraph accelerometer (Actigraph, Pensacola, FL). Participants were instructed to wear the accelerometer on the midline of their right hip for all waking hours, excluding during water activities (e.g., swimming, showering). After two weeks, participants returned for a second lab visit and returned the accelerometers.

Measures

Physical Activity Single-Category Implicit Association Test—The physical activity SC-IAT reported in Study 1 was again used to measure automatic evaluations of physical activity. The SC-IAT data were scored using the D-score algorithm (Greenwald et al., 2003) and EZ-diffusion model algorithms (Wagenmakers et al., 2007). Outlier screening resulted in less than 1% trials being discarded. The Spearman-Brown corrected split-half reliability of the D-scores was .73.

Consciously-held attitudes toward physical activity—Participants self-reported their affective and instrumental attitudes toward physical activity using subscales used in previous research on the theory of planned behavior and physical activity (Rhodes, Blanchard, Matheson, & Coble, 2006). Participants were asked “how would regular physical activity over the next two weeks be?” using 0–100 visual analogue response scales. The affective attitudes items were anchored with *enjoyable* to *unenjoyable*, *pleasant* to *unpleasant*, and *exciting* to *boring*. The instrumental attitudes items were anchored with *useful* to *useless*, *wise* to *unwise*, and *beneficial* to *harmful*. Scores were calculated as the average of the reverse-scored items so that higher scores indicated more favorable evaluations toward physical activity (affective $\alpha = .79$; instrumental $\alpha = .89$). These scales of consciously-held attitudes toward physical activity have shown to be associated with adults’ physical activity motivation (Rhodes et al., 2006).

Intentions for physical activity—Intentions for physical activity were calculated as the mean response of four items ($\alpha = .93$) adapted (Dishman et al., 2002; Motl et al., 2002) to match the American national guideline recommendations (Physical Activity Guidelines Advisory Committee, 2008). Specifically, participants were presented with the items, “Over the next 2 weeks, I intend to engage in ...” (1) “at least 1 hour/day (60 min) of mild aerobic activity (e.g., walking),” (2) “at least 2.5 hours/week (150 min) of moderate aerobic activity,” (3) “at least 1.25 hours/week (75 min) of vigorous aerobic activity,” and (4) “moderate- or high-intensity muscle-strengthening activities involving all my major muscle groups on at least 2 days/week.” Participants rated each item on visual analogue scales ranging from 0 (*do not intend at all*) to 100 (*strongly intend*).

Physical activity—Physical activity was measured via activity count estimates from 2-weeks of accelerometer measurements. Any period of 90 minutes of consecutive zero activity counts and days that the accelerometer had less than ten hours with activity counts more than zero were treated as missing data (Choi, Liu, Matthews, & Buchowski, 2011). Total physical activity was calculated as the average activity counts per valid hours over the 13 days of data collection. This variable was log-transformed to normalize its distribution (before transformation: skew = 2.99, $SE = 0.21$; after transformation: skew = 0.25).

Results and Discussion

Table 3 presents descriptive statistics for, and correlations among, the study variables. The average D-score showed that people responded faster during the block when *physical activity* was paired with *good* as a category than in the block when it was paired with *bad*. People also tended to be more efficient in information processing, were less conservative in

their responses, and spent less time in non-decision processing when *physical activity* was paired with *good* in a response category than when it was paired with *bad*. Consciously-held affective and instrumental attitudes toward physical activity and physical activity intentions were unrelated to the D-score and the process component scores. People were more physically active if they had strong intentions for physical activity and were more efficient in processing information during the block with *physical activity/good* vs. *bad* categories than during the block with *good* vs. *physical activity/bad* categories.

To test if the information processing score of the physical activity SC-IAT was distinct from consciously-held attitudes toward physical activity, affective and instrumental attitudes were regressed onto the information processing efficiency, response conservativeness, and non-decision processing time scores. Table 4 shows that none of the scores significantly related to consciously-held affective or instrumental attitudes. Thus, the process component scores of the physical activity SC-IAT had little, if any, overlap with consciously-held attitudes toward physical activity.

