The Physical Activity Regulation Scale: Development and validity testing

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The Physical Activity Regulation Scale (PARS): Development and Validity Testing

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Abstract

Objective: Behavioral regulation tactics used to manage actions after the formation of a physical activity (PA) intention are common to many theories, yet comprehensive measures of PA regulation are scant. **Purpose**: To develop a reliable instrument of PA regulation and test predictive validity and its capacity to mediate the intention-PA relationship. **Methods:** To achieve a pool of candidate items, we used the behavior change technique taxonomy as a template, followed by a critical literature review of PA regulation measures to extract exemplar items, and then concluded with a Delphi feedback method (*N*=4). The main study included a sample representative of the Canadian adult population to explore and then confirm the construct and discriminant validity, and internal consistency reliability of the measure using two independent samples (*N*=683 and *N*=727). Finally, using a two-week prospective design, the full sample was used to investigate test re-test reliability, and predictive validity of self-reported PA at Time 2. **Results:** Exploratory and confirmatory factor analyses resulted in a reliable 14-item, four-factor measure (internal consistencies >.80) of 1) proactive regulation, 2) reactive regulation, 3) social monitoring, and 4) self-monitoring, we named the Physical Activity Regulation Scale (PARS). The PARS factors explained 18% of PA at Time 2, and mediated the relationship between intention and PA. **Conclusion:** While continued testing is needed, the initial evidence is supportive that the PARS may be a useful PA behavioral regulation measure to include for use within various theoretical models applied to understand PA.

Key Words: Self-Monitoring; Planning; Emotion Regulation; Exercise; Adults

The health benefits of physical activity (PA) are well-established (Rhodes et al., 2017; Warburton & Bredin, 2017). In particular, moderate to vigorous intensity aerobic PA, performed 150 minutes or more per week is linked to the reduced odds of over 25 chronic health conditions with relative risk reduction between 20 and 40 percent (Warburton & Bredin, 2017). Despite long-standing general public knowledge of these benefits (Martin et al., 2000), many adults do not engage in this recommended level of PA (Guthold et al., 2018). Clearly, effective PA promotion efforts are needed.

An understanding of the determinants behind PA to improve the effectiveness of promotion has been a longstanding line of research inquiry for over half a century (Rhodes, McEwan, et al., 2019). Motivational theories that focus on expectations of behavioral outcomes (Connell Bohlen et al., 2021) or needs fulfilment (Teixeira et al., 2012) have established efficacy in predicting PA. Furthermore, experimental research has demonstrated that interventions targeting these motivational constructs can produce changes in PA over time (Gourlan et al., 2016; Rhodes, Boudreau, et al., 2021). Despite the impact of these theoretical constructs on PA, most PA promotion approaches also acknowledge that behavioral enactment involves self-regulation against the backdrop of barriers to action, competing goals, or automatic tendencies that direct action away from PA (Hagger et al., 2016; Mann et al., 2013; Rhodes, 2021).

Self-regulation is a broad term that encompasses dynamic internal and contextual processes of taking action to move toward an end state (Bandura, 1991; Karoly, 1992). Thus, self-regulation is an umbrella term that encompasses many domains of psychology and has engendered broad and diverse theories, from cybernetics (Carver & Scheier, 1982), to dual-process models (Hofmann et al., 2009), and trait explanations (Roberts et al., 2014) to resources of self-control (Baumeister et al., 2007). All self-regulation approaches, however, attempt to explain how affect, cognition, and behavioral sub-processes contribute to the achievement of the desired end state (see Inzlicht et al., 2021 for a comprehensive review).

Because PA promotion specifically pertains to behavioral performance, theoretical approaches that are concentrated on behavioral regulation, specifically, managing or changing behavioral actions (Cane et al., 2012), are often a primary focus of researchers in this domain. Furthermore, the most common approach to understand behavioral regulation in PA has been through the lens of specific tactics that can be employed by a person to achieve an intended action (Bagozzi, 1992; Knittle et al., 2020; Mann et al., 2013; Michie et al., 2009). These approaches are the hallmark constructs of action control theories, that focus on bridging the intention-behavior gap (see Rhodes & Yao, 2015 for a review). For example, in the transtheoretical model (Prochaska & Velicer, 1997), behavioral processes of change represent five categories of behavioral regulation tactics (i.e., helping relationships, counterconditioning, stimulus control, self-liberation, and contingency management) to enable change from decision to behavioral action. In the health adoption process approach (Schwarzer, 2008), coping (back-up plans) and action planning (detailed contextual plans) represent key behavioral regulation tactics to move from intention to behavioral enactment. Similar to action planning, implementation intentions involve detailed, contextual “if-then” plans to build a mental link between a cue and a behavioral response (Gollwitzer & Brandstatter, 1997; Hagger et al., 2016). In control theory (Carver & Scheier, 1982, 1998), a goal and subsequent behavioral performance is regulated through a continuous feedback loop from a comparator and a monitoring system.

