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Integrated social- and neuro-cognitive model of physical activity behavior in older adults with metabolic disease

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Abstract

Background—Despite the proven benefits of physical activity to treat and prevent metabolic diseases, such as diabetes (T2D) and metabolic syndrome (MetS), most individuals with metabolic disease do not meet physical activity (PA) recommendations. PA is a complex behavior requiring substantial motivational and cognitive resources. The purpose of this study was to examine social cognitive and neuropsychological determinants of PA behavior in older adults with T2D and MetS. The hypothesized model theorized that baseline self-regulatory strategy use and cognitive function would indirectly influence PA through self-efficacy.

Methods—Older adults with T2D or MetS ($M_{\text{age}}=61.8 \pm 6.4$) completed either an 8-week physical activity intervention ($n=58$) or an online metabolic health education course ($n=58$) and a follow-up at six months. Measures included cognitive function, self-efficacy, self-regulatory strategy use, and PA.

Results—The data partially supported the hypothesized model ($\chi^2=158.535(131)$, $p>.05$, CFI=.96, RMSEA=.04, SRMR=.06) with self-regulatory strategy use directly predicting self-efficacy ($\beta=.33$, $p<.05$), which in turn predicted PA ($\beta=.21$, $p<.05$). Performance on various cognitive function tasks predicted PA directly and indirectly via self-efficacy. Baseline physical activity ($\beta=$

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Conflicts of Interest

Authors declare no conflicts of interest.

Ethical Adherence

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

62, $p<.01$) and intervention group assignment via self-efficacy ($\beta=-.20$, $p<.05$) predicted follow-up PA. The model accounted for 54.4% of the variance in PA at month six.

Conclusions—Findings partially support the hypothesized model and indicate that select cognitive functions (i.e. working memory, inhibition, attention, and task-switching) predicted PA behavior six months later. Future research warrants the development of interventions targeting cognitive function, self-regulatory skill development, and self-efficacy enhancement.

Keywords

type 2 diabetes; older adults; physical activity; behavioral adherence; cognitive function; self-regulatory capacity

INTRODUCTION

Approximately 285 million people, worldwide, live with diabetes, 90% of whom have type 2 diabetes (T2D)(1). An estimated 20-30% of adults in most countries worldwide have metabolic syndrome (MetS)—a metabolic disease that increases risk of T2D five fold (2). Prevalence of both T2D and MetS increases with age such that more than 1 in 4 older adults have T2D and an estimated 1 in 2 has MetS (3,4). As the population is increasingly represented by older adult individuals, the consequences of metabolic disease, namely T2D and MetS, present substantial individual, community, and societal impact—including an estimated \$245 billion of health care costs (3). T2D is associated with multiple comorbidities including cardiovascular disease, obesity, kidney disease, amputation, blindness, and premature death (3). Metabolic dysregulation affects brain function and structure (5-11). Individuals with poor glucoregulatory control are more likely to show cognitive impairment compared to individuals with consistent glucose regulation (5). Treatments targeting glycemic control may attenuate cognitive function decline in individuals with metabolic disease (9).

Lifestyle modification, specifically physical activity, can drastically improve glucoregulatory control and disease trajectory of metabolic disease (3,11-13). Indeed, lifestyle modification is considered a first-line therapy for T2D (14). Physical activity, with or without weight loss, improves glucose tolerance and insulin sensitivity (15), as muscle-mediated glucose uptake remains functional even after insulin resistance develops. Regular physical activity leads to: improved insulin action, consistent blood glucose control, improved fat oxidation, improvements in lipid profile, improvements in diabetic peripheral neuropathy, increased muscle mass and potential for weight loss (16,17). The current recommendations for aerobic exercise training are: at least 3 days/week with no more than two consecutive days between bouts, at a moderate intensity of about 40-60% of maximal aerobic capacity, with duration summing to at least 150 minutes/week (18).