To test if the process component scores related to physical activity after accounting for intentions, physical activity was regressed onto intentions and the three process component scores. By including intentions as a predictor in the model, the effects of the scores represent the shared variability with physical activity that is unexplained by intentions (Conroy et al., 2010). Table 4 shows that intentions positively related to physical activity, and that the information processing efficiency score positively related to variability in physical activity that was not accounted for by intentions. People who processed information more efficiently when categorizing *physical activity* with *good* relative to *bad* in the SC-IAT engaged in more physical activity across the next two weeks. Neither response conservativeness nor non-decision processing time scores significantly related to physical activity.

In a follow-up analysis, the same model was tested with the D-score included as an additional predictor. The model was also significant. The results revealed that the information processing efficiency score ($b = 0.18$, $SE = 0.08$, $p < .05$), but not the D-score ($b = -0.24$, $SE = 0.19$, $p > .05$), significantly positively related to physical activity after controlling for intentions ($R^2 = 0.20$, $F(5,83) = 4.13$, $p < .01$). These results lead to the conclusion that the information processing efficiency score of a physical activity SC-IAT may have greater construct validity as a measure of automatic evaluations than the traditional D-score.

General Discussion

Two studies were conducted to test construct validity of the information processing efficiency score as a measure of automatic evaluations of physical activity. Results of study 1 revealed that the information processing efficiency score did not share significant variability across distinct SC-IATs. Results of study 2 showed that the score was independent from consciously-held attitudes toward physical activity and positively related to prospective objectively-measured physical activity, above and beyond the traditional D-score. It may be that calculating process component scores of SC-IAT responses with the EZ-diffusion model separates true score variability from construct-irrelevant variability.

Previous research suggests that there is shared measurement artifact across the D-score and the response conservativeness score of IATs (Back et al., 2005; Klauer et al., 2007; McFarland & Crouch, 2002; Mierke & Klauer, 2003). The results of the present study 1 support these previous findings, showing that the response conservativeness score was positively related across distinct SC-IATs, after accounting for shared variability of SC-IAT process component scores. As such, it seems likely that the variability separated into the response conservativeness score includes measurement artifact. The process-component scores were calculated based on the same response time data, so it is not surprising that the distinct SC-IATs each loaded onto a latent factor. Importantly, common variability between indicators does not necessarily reflect an underlying construct free of measurement artifact (DeShon, 1998). The latent factor may also reflect shared construct-irrelevant variability or even a distinct construct. Further validity testing is necessary to establish the meaning of this shared variability. To our knowledge, this was the first study to investigate the shared variability between process component scores of an SC-IAT. Study 1 provides evidence that the information processing efficiency score is separate from conceptually unrelated tests, supporting construct validity of the score as a measure of automatic evaluations of physical activity.

The results of study 2 further supported construct validity of the information processing efficiency score. That the information processing efficiency score was unrelated to consciously-held attitudes toward physical activity converges with previous research indicating that automatic evaluations of physical activity (as measured with the D-score) were distinct from consciously-held attitudes toward physical activity (Hyde et al., 2010). In contrast to these results, Klauer and colleagues (2007) found that the information processing efficiency score of a political IAT related to consciously-held political attitudes. Automatic evaluations and consciously-held attitudes are strongly related for concepts, such as politics, that are deliberated often and perceived as important (Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005; Hofmann, Gschwendner, Nosek, & Schmitt, 2005). It cannot be ruled out that performance on SC-IATs reflects consciously-held attitudes, but, in support of construct validity, the results suggest that consciously-held attitudes toward physical activity are not captured by the information processing efficiency score.

Also in study 2, it was found that people who were more efficient in information processing when *physical activity* shared a response category with *good* than with *bad* subsequently participated in more physical activity over the next two weeks, even after accounting for the variability in physical activity explained by intentions. Favorable automatic evaluations of physical activity would be expected to lead to approach behavioral responses to physical activity stimuli (Chen & Bargh, 1999), and previous studies found relations between automatic evaluations (measured via D-score of SC-IAT) and physical activity (Conroy et al., 2010; Hyde et al., 2012). It may be that these previous findings underestimated relations between automatic evaluations on physical activity because they used the D-score scoring method.

The D-score was related to the information processing efficiency score; however it was also related to the response conservativeness score. Only the information processing efficiency score was shown to relate to physical activity and it positively related to physical activity

above and beyond the D-score. In contrast, response conservativeness was shown to reflect measurement artifact. It may be that the D-score confounds automatic evaluations with construct-irrelevant variability, thereby underestimating the strength of the relation between automatic evaluations and behavior. The information processing efficiency score may be a more valid measure of automatic evaluations, and utilization of this score may reduce the risk for incorrect inferences about non-conscious processes.