Overall, reviews of observational and experimental research of the behavioral regulation variables in these aforementioned theories have established their importance in predicting and changing PA (e.g., Carraro & Gaudreau, 2013; Knittle et al., 2018; Michie et al., 2009; Rhodes, La, et al., 2021; Zhang et al., 2019). For example, aggregates of the behavioral processes of change variables predict the intention-behavior gap (Rhodes & Plotnikoff, 2006; Rhodes et al., 2008), action planning and/or implementation intentions have a substantive evidence base in predicting and changing PA (da Silva et al., 2018; Hagger & Luszczynska, 2014; Rhodes et al., 2020; Zhang et al., 2019), and self-monitoring is one of the most established markers of physical activity intervention success, particularly when combined with any other behavioral regulation variable (Knittle et al., 2018; Michie et al., 2009).

Despite the clear importance of behavioral regulation in the PA domain, there have been some potential shortcomings in its application and conceptualization that warrant continued research. First, the breadth of behavioral regulation tactics has not been addressed thoroughly. For example, most of the behavioral regulation tactics applied in PA are intra-personal in nature (self-monitoring, individual planning). It may be of utility to explore tactics that involve social variables in behavioral regulation, which foster a sense of commitment through the inclusion of others in the behavioral enactment process (Beauchamp & Rhodes, 2020). Social variables are frequently applied as antecedents of intentions and goals (Deci & Ryan, 2000; Fishbein & Ajzen, 2010), yet there is some evidence to suggest they can also be important to behavioral regulation (Beauchamp, 2019; Kulis et al., 2022). In addition, most of the behavioral regulation tactics applied in theories prominent in the physical activity domain have tended to involve prospective, proactive tactics (formulated before the behavioral performance situation), that are used to select one behavioral option over another, prioritize that option, and pre-emptively modify the circumstances for that option to organize a behavioral response as a later point. For example, action planning typically involves pre-emptive organization of the circumstances and situation (when, where, what, how, etc.) of a behavioral performance to increase the likelihood of following through on intentions (Hagger & Luszczynska, 2014; Rhodes et al., 2020). Recent research in physical activity, however, has increased its emphasis on dynamic, situational influences of behavior (Ruissen et al., 2021). For example, affect incidental to behavior yet present at the time of performance has been linked to PA (Liao et al., 2015; Ruissen et al., 2022). It would therefore seem that intra-psychic tactics such as emotion regulation, that encompass approaches to direct one's focus to behavioral performance in times of challenge (i.e., tactics enacted at the point of behavioral performance) (Braver, 2012; Duckworth et al., 2016; Hofmann & Kotabe, 2012; Inzlicht et al., 2021) may be a critical addition to these prospective tactics. Recent research applying acceptance and commitment therapy approaches to PA intervention have also supported using these reactive behavioral regulation tactics (Pears & Sutton, 2021). Of course, some behavioral regulation tactics may include proactive and reactive elements, but additional item content in behavioral regulation measures that accounts for reactive tactics may hold utility to broaden measure representation.

Second, from a more pragmatic perspective, there are relatively few measures of behavioral regulation in PA for researchers to employ (e.g., Marcus et al., 1992; Petosa, 1993; Sniehotta, Schwarzer, et al., 2005; Umstattd et al., 2009). Some of these sources were created for the specific applied study, others have not been published in peer-reviewed literature (making it hard to find and perhaps not subject to quality control), and others were created for specific populations (e.g., cardiac patients or older adults). It stands to reason that a behavioral regulation measure developed for the general population of adults and formally tested with reliability and validity approaches would help to complement this sparse measurement landscape.

With these limitations in mind, the purpose of this paper was to develop and test a behavioral regulation measure of PA. Specifically, we sought to develop an instrument for the different purposes that behavioral regulation may take within various theoretical models of PA. To achieve breadth in the selection of behavioral regulation tactics, the behavior change technique (BCT) taxonomy by Michie and colleagues (2013) was used as a template. This taxonomy includes 93 BCTs (considered the irreducible, active component of an intervention) extracted from six classification systems, using a Delphi exercise of 14 experts in behavior change, followed by a sorting task conducted by an additional 18 experts to create the final taxonomy (Michie et al., 2013). The BCT taxonomy is one of the great advancements in recent years to represent the broad array of different approaches to change behavior and it can assist in creating boundary conditions of the types of tactics that could be considered in behavioral regulation models (Connell et al., 2019).

We hypothesized that a small number of correlated, yet empirically distinct factors would be extracted from exploratory factor analysis (to explore the underlying factor structure), followed by confirmatory factor analysis (to verify the factor structure found in the exploratory factor analysis) procedures using independent samples. Further, we expected 1) that these factors would significantly predict physical activity with independent contributions to this prediction equation and 2) mediate the relationship between intention and behavior as theorized in action control approaches (Rhodes & Yao, 2015). Because the purpose of the study was to explore the factor structure of behavioral regulation tactics, we had no specific a priori hypotheses about the exact factors that would be extracted from these analyses. However, we expected that some representation of proactive (formulated before behavioral enactment) and reactive (enacted at the point of behavioral enactment) tactics would be generated in these analyses.