Despite evidence of the benefits of physical activity and the American Diabetes Association's position that it is a cornerstone of treatment, epidemiological data indicate that most individuals do not meet physical activity recommendations (19). Adherence to complex behaviors, such as regular physical activity, is difficult. Being physically active requires a combination of difficult tasks such as substantial expenditure of effort, and

continued perseverance (20). Adopting and maintaining physical activity requires self-regulated behavior and repeatedly inhibiting habitual responses (such as playing video games or watching television) and replacing them with other behaviors (such as going for a walk).

Self-regulation involves personal ability to subject thoughts, emotions, behaviors, and desires to a goal, cause or purpose (21). Two approaches to examining self-regulation involved in behavior change include: 1) a psychosocial paradigm, which generally emphasizes self-reported intentions and goal-setting techniques and 2) a neurocognitive perspective, which emphasizes cognitive abilities (22). Self-regulation has long been incorporated into psychosocial models of behavior change. A useful psychosocial theory is the social cognitive theory (23,24), which specifies a core set of psychosocial determinants (i.e., self-efficacy, outcome expectations, self-regulation and goals, and sociocultural factors) for effectively understanding a broad range of health behaviors, including physical activity. Social cognitive theory suggests that behavior change occurs through changes in motivation and self-regulation and hypothesizes that self-efficacy, the central construct, has both direct and indirect influences on behavioral outcomes (24). Built into social cognitive theory is the integration of both motivational and cognitive aspects of self-regulation and the assumption that cognitive factors significantly contribute to successful behavior change. The cognitive elements of self-regulation are important to understand. Cognitive control skills (as called executive control or executive function) such as planning and scheduling, inhibition, working memory, and cognitive flexibility are necessary for behavior change and may have the potential to affect an individual's capability to successfully initiate, and maintain, physical activity behavior change. Cognitive, more specifically, executive function is especially important during the initial phase of behavior change when a new behavior, such as physical activity, is adopted.

McAuley and colleagues (22) first integrated these two perspectives of self-regulation and conceptualized self-regulatory capacity as the combination of cognitive functioning and self-regulatory skill use. They established that self-regulatory capacity predicted adherence to a yearlong exercise trial indirectly through physical activity self-efficacy in healthy older adults. It is especially useful to examine adherence mechanisms in populations who exhibit low physical activity participation. Older adults with metabolic disease may be at heightened risk of non-adherence to physical activity due to a coinciding increase in behavioral demands (e.g., glucose tracking, nutrition planning, medication timing, etc.) and decrease in cognitive function. Disease-related impairments in cognitive functioning may affect behavior change strategies and behavioral adherence. The purpose of this study was to examine an integrated model of both socio- and neuro-cognitive influences on physical activity behavior change in older adults with diabetes. The model examines how self-efficacy, self-regulatory strategy use, and cognitive function influence physical activity behavior over time. It was hypothesized that baseline use of self-regulatory processes of self-monitoring/goal-setting and cognitive functioning as indicators of self-regulatory capacity, would indirectly influence physical activity behavior through self-efficacy.

METHODS

Participants

Individuals between the ages of 50 to 75, diagnosed with T2D or MetS, were recruited to participate in a six-month physical activity research study. Additional inclusion criteria included: physician clearance to exercise, ability to communicate in English, not regularly physically active (less than 2x/week for last six months) and a score of 21+ on the Telephone Interview for Cognitive Status (25). Further details, including the CONSORT diagram and intervention information, were reported previously (26).

Measures

Physical Activity—Objective physical activity was measured via accelerometry (Actigraph, Pensacola, FL, Model GT1M or GT3X). Participants wore the activity monitor on their non-dominant hip during all waking hours, except for bathing or swimming, for seven full days. Participants recorded time and days the accelerometer was worn on a home log, which was used to verify wear-time. The activity data were checked for long periods of non-wear time (0's) and were validated with the criteria of: 1) at least 10 hours of wear time per day (27), 2) at least 3 days of valid data, and 3) a 60-minute interruption period (28,29). If there were more than 20,000 counts per minute the data were considered inaccurate (27). Activity data were collected in one-minute intervals (epochs), with the total number of counts for each day summed and divided by the number of days of monitoring to calculate average daily activity. Freedson cut-points for older adults were used to estimate time spent in sedentary, light, and moderate-to-vigorous physical activity (30). The software used for analyzing the accelerometer data was ActiLife 5.2 and Meterplus.