Limitations & Conclusions

There are important limitations of these two studies that should be addressed in future research. The samples in these studies were mostly healthy, Caucasian, young adults so conclusions may not generalize to broader populations. The studies were only powered to detect medium-sized effects, so it cannot be ruled out that the information processing efficiency score captures a small amount of measurement artifact or consciously-held attitudes. It can only be concluded that the score is not primarily an indication of these forms of construct-irrelevant variability.

To partition the SC-IAT into process component scores, a simplified version of the diffusion model was used. This EZ-diffusion model is useful for estimating the score of interest for these studies, but the unmet assumption of the model in this study (i.e., that there were no a priori response biases) may have led to slight misspecifications, including an underestimation of information processing efficiency (Ratcliff, 2008; Wagenmakers et al., 2007). It may be that this construct-irrelevant variability contained in the information processing efficiency score led to underestimated associations with attitudes and behavior. Estimating information processing with the full diffusion model would likely result in a more precise score (Ratcliff & Rouder, 1998). The EZ-diffusion model provides a parsimonious way to separate SC-IAT response accuracy and times into theoretically-meaningful process component scores without the requirement of high error rates or intensive model estimations. Alternative techniques for decomposing physical activity SC-IAT data such as a quad model of implicit task performance, a linear ballistic accumulation model, or a two-stage dynamic signal detection model may also be able to further disentangle physical activity SC-IAT processes (Brown & Heathcote, 2008; Calanchini & Sherman, 2013; Conrey et al., 2005; Pleskac & Busemeyer, 2010)

Given that the process component scores were calculated as differences between the two SC-IAT test blocks, there is a risk of inflated scaling when the two scores do not show multivariate normality (Delmail, 2009). In the present studies, the scores used to calculate the information processing efficiency score showed multivariate normality, so there is minimal risk of inflated scaling. The scores used to calculate the response conservativeness and non-decision processing time scores did not show multivariate normality; therefore there is a risk that the relations between these scores and other study variables were underestimated.

The second study demonstrated that the information processing efficiency score was not equivalent to consciously-held attitudes toward physical activity. Future research should extend this nomological network to include other evidence of both convergent and discriminant validity in relation to constructs including affective responses to physical

activity (Rudman, 2004), self-concepts (Greenwald & Farnham, 2000), and executive control (Klauer, Schmitz, Teige-Mocigemba, & Voss, 2010). Additionally, there is yet to be a gold standard criterion of automatic evaluations. We proposed that automatic evaluations of physical activity should predict physical activity after accounting for intentions, but it will be important to test convergent validity of the information processing efficiency score with other theory-driven criteria.

Automatic evaluations impact the way people attend to, perceive, and process information about opportunities to engage in physical activity (Lowe & Norman, 2013). As research investigating how automatic evaluations influence physical activity behavior continues to develop, important consideration is needed for what these measurement scores truly reflect. It is becoming increasingly clear that IAT scores reflect construct-relevant automatic associative processes and construct-irrelevant variability from conscious processes (Calanchini & Sherman, 2013). These studies demonstrated that the EZ-diffusion model can be applied to physical activity SC-IATs to separate construct-irrelevant variability from the resultant score representative of automatic evaluations. By doing so, this novel scoring technique reduces the risk that misleading or inaccurate conclusions are made about the influence of automatic evaluations on physical activity.

In conclusion, these studies demonstrated that the information processing efficiency score may be applied to physical activity SC-IATs to reduce construct-irrelevant variability and improve validity of automatic evaluations. Additionally, it may be that the information processing efficiency score can be valuable for understanding the mechanisms and dynamics of automatic evaluations of physical activity, given that valid measures allow for more sensitivity in the detection of score change. Utilizing this score may provide for more precision when determining how much of an impact automatic evaluations of physical activity have on physical activity-related cognition, affect, or behavior.

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- We use the EZ-diffusion model to score a single-category implicit association test
- The new score does not represent measurement artifact
- The new score is distinct from controlled evaluations of physical activity
- The new score relates to unintentional physical activity more so than the D-score
- This novel score is a valid measure of automatic evaluations of physical activity

Figure 1.

Study 1: The Alternative Models Testing Whether the Process Component Scores (IPE = Information Processing Efficiency, RC = Response Conservativeness, NDP = Non-Decision Processing Time) Shared Variability across the Physical Activity (PA), Sedentary (SB), and Flower (FL) Single-Category Implicit Association Tests.