Method

Sample and Design

This study was conducted on SurveyMonkey, and there were two measurement time points. The first survey ran from August 17-20, 2020. Participants were invited by a market research firm which has a database of approximately 120,000 Canadian panelists. The panel is representative of the Canadian adult population regarding various demographic variables. We requested an adult sample that is similar to the population in terms of age, gender, and regional density (Statistics Canada, 2019). Participants who completed the first survey were invited by the same firm to complete the second survey two weeks later. The second survey was completed September 3-8, 2020. We chose to launch the surveys during this time period because COVID-19 pandemic lockdown measures (e.g., gym closures) in Canada had been temporarily lifted. Therefore, perceptions of PA intentions, self-regulation, and behavior would have been closer to normal. All participants also provided informed consent and the study was approved by The University of Victoria's research ethics board. Some data from this research (intentions and PA) were analyzed as part of a previous project (Lithopoulos et al., in press). However, the research aims differ because the previous project was unrelated to self-regulation.

Self-Regulation Measure Development

Based on the BCT taxonomy (Michie et al., 2013), BCTs relating to behavioral regulation were identified by the project team through discussion. Behavioral regulation was considered tactics applied to directly manage or change PA actions, presumably after an intention has been formed (Cane et al., 2012; Rhodes & Yao, 2015). Specifically, we focused on BCTs that would conceivably assist in managing and improving the chances of behavioral action among individuals who already intend to engage in the behavior (e.g., Duckworth et al., 2016; Rhodes & Yao, 2015; Schwarzer, 2008; Sheeran & Webb, 2016). The final list of BCTs, corresponding with the numbers in the Michie et al. (2013) taxonomy, is as follows: problem solving 1.2; action planning 1.4; review of behavior goals 1.5; discrepancy between current behavior and goal 1.6; behavioral contract 1.8; commitment 1.9; feedback on behavior 2.2; self-monitoring of behavior 2.3; prompts/cues 7.1; self-incentive 10.7 (later removed because of similarity to self-reward 10.9); self-reward 10.9; reduce negative emotions 11.2; restructuring the physical environment 12.1; restructuring the social environment 12.2; avoidance/reducing exposure to cues for the behavior 12.3; and distraction 12.4 (later removed because of overlap with 12.3).

A literature review was then conducted to locate self-regulation measures in the PA domain related to each identified BCT to create a pool of candidate items. We used a critical review methodology to guide the literature review. A critical review is not systematic but instead seeks to identify the most significant items in a field to develop theory (Grant & Booth, 2009). The review identified the seven measures previously noted (de Bruin et al., 2012; Marcus et al., 1992; Petosa, 1993; Plotnikoff et al., 2001; Sniehotta, Scholz, et al., 2005; Sniehotta, Schwarzer, et al., 2005; Umstattd et al., 2009) and an emotion regulation measure pertinent to BCT 11.2 (Bjureberg et al., 2016). Items were created by the study team if suitable measures could not be located.

After a pool of items had been created, four members of the study team independently participated in a Delphi-type process involving scoring and feedback for each item. The Delphi process involves two or more rounds of scoring among a pool of domain experts, where the range of the scores decrease across the rounds as the group is expected to converge towards a consensus. For round one, the researchers received a table with each BCT definition, associated items, an area to provide content validity index scoring (i.e., 1 = not relevant, 2 = somewhat relevant, 3 = quite relevant, 4 = highly relevant; Polit et al., 2007), and they also provided written feedback in the margins (see Supplementary Material 1). It was decided that a minimum of

3.25/4 (81.25%) as an average across the raters was necessary for an item to be retained without change. The full results of the three-round Delphi process can be viewed in Supplementary Material 2, and the final measures to result from the Delphi process can be viewed in Supplementary Material 3. It is also important to note that the original scoring scale presented to the researchers for each self-regulation item was: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree. The scale was later expanded to seven points to improve reliability and validity (Lozano et al., 2008). Therefore, the final scale later used in the two surveys was: 1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, 7 = strongly agree.

Other Measures

This study also measured intentions to engage in regular moderate to vigorous aerobic PA (Ross et al., 2020) at the Time 1 survey using three items that were scored on a seven-point scale that ranged from strongly disagree to strongly agree. The intention items were adapted from Rhodes and Courneya (2004), and had the following internal consistency reliability: Cronbach's $\alpha = .97$, McDonald's $\omega = .97$. Moderate to vigorous aerobic PA was also measured at Time 2 using an adapted version of the Godin Leisure-Time Exercise Questionnaire (Godin et al., 1986). Frequency per week was multiplied by duration for both moderate and vigorous PA and then the totals were summed. This method has been used in many previous studies (e.g., Jones et al., 2004). The full measures can be viewed in Supplementary Material 4.