Neurocognitive Measures—Following the recommendations of Miyake and colleagues (31), multiple measures of cognitive function were used to determine individual contributions of different processes. Specific measures were included to assess types of functioning that have been identified as vulnerable to metabolic disease, such as memory and prefrontal cortex function. All cognitive testing took place in a quiet, well-lit room. Each task was explained thoroughly with a practice run to assure understanding. The order of the tasks was consistent for all participants and time-points. However each computer task had three run files with different trial order, which were randomly counterbalanced across the three time-points. Outcome variables were standardized due to differing magnitude of variance according to task.

Stroop task: A modified Stroop task, a measure of attention and inhibition, consisted of three conditions: congruent, neutral, and incongruent (32,33). The congruent condition contained words displayed in a color that matches the word of the stimuli (e.g., 'BLUE' in blue color) whereas the neutral condition contained words that were matched for the length and frequency of the color of the stimuli but not a color category (e.g. 'SHIP' in blue color). The incongruent stimuli presented words presented in a different color than the written word (e.g. 'BLUE' in red color). The task of the participant was to identify the color in which the word was presented. There were 48 trials of each condition randomly presented summing to a total of 144 trials. Outcome variables included reaction times and response accuracy.

Interference cost was calculated by subtracting congruent from incongruent trials. STIM software was used for the Stroop task.

n-back task: A modified serial n-back task involving three consecutive conditions was used (34). Each condition required the participants to discriminate between 5 distinct shapes: blue circles, green triangles, purple stars, red squares, and yellow crosses as the stimuli. In the first condition (0-back), participants were instructed to respond as quickly and accurately as possible with a right button press when the yellow cross appeared and with a left button press when any other shape appeared. In the 1-back and 2-back conditions, participants were instructed to respond with a right button press if the shape on the current trial was the same as the previous trial (for the 1-back) or two trials previous (for the 2-back). If the current trial shape was different, participants responded with a left button press. Each consecutive condition had 80, 79, and 78 trials, respectively. Response accuracy and reaction time were measured and inverse efficiency (reaction time divided by accuracy) was calculated (35). Hits, misses, false alarms and correct reject trials were calculated. Working memory *high cost* was calculated by subtracting 2-back hits from 1-back hits. The zero-back condition was used to represent attention and processing speed. The task was conducted using STIM software.

Dual Task: The Dual Task measured task coordination and task-switching (32,36). Two conditions were presented in which participants responded to one (single task) or two (dual task) stimuli. The single task trials involved the presentation of either a single letter (A or B) or number (2 or 3) stimulus, whereas the dual task trials presented two stimuli, a letter and a number. Participants were instructed to press a corresponding key to each stimulus (A, B, 2, 3). In the dual condition, participants responded by pressing two corresponding keys. Outcome variables included single and dual reaction times and accuracies; dual-condition reaction time was divided by dual-condition accuracy to create an inverse efficiency score. E-prime software was used for the dual task.

Psychosocial Assessments—Participants completed a questionnaire battery assessing self-efficacy and self-regulatory strategy use. Several aspects of physical activity related self-efficacy were assessed. The Barriers-specific Self-Efficacy Scale (37), a 13-item questionnaire, was used to assess beliefs in personal abilities to exercise in the face of various types of barriers such as discouragement or bad weather. Physical activity self-efficacy was measured relative to personal beliefs in ability to 1) walk/exercise for the next month, two months, three months etc. (38); 2) walk continuously at a fast pace for 5 minutes, 10 minutes, 15 minutes, etc. (39,40); and to 3) integrate regular (~5 days/week) walking exercise into their lifestyle (40). All self-efficacy items were presented on a continuum from 0 to 100 with 0 representing “not confident at all” in personal ability to complete the task and 100 representing “completely confident” to complete the task. All efficacy scales showed excellent internal reliability ($\alpha = .96, .98, .99, .98$ respectively).