Figure 2.

Study 1: Unstandardized Parameter Estimates of Final Measurement Model with Three Latent Orthogonal Factors (Physical Activity, Sedentary Behavior, and Flower) and an Additional Response Conservativeness Latent Factor. IPE = Information Processing Efficiency, RC = Response Conservativeness, NDP = Non-Decision Processing Time, PA = Physical Activity, SB = Sedentary Behavior, FL = Flower.

Study 1: Descriptive Statistics of D-Score and the Process Component Scores for Physical Activity, Sedentary, and Flower Single-Category Association Tests

Table 1

	<i>N</i>	D-score	Information processing efficiency	Response conservativeness	Non-decision processing time
Physical activity	104	0.52 (0.57)	0.52 (0.70)	0.05 (0.40)	0.04 (0.07)
Sedentary	104	0.25 (0.54)	0.29 (0.66)	0.09 (0.44)	0.004 (0.07)
Flower	79	0.43 (0.51)	0.41 (0.62)	0.15 (0.31)	0.02 (0.07)

Note. Sample mean with standard deviation in parentheses.

* $p < .05$

Study 1: Correlations between the D-Score and Process Component Scores of the Physical Activity Single-Category Association Test with those of the Physical Activity, Sedentary, and Flower Single-Category Association Tests

Table 2

	Physical activity				Sedentary				Flower			
	1.	2.	3.	4.	1.	2.	3.	4.	1.	2.	3.	4.
Physical activity												
1. D-score	--	.71*	.69*	.08	.07	.07	.02	.08	.20	.00	.01	.24*
2. Information processing efficiency		--	.43*	-.20*	-.02	.06	-.10	.10	.17	.17	.02	.13
3. Response conservativeness			--	-.36*	.01	.07	-.04	.01	.12	-.05	-.02	.20
4. Non-decision processing time				--	.13	-.01	.29*	.08	-.02	-.08	.12	-.06

Note.

* $p < .05$

Study 2: Descriptive Statistics and Correlations of Consciously-Held Attitudes, Intentions, Physical Activity, D-score, and Process Component Scores

Table 3

	<i>M</i>	<i>SD</i>	2.	3.	4.	5.	6.	7.	8.
1. Consciously-held affective attitudes	81.99	18.37	.36*	.04	-.03	.06	.08	.13	-.13
2. Consciously-held instrumental attitudes	84.86	20.22	--	.13	-.05	-.16	-.17	-.17	.00
3. Intentions	75.04	22.12		--	.36*	.13	.06	.07	-.02
4. Physical activity	10.23	0.28			--	.12	.25*	.05	-.05
5. D-score	0.89	0.51				--	.69*	.59*	.25*
6. Information processing efficiency	0.94	0.72					--	.29*	-.04
7. Response conservativeness	0.20	0.32						--	-.46*
8. Non-decision processing time	0.03	0.05							--

Note.

* $p < .05$

Table 4

Study 2: Multiple Regression Estimates of Process Component Scores Predicting Consciously-Held Attitudes toward Physical Activity and Physical Activity

	Consciously-held affective attitudes toward physical activity			Consciously-held instrumental attitudes toward physical activity			Physical activity behavior (Log-transformed)		
	β	b	SE	β	b	SE	β	b	SE
Intercept	--	80.86*	3.67	--	91.18*	3.99	--	9.84*	0.10
Information processing efficiency	0.05	1.36	2.85	-0.12	-3.32	3.10	0.24*	0.09*	0.04
Response conservativeness	0.07	4.22	7.21	-0.17	-10.95	7.84	-0.08	-0.07	0.10
Non-decision processing time	-0.09	-31.13	41.75	-0.08	-30.14	45.40	-0.06	-0.32	0.58
Physical activity intentions	--	--	--	--	--	--	0.34*	0.00*	0.00

Note. Consciously-held affective attitudes toward physical activity: Adj. $R^2 = -0.01$, $F(3,87) = 0.74$, $p = .53$; Consciously-held instrumental attitudes toward physical activity: Adj. $R^2 = 0.02$, $F(3,87) = 1.49$, $p = .22$; Physical activity behavior (log-transformed): Adj. $R^2 = 0.14$, $F(4, 84) = 4.72$, $p < .01$.