Data Preparation and Analysis

The data were prepared using SPSS version 24. Any extreme outliers were removed (values more than three times less or greater than the middle 50%; Pallant, 2011). Also, a missing value analysis was conducted including Time 1 intentions, Time 1 and Time 2 self-regulation items, and Time 2 aerobic moderate to vigorous PA. The full sample was divided into two random samples of approximately equal size for exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) using self-regulation items. The purpose of dividing the full sample to two random samples is to explore the underlying factor structure using EFA and then verify the factor structure (identified in EFA) by CFA. The randomization makes the two subsets comparable. EFA was conducted in SPSS using sample 1. The process was iterative using principal axis factoring and oblique rotation (promax method for large samples). To determine the number of factors, eigenvalue (values greater than 1) and scree plot examination was done (Tabachnick & Fidell, 2012). Items with poor loadings (less than .40) or cross-loadings on multiple factors were removed (Howard, 2016).

Using sample 2, CFA was conducted using JAMOVI version 2.0.0 to verify the factor structure identified with sample 1. The first indicator variable for each factor was fixed to 1 to set the scale (Schumacker & Lomax, 2010). Items that did not significantly load onto one of the factors in the positive direction, or items that had large standardized residuals with the other items (greater than 3.29) were to be removed (Schumacker & Lomax, 2010). The following fit indices were also used to evaluate how the model fit the data: χ^2 (non-significant value), SRMR (.05 or lower), CFI (.95 or higher), TLI (.95 or higher), and RMSEA (.08 or lower; Hu & Bentler, 1999; Schumacker & Lomax, 2010). Discriminant validity was assessed using the average variance extracted (AVE) technique (Carter, 2016). Full information maximum likelihood was selected to handle missing data for the CFA (Allison, 2003). Internal consistency reliability was evaluated using Cronbach's α and McDonald's ω. Stability over time was tested by calculating intraclass correlation coefficients (ICC) between Time 1 and Time 2 for self-regulation factors generated from the CFA at the scale level (average of the items for each factor). Two-way mixed effects models with absolute agreement were estimated using average measures. Values less than .5 demonstrate poor reliability, values between .5 and .75 demonstrate moderate reliability, values between .75 and .9 demonstrate good reliability, and values higher than .9 indicate excellent reliability (Koo & Li, 2016). Latent correlations over time for each factor were also estimated using CFA, and potential change over time in mean values for each factor was tested using repeated measures ANOVA.

Predictive or nomological validity was assessed using structural equation modeling (SEM) using JAMOVI, and diagonally weighted least squares was used as the estimation technique. This technique was used to mainly handle the non-normal, highly variable PA data at Time 2. The first indicator variable for each factor was fixed to 1 to set the scale (Schumacker & Lomax, 2010). The first model tested whether the Time 1 self-regulation factors extracted from CFA can predict moderate to vigorous aerobic PA collected at Time 2. The second model tested the robustness of the first by exploring whether a formative self-regulation scale (i.e., single factor) more effectively predicted PA than the multiple factor self-regulation measure (Petter et al., 2007). This test was done by constraining each self-regulation factor path to PA as equal, and each factor variance was fixed to 1 (e.g., Rhodes et al., 2006). The third and final model tested indirect effects between intentions at Time 1 and PA at Time 2 through self-regulation factors at Time 2. This model tests a key hypothesis of action control theories, namely that self-regulatory factors bridge intention and behavior (Rhodes & Yao, 2015). Per guidelines provided by Cohen (1988), small, medium, and large effect sizes were interpreted when R^2 was greater than or equal to .02, .13, and .26, respectively.

Results

The full sample (N = 1,410) had a mean age in years of 46.85 (SD = 15.95). See Table 1 for more demographic information. Also, 1,143 of the original 1,410 participants completed

Time 2 (81% retention). Regarding outliers, there were 24 outliers that were removed for Time 2 aerobic moderate to vigorous physical activity (original skewness = 6.36, original kurtosis = 71.15; final skewness = 1.62, final kurtosis = 2.55). Little's missing completely at random (MCAR) test also produced a non-significant result: $\chi^2 = 162.73$, df = 147, $p = .18$.

Exploratory Factor Analysis

Sample 1 had 683 participants. After removing non-loading items and cross-loading items, the EFA was acceptable. This EFA showed four factors on the scree plot with eigenvalues ranging from 1.49-11.06. At this stage, factor 1 (proactive regulation; 46.06% variance explained) was composed of 7 items relating to the BCTs of problem solving (1.2) and action planning (1.4). Factor 2 (reactive regulation; 10.10% variance explained) was composed of 8 items including: review of behavior goals (1.5) item 3 (see Supplementary Material 3 for the final measures from the Delphi process), the three reduce negative emotion (11.2) items, restructuring the physical environment (12.1) item 1, and the three avoidance/reducing exposure to cues for the behavior (12.3) items. Factor 3 (social monitoring; 6.74% variance explained) was composed of 6 items including: behavioral contract (1.8) item 3, feedback on behavior (2.2) items 2 and 3, prompts/cues (7.1) item 3, and restructuring the social environment (12.2) items 1 and 3. Factor 4 (self-monitoring; 6.19% variance explained) was composed of the three self-monitoring of behavior (2.3) items. Internal consistency reliability estimates are as follows: proactive regulation: Cronbach's α = .96, McDonald's ω = .96; reactive regulation: Cronbach's α = .87, McDonald's ω = .88; social monitoring: Cronbach's α = .80, McDonald's ω = .82; self-monitoring: Cronbach's α = .90, McDonald's ω = .90.