Self-regulatory strategy use specific to physical activity was measured by the 12-item Physical Activity Self-Regulation (PASR) scale (41). Its subscales include the following domains: self-monitoring, goal setting, eliciting social support, reinforcement, time

management, and relapse prevention. Internal consistency for subscales ranged from $\alpha = .72$ to $.92$. Table 1 contains baseline values for all assessments.

Procedures

Older adults ($n = 125$) with metabolic disease were recruited—via flyers, diabetes support groups, partnerships with local clinics, and community e-blasts—to participate in a six-month, two-armed, randomized physical activity clinical trial (#NCT01790724). Participants were randomized to either an eight-week exercise intervention ($n = 63$) or an eight-week metabolic health education program ($n = 62$). The metabolic health education group was delivered online with discussion groups and interactive content. The physical activity program was a theoretically-driven program with on-site walking and group workshops. It was titrated such that participants came on-site 3x/week for the first two weeks with gradual decrease to continuing the program completely at home by week six. Olson and McAuley report details of intervention design and effects (26). Testing was completed at baseline, post-intervention (month 2) and at a four-month follow-up (month 6). The primary outcome was physical activity at follow-up. An institutional review board approved all procedures—including an informed consent. Physician consent to exercise and confirmation of MetS or T2D was obtained before participation. More information on study procedures and participant flow is reported elsewhere (26).

Data Analysis

The theorized model of physical behavior was analyzed with a path analysis using a covariance framework with latent variables using the *Mplus* statistical software package (version 7.2) with robust maximum likelihood estimation (42). Model fit was evaluated using multiple criteria [e.g. non-significant p value associated with χ^2 , comparative fit index (CFI) $.95$ and the root mean square error of approximation (RMSEA) $.08$, and a standardized root mean square residual $.08$] (43). Measurement models were assessed for the latent constructs before they were entered into a theoretical structural model. Factor determinacy coefficients were estimated as a measure of internal consistency, with values ranging from 0 to 1—higher values reflecting better representation of the factor by the observed, manifest items. The hypothesized structural model was tested first. Subsequent exploratory model testing included both indirect paths (through self-efficacy) and direct path regression of physical activity. Then, the structural model was trimmed of non-significant paths. Collinearity checks were conducted: high correlations were observed only between manifest variables of the same latent construct (i.e. barriers self-efficacy correlated highly with exercise self-efficacy). The following variables were used as covariates: age, income, group, gender, baseline HbA1c and baseline physical activity. Baseline variables with missing data included: baseline physical activity (.9%) and income (4.3%). Multiple ($n = 5$) imputations (44) were utilized with baseline missing data in order to prevent case-wise deletion. Imputed data was compared to original data with no significant differences.

Sample size was based on: (a) data from previous estimations of change in physical activity across time (39) using social cognitive predictors and (b) the expectation that subjects will be lost to attrition across the time of study. In the event that we were able to retain 96 participants from the target $n = 120$, we calculated we would have power in excess of $.90$ to

detect a conservative effect (i.e., small to medium changes in variation (.02 - .15) in the primary outcome measure, physical activity. Additionally, this project was in nature a pilot study.

Nine individuals who were randomized did not receive the intervention. Three of these individuals could not be reached after baseline testing and thus were not randomized to group assignment. The other six participants communicated that they were not willing to participate in their assigned group ($n=2$), had personal/family issues that precluded participation ($n = 3$) or had significant, new health issues ($n = 1$). As this research targets understanding adherence mechanisms in purposeful behavior change, as contrasted with behavioral economics perspectives of nudging people towards healthier behaviors, individuals who received the intervention ($n = 116$), and thus purposefully engaged in becoming healthier, were included in the analysis.