Confirmatory Factor Analysis and Stability Over Time

There were 727 participants in sample 2. After the removal of problematic items (e.g., had large standardized residuals with the other items), the CFA was acceptable and generally confirmed the factor structure observed during the EFA phase. However, restructuring the physical environment (12.1) item 1 was later removed because it did not fit theoretically with the other items in the reactive regulation factor (i.e., the item is an indicator of proactive regulation). Therefore, a final CFA was conducted excluding this item.

The final items, standardized factor loadings, and error variances can be found in Table 2. Fit indices for this model are: $\chi^2 = 248.00$ (df = 71), $p < .001$, SRMR = .04, CFI = .98, TLI = .97, and RMSEA = .06 (90% CI = .05-.07). This information demonstrates the model fits the data well. Discriminant validity was also supported because the AVE for each factor was larger than its shared variance with any other factor. The factor AVEs are as follows: proactive regulation = .86; reactive regulation = .70; social monitoring = .63; self-monitoring = .74. The factor correlations (and shared variances) are as follows: proactive regulation and reactive regulation = .63 (.40); proactive regulation and social monitoring = .38 (.14); proactive regulation and self-monitoring = .59 (.35); reactive regulation and social monitoring = .37 (.14); reactive regulation and self-monitoring = .65 (.42); social monitoring and self-monitoring = .45 (.20). Internal consistency reliability estimates are as follows: proactive regulation: Cronbach's $\alpha = .96$, McDonald's $\omega = .96$; reactive regulation: Cronbach's $\alpha = .89$, McDonald's $\omega = .90$; social monitoring: Cronbach's $\alpha = .82$, McDonald's $\omega = .83$; self-monitoring: Cronbach's $\alpha = .90$, McDonald's $\omega = .90$.

Regarding stability over time, the ICC for proactive regulation was .81 (95% CI = .78-.84) (latent correlation between Time 1 and Time 2 = .71), the ICC for reactive regulation was .85 (95% CI = .84-.87) (latent correlation between Time 1 and Time 2 = .80), the ICC for social monitoring was .81 (95% CI = .79-.83) (latent correlation between Time 1 and Time 2 = .73), and the ICC for self-monitoring was .88 (95% CI = .86-.89) (latent correlation between Time 1 and Time 2 = .85). Proactive regulation decreased between Time 1 and Time 2, reactive regulation increased slightly between Time 1 and Time 2, social monitoring remained stable between Time 1 and Time 2, self-monitoring remained stable between Time 1 and Time 2 (see Table 1 of Supplementary Material 5 for full ANOVA information).

Structural Equation Modeling

For model 1 (i.e., Time 1 self-regulation predicting Time 2 aerobic moderate to vigorous PA), the fit indices were: $\chi^2 = 105.00$ (df = 81), $p = .04$, SRMR = .03, CFI = .99, TLI = .99, and RMSEA = .02 (90% CI = .004-.025). Thus, the available information suggests the model fits the data well. The paths from self-regulation proactive regulation ($\beta = .19$), reactive regulation ($\beta = .18$), social monitoring ($\beta = -.20$), and self-monitoring ($\beta = .19$) were all significantly related to PA (*p*s < .001), and, together, these four constructs explained 18% of the variance in the outcome (medium effect size). For model 2 (i.e., formative scale versus the multiple factor measure), each self-regulation factor path to PA was constrained as equal to explore whether a formative self-regulation scale (i.e., single factor) more effectively predicted PA than the multiple factor measure (Petter et al., 2007). This model confirmed the robustness of the first model (i.e., the four factor measure) by demonstrating that the second model was significantly worse than the first model ($\chi^2 = 94.10$, df = 6, $p < .001$, $R^2 = .12$).

For model 3 (i.e., Time 1 intentions predicting Time 2 self-regulation, which predicts Time 2 moderate to vigorous aerobic PA), the fit indices were: $\chi^2 = 911.00$ (df = 128), $p < .001$, SRMR = .07, CFI = .98, TLI = .98, and RMSEA = .075 (90% CI = .07-.08). See Table 3 for full parameter estimate information (see also Table 2 of Supplementary Material 5 for bootstrapped estimates). Intentions predicted proactive regulation (β = .77; R^2 = .59), reactive regulation (β = .85; R^2 = .72), social monitoring (β = .46; R^2 = .21), and self-monitoring (β = .80; R^2 = .64) significantly (ps < .001) with large effect sizes except for social monitoring, which was a medium effect size. Proactive regulation (β = .11; p = .003), reactive regulation (β = .25; p < .001), social monitoring (β = -.16; p < .001), and self-monitoring (β = .25; p < .001) also significantly predicted PA with a combined influence in the medium effect size range (R^2 = .24). There were only two paths that differed significantly in strength (reactive regulation > proactive regulation; χ^2 = 4.43, df = 1, p = .04). Finally, regarding indirect effects, paths including proactive regulation (β = .09; p = .003), reactive regulation (β = .21; p < .001), social monitoring (β = -.07; p < .001), and self-monitoring (β = .20; p < .001) were each significant.

Exploratory Analyses

We also later tested (due to the suggestion of a reviewer) whether people intending to engage in regular aerobic PA over the next two weeks and met PA guidelines (i.e., 150 minutes or more per week; Ross et al., 2020) two weeks later had higher scores on the self-regulation factors (measured at Time 2) than the other possible intention-behavior profiles (i.e., non-intenders/not meeting guidelines, intenders/not meeting guidelines, non-intenders/meeting guidelines). It was expected that intenders/meeting guidelines would have higher scores than the other groups because these individuals would rely more on those self-regulation tactics to be physically active. The main results of the analyses are as follows: (a) proactive regulation ANOVA: intenders/meeting guidelines > all other groups; (b) reactive regulation ANOVA: intenders/meeting guidelines > all other groups; (c) social monitoring ANOVA: intenders/meeting guidelines > not intenders/not meeting guidelines; not different from other two groups; (d) self-monitoring ANOVA: intenders/meeting guidelines > all other groups (see Table 3 of Supplementary Material 5 for full results).

Discussion

The purpose of this study was to develop and test the structural and functional properties of a PA behavioral regulation measure. Specifically, we sought to develop an instrument, titled here the physical activity regulation scale (PARS), for use within various theoretical models applied to understand PA. We used behavioral regulation constructs within the BCT taxonomy V1 (Michie et al., 2013) to achieve breadth in the selection of items and to assist in creating boundary conditions of the types of behavioral regulation tactics (Connell et al., 2019).

We hypothesized that a small number of correlated, yet empirically distinct factors would be extracted from exploratory, followed by confirmatory factor analysis procedures using independent samples. This hypothesis was supported. We also expected that some representation on a continuum of proactive (formulated before behavioral enactment) and reactive (enacted at the point of the behavioral circumstance) tactics would be generated among the factors (Braver, 2012; Duckworth et al., 2016; Hofmann & Kotabe, 2012; Inzlicht et al., 2021). This expectation also had support. Specifically, our measure development process supported four independent PA behavioral regulation constructs from these data: proactive regulation, reactive regulation, social monitoring, and self-monitoring.

This four-factor PARS model yielded a good overall model fit, with adequate internal consistency and stability (e.g., good ICCs, strong latent correlations over time) across the constructs, and modest intercorrelations among the four factors. Importantly, from a functional standpoint, the four factors were all significant independent predictors of PA as hypothesized. Specifically, the four PARS factors explained 18% of PA behavior (see model #1), and performed better independently (all four factors) than as a formative scale (summed average).

Also, the PARS mediated the relationship between intention and behavior as hypothesized. Finally, as expected, intenders/meeting physical activity guidelines generally had higher scores on the self-regulation factors than the other intention-behavior profiles. Thus, the initial evidence is supportive that the PARS may be a useful PA behavioral regulation measure to include as a mediator in theories that feature intention or goal related constructs (Rhodes & Yao, 2015).

Our analyses showed that action planning, specifically plans about where, when, how and how often, were the best representation of *proactive PA regulation,* independent of the other PARS factors. Planning (and goals) is the first factor of the 16 super-clusters of the BCT taxonomy (Michie et al., 2013), highlighting its importance in understanding behavior change. The critical importance of planning as a proactive tactic in behavioral regulation is also highlighted in most reviews of self-regulation (e.g., Inzlicht et al., 2021; Karoly et al., 2005; Mann et al., 2013). Thus, it is not surprising that planning was extracted as the first factor in the PARS. From a theoretical standpoint, action planning assists individuals in identifying salient cues that lead to action (Hagger et al., 2016; Schwarzer, 2008). Action plans are also synonymous with implementation intentions (Gollwitzer, 1999; Hagger & Luszczynska, 2014; Michie et al., 2013), although the theorizing for how they work to influence behavior has been conceptualized differently (Hagger & Luszczynska, 2014). Several reviews support the observational (Carraro & Gaudreau, 2013; Hagger & Luszczynska, 2014; Rhodes et al., 2020; Zhang et al., 2019) and experimental (Carraro & Gaudreau, 2013; da Silva et al., 2018; Hagger & Luszczynska, 2014; Rhodes et al., 2020) evidence for action planning as a determinant of PA. Furthermore, several theories used regularly to explain and change PA specifically include action planning within their formulation, particularly as a mediator of the intention and PA relationship (de Vries et al., 2005; Hagger & Chatzisarantis, 2014; Heckhausen & Gollwitzer, 1987; Rhodes, 2021; Schwarzer, 2008). Our findings in this study replicated these approaches, where action planning had a direct association with PA (Model 1 β = .19) independent of the other PARS factors, and contributed to the indirect association (β = .09) of intention with PA. Thus, the inclusion of action planning within the PARS facilitates and substantiates its use within such theoretical approaches.