RESULTS

Participants

Participant characteristics have been reported elsewhere (26). Participants ($n=116$) ranged from 50 to 75 years ($M_{\text{age}} = 61.8 \pm 6.4$). Most were female (64.7%), Caucasian (81%), and college-educated (54.8%). The majority ($n = 99$, 85.3%) of participants had been diagnosed with T2D; the rest ($n = 17$, 14.6%) had been diagnosed with MetS. Mean glycosylated hemoglobin was above the T2D diagnostic criterion of 6.5% ($M_{\text{HbA1c}} = 7.11 \pm 1.4$) and mean body mass index fell in the obese category ($M_{\text{BMI}} = 35.8 \pm 6.4$). Approximately two-thirds of the participants were taking oral medication for T2D and almost a quarter utilized insulin therapy. See Figure 1 for participant flow diagram (26).

Measurement Model

A series of confirmatory factor analyses of each latent measure was first conducted to assess factor structure of latent constructs. *Self-efficacy* was represented at month two by 1) barriers self-efficacy, 2) exercise efficacy, 3) walking (duration) efficacy and 4) lifestyle physical activity efficacy. Baseline *self-regulatory strategy use* was represented by all of its six subscales. Models for both latent constructs fit the data well: *self-efficacy* ($\chi^2 = 3.85(2)$, $p > .05$, CFI = .98, RMSEA = .10, SRMR = .03) and *self-regulatory strategy use* ($\chi^2 = 14.76(9)$, $p > .05$, CFI = .98, RMSEA = .07, SRMR = .03). Factor determinancy scores for self-efficacy and self-regulatory strategy use were excellent ($\alpha = .96$ and $.95$, respectively). Due to power constraints and the range of cognitive function constructs, performance on each cognitive function task was modeled as a separate manifest variable. After confirming that the 2-factor measurement model fit the data well ($\chi^2 = 29.93(4)$, $p > .05$, CFI = 1.00, RMSEA < .05, SRMR = .04), testing of the hypothesized structural model (including cognitive performance) was conducted.

Structural Model

The hypothesized model fit the data ($\chi^2 = 158.53(131)$, $p > .05$, CFI = .96, RMSEA = .04, SRMR = .06). Self-regulatory strategy use directly predicted self-efficacy ($\beta = .33$, $p < .05$), which in turn directly predicted physical activity ($\beta = .21$, $p < .05$). As hypothesized,

baseline dual task inverse efficiency ($\beta = -.13, p < .05$), Stroop interference cost ($\beta = -.13, p = .055$) predicted self-efficacy at month two. N-back cost ($\beta = -.11, p < .05$) and n-back zero inverse efficiency ($\beta = -.13, p < .05$) directly predicted physical activity at month six. Self-regulatory strategy use ($\beta = .07, p < .05$) and dual task performance ($\beta = -.03, p < .05$) indirectly predicted physical activity via self-efficacy (See Figure 2).

Older age was associated with more self-regulatory strategy use ($\beta = .22, p < .05$). Having lower income was associated with worse performance on n-back high cost ($\beta = -.27, p < .05$) and n-back zero performance ($\beta = -.25, p < .05$). Being female was associated with higher self-efficacy ($\beta = .18, p < .05$) and lower dual-task inverse efficiency ($\beta = -.14, p < .05$). Being in the intervention exercise group (coded as '1') predicted higher self-efficacy ($\beta = .93, p < .01$), by almost a full efficacy unit, which was 10%. Group indirectly predicted physical activity through self-efficacy ($\beta = .20, p < .05$). Higher baseline physical activity was associated with more self-regulatory strategy use ($\beta = .22, p < .05$), lower Stroop interference cost ($\beta = -.18, p < .05$), and lower n-back zero inverse efficiency ($\beta = -.25, p < .01$). Baseline physical activity directly predicted physical activity at month six ($\beta = .62, p < .01$). The model predicted 36.7% of the variance in self-efficacy and 54.4% of the variance in physical activity. Not surprisingly, baseline physical activity alone accounted for 36.6% of the variance in follow-up physical activity and thereby was important to include in the final structural model.