The second factor in the PARS featured *reactive PA regulation*, with item content that focused heavily on managing internal affective states, and some content representation of managing external environments that were perceived as conducive to sedentary activities. While research on the importance of affect on PA has burgeoned (see Stevens et al., 2020 for a review), regulation of affect has seen less research attention (Pears & Sutton, 2021; Rhodes, Gray, et al., 2019). Like proactive PA regulation, our results supported the direct prediction of reactive PA regulation on PA (Model 1 β = .18) and its role in the indirect relationship of intention and PA relations (β = .21). Furthermore, to our knowledge, the inclusion of this reactive PA regulation factor in the PARS represents a novel extension of past self-regulation instruments in PA where the focus is almost exclusively on proactive regulation. Thus, the inclusion of this factor may be a helpful extension for researchers desiring specific content coverage of affect regulation.

Social and self-monitoring constructs comprised the third and fourth factors in our analyses, respectively. Self-monitoring has been well-established as a pivotal behavioral regulation construct in PA interventions (Knittle et al., 2018; Michie et al., 2009) so its inclusion in PARS was expected. From a theoretical standpoint, self-mentoring is foundational in systems featuring control theory (along with action planning) (Carver & Scheier, 1998). Our observational data echo these findings where self-monitoring predicted PA (Model 1 β = .19) independent of the other factors and had a significant mediating effect in the indirect relationship of intention and PA relations (β = .20). Social monitoring of PA, by contrast, had a negative association with PA (Model 1 β = -.20) and a very small mediating effect between intention and PA after controlling for the other PARS factors. While the basic tenets for how social monitoring would affect PA is similar to self-monitoring (Carver & Scheier, 1982), just at the inter-personal level rather than the intra-personal level, the negative relationship may be signaling a suppressor effect. That is, people who rely on others to assist them in regulating PA, independent of taking the personal responsibility to self-monitor, and enact prospective and reactive regulation, may be more a marker of being less engaged toward enacting PA. As we noted in the introduction, social processes in behavioral regulation are less understood compared to self-regulation processes (Beauchamp, 2019; Kulis et al., 2022) so replication of these results in an independent sample is likely warranted to fully understand this effect.

While the four-factor model in PARS makes theoretical sense and had empirical support, there were some BCTs absent from the final formulation that warrant mention. For example coping planning (also called problem solving or barrier control) is a common BCT within PA interventions (Kwasnicka et al., 2013; McEwan et al., 2019) and some prominent theories such as the health action process approach (Schwarzer, 2016). Items for this construct were factor complex between prospective and reactive behavioral regulation factors. This makes sense, as problem solving can be enacted either prospectively or in the moment (Duckworth et al., 2016), even if most intervention approaches with this construct are addressed prospectively (Rhodes et al., 2020). Similar factor complexities were observed with such self-regulation factors as social and environmental restructuring and prompts and cues. Thus, all of these elements do reside within the variance of the PARS, yet they did not suggest a clean factor structure with unique measurement properties in their own right.

There were also noteworthy limitations to our study that warrant mention. First, our study included three items each of 15 BCTs which were used to create the PARS, supporting a considerable breadth and scope of possible behavioral regulation variables. However, there are variables that were not included in our item generation process, most notably identity related BCTs and BCTs related to habit (repetition and substitution). These were omitted because, in theory, they involve additional mediating variables (i.e., identity and habit) between a goal and behavior, yet their inclusion may produce additional independent behavioral regulation factors. Relatedly, our lack of an a priori theoretical structure compared to exploratory factor analysis methods may have limited the breadth of the instrument. It is also important to note that there are several BCT taxonomies other than the Michie et al. (2013) approach used in this study and these may offer additional insights into key behavioral regulation tactics. For example, the compendium of self-enactable BCTs (Knittle et al., 2020) highlights task crafting (i.e., for enjoyment, skills, and ability) which may be useful item content for behavioral regulation. In addition, there might be some issues with readability of the items as some of the items were study-created (Flesch reading level of the measure is 10th grade). It may be worthwhile to alter the wording and simplify some items. Our dependent variable was also self-reported behavior, which may not be the same as directly-measured PA. Replication of our prediction findings with accelerometry is advised. Follow-up experimental testing with known groups (e.g., a manipulation promoting the formation of behavioral regulation tactics) to examine the sensitivity of these measures is also recommended. Also, our population-based adult sample served as a strong foundation for this measurement development process, yet the generalizability to various clinical populations or child/youth populations and other health behaviors would require additional research. Finally, it is not fully clear how the COVID-19 pandemic influenced the results. The Time 1 survey ran from August 17-20, 2020, and the Time 2 survey ran from September 3-8, 2020. Because data-collection was collected remotely, we could not control whether participants completed measures at exactly at a 2-week interval, for the test-retest reliability assessment. Further, we launched these surveys during this time period because lockdown measures in Canada that would have limited PA such as gym closures had been lifted. However, how the pandemic affected responses is currently unknown and thus replication would be useful.

In summary, we developed and tested the structural and functional properties of a physical activity regulation scale (PARS). The study resulted in a reliable 14-item, four factor measure of 1) proactive regulation, 2) reactive regulation, 3) social monitoring, and 4) self-monitoring. The four PARS factors explained 18% of PA behavior (See Model 1), and mediated the relationship between intention and behavior. While continued testing is needed and some revisions will likely improve the measure over time, the initial evidence is supportive that the PARS may be a useful PA behavioral regulation measure to include for use within various theoretical models applied to understand PA.

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Table 1.

Demographic Information for Full Sample (N = 1,410)

	M (*SD*)	Frequency (%)
Age in years	46.85 (15.95)	
Gender		
Male		639 (45.3)
Female		687 (48.7)
Transgendered		4 (.3)
Did not indicate		80 (5.7)
Member of visible minority group		
Yes		273 (19.4)
Did not indicate		78 (5.5)
Highest level of education		
High school or less		177 (12.5)
At least some technical college		339 (24.1)
At least some university		576 (40.9)
Advanced university degree		234 (16.6)
Did not indicate		84 (6.0)
Annual household income before taxes (CAD)		
$49,999 or less		298 (21.1)
$50,000-$99,999		454 (32.2)
$100,000-$149,999		252 (17.9)
$150,000+		147 (10.4)
Did not indicate		259 (18.3)
Employment status		
Full-time (35+ hours per week)		658 (46.7)
Part-time (< 35 hours per week)		155 (11.0)
Student		54 (3.8)
Homemaker or not employed		410 (29.0)
Did not indicate		133 (9.5)
Diagnosed with health condition		
Angina		64 (4.5)
Heart attack		83 (5.9)
Stroke		72 (5.1)
Diabetes		146 (10.4)
Cancer		131 (9.3)
High blood pressure		310 (22.0)
High blood cholesterol		258 (18.3)

Table 2.
Final Items, Standardized Factor Loadings, and Error Variances for CFA using Sample 2

Item	Factor Loading (error variance)			
	1	2	3	4
[1]To be physically active, I have made a detailed plan regarding (1.4) . . .				
. . . when to be physically active.	.86 (.27)			
. . . where to be physically active.	.95 (.11)			
. . . how to be physically active.	.95 (.09)			
. . . how often to be physically active.	.94 (.12)			
[2]When I am upset, I use strategies to feel better so I can be physically active (11.2).		.86 (.26)		
[2]When I am upset, I have ways of coping so I can focus on my physical activity plans (11.2).		.93 (.14)		
[3]I recognize and accept when I am in a bad mood so I can focus on being physically active (11.2).		.88 (.22)		
[4]I avoid spending long periods of time in environments that promote inactivity (12.3).		.64 (.59)		
[4]There is someone who could provide feedback on my physical activity participation when needed (2.2).			.85 (.27)	
[4]There is someone who will comment on whether I am meeting my physical activity goals (2.2).			.91 (.18)	
[5]I ask someone to remind me to be physically active (7.1).			.59 (.65)	
[5]I keep track of my physical activities (2.3).				.88 (.23)
[5]I record my physical activities (2.3).				.83 (.31)
[3]I keep track of my physical activity level (2.3).				.89 (.22)

Note. Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.
[1]Adapted from Sniehotta, F. F., Schwarzer, R., Scholz, U., & Schuz, B. (2005). Action planning and coping planning for long-term lifestyle change: Theory and assessment. European Journal of Social Psychology, 35, 565-576.
[2]Adapted from Bjureberg, J., Ljótsson, B., Tull, M. T., Hedman, E., Sahlin, H., Lars-Gunnar Lundh, L. G., Bjärehed, J., DiLillo, D., Messman-Moore, T., Hellner Gumpert, C., & Gratz, K. L. (2016). Development and validation of a brief version of the difficulties in emotion regulation scale: The DERS-16. Journal of Psychopathology an Behavioral Assessment, 38, 284-296.

[3]Study created
[4]From Marcus, B. H., Rossi, J. S., Selby, V. C., Niaura, R. S., & Abrams, D. B. (1992). The stages and processes of exercise adoption and maintenance in a worksite sample. Health Psychology, 11, 386-395.
[5]Adapted from Petosa, P. S. (1993). Use of social cognitive theory to explain exercise behavior among adults Ohio State University].

Table 3.
Parameter Estimates for Model 3

Description	Estimate	*SE*	95% CIs Lower	95% CIs Upper	*β*	*p*
Intentions → proactive regulation	1.02	.03	.97	1.07	.77	< .001
Intentions → reactive regulation	.91	.02	.86	.95	.85	< .001
Intentions → social monitoring	.56	.02	.52	.60	.46	< .001
Intentions → self-monitoring	1.06	.03	1.01	1.11	.80	< .001
Proactive regulation → PA	11.53	3.85	3.98	19.08	.11	.003
Reactive regulation → PA	31.50	6.37	19.02	43.98	.25	< .001
Social monitoring → PA	-17.97	3.35	-24.54	-11.39	-.16	< .001
Self-monitoring → PA	25.55	5.15	15.45	35.66	.25	< .001
Intentions → proactive regulation → PA	11.80	3.93	4.10	19.50	.09	.003
Intentions → reactive regulation → PA	28.60	5.79	17.24	39.95	.21	< .001
Intentions → social monitoring → PA	-10.02	1.92	-13.78	-6.26	-.07	< .001
Intentions → self-monitoring → PA	27.09	5.48	16.36	37.82	.20	< .001