DISCUSSION

Our results support an integrated neuro- and social-cognitive model of physical activity in older adults with metabolic disease. These results suggest that successful self-regulation requires a combination of biological capacity and skill-development. In the case of diseases, such as T2D or MetS, which may affect both biological and behavioral resources, it is essential to understand both aspects of self-regulation. These results provide preliminary evidence that it is important to integrate neurocognitive and social cognitive perspectives in physical activity behavior interventions for older adults with metabolic disease. Self-regulatory demands of metabolic disease are high and tertiary disease complications, such as cognitive function impairment, may impair individual ability to regulate health behavior.

Model Direct & Indirect Paths: Self-Efficacy

Our initial hypothesis, that all cognitive function domains would indirectly influence physical activity via self-efficacy, was not supported by the data. There are several potential reasons for this. It is important to note that half of the participants received a physical activity intervention. Given the group effect on self-efficacy, one could theorize that the role of self-efficacy is more prominent in individuals who are actively involved in physical activity behavior change. Alternatively, not all cognitive functions necessarily operate in the same way with regard to influencing adherence to physical activity programs. However, performance on 1) an inhibitory control task and 2) a test of task switching or *dual-tasking* did influence physical activity indirectly through self-efficacy for physical activity. Our results encourage the theoretical integration of self-regulatory and cognitive processes as potential sources of self-efficacy information and/or facilitators of self-efficacy information

selection. Although humans have a remarkable capacity for self-regulation, self-regulatory failure is common (21,45). Experiencing self-regulatory failure may be demoralizing and further derail self-managements attempts, possibly through compromised self-efficacy beliefs. Social cognitive theory presents efficacy information as specifically important during the adoption phase of behavior change; perhaps some aspects of cognitive functioning are more critical during behavioral adoption, versus maintenance.

The study population, i.e., older adults with diagnosed metabolic disease, may have caused the deviations from our *a priori* hypothesized model. From these data, it is impossible to determine whether the results may be different in healthy older adults, as there was no comparison group of healthy older adults. However, our results indicating that performance on inhibition and task-switching tasks predicted physical activity indirectly through self-efficacy were congruent with those reported by McAuley and colleagues, using a generally-healthy older adult sample (22). In this study, only half of the participants received a physical activity intervention, compared to McAuley and colleagues' where all participants received a physical activity intervention. Given the group effect on self-efficacy, one could theorize that the role of self-efficacy is more prominent in individuals who are involved in a targeted physical activity behavior change intervention. Another possible explanation is that these results indicate shorter-term adherence, with the primary physical activity outcome at month six, compared to McAuley and colleagues' trial, which examined physical activity behavior over the course of an entire year.

Cognitive Function Domains & Behavior Change

The model presented here includes several tasks that assess distinct aspects or subdomains of cognitive functioning, including: working memory, attention/processing speed, inhibition, and dual-tasking. Executive functions, which include working memory, inhibition, and task-switching/flexibility, serve a critical higher-level role in behavior regulation and act as a primary mechanism of effortful self-control. Although attention or processing speed is typically categorized as a general cognitive function, rather than specifically an executive function domain, it is closely linked to inhibition. We submit that each of these domains plays an important role in successful behavior change.

Working memory performance, assessed here by the serial n-back task, directly predicted physical activity. Largely, the working memory literature from cognitive psychology and the psychological literature on self-regulation have failed to overlap. More recently, some research has integrated perspectives. Hofmann and colleagues (46) argue that the mechanisms underlying working memory are fundamentally related to those involved in self-regulatory goal pursuit. Goal-setting and self-monitoring may also be dependent on working memory as it involves regular context-relevant, flexible updating of goal-representations. Goal-directed behavior also requires top-down and voluntary control of attention (47). Attention is typically focused on stimuli that are task-relevant, involving urgency and/or close proximity in time and space (48). This tendency makes goal-directed behavior involving long-term, complex behavior change difficult. Hall and Fong (49) highlight this temporal juxtaposition in their temporal self-regulation theory, which emphasizes the role of cognitive function for successful behavior change in *unsupportive*

environments (e.g. strong pre-potent responses, time-lag for rewards, unfavorable cost-benefit ratio, etc.). Despite divergent theoretical perspectives of attention, attentional failure may prevent successful behavior change due to biased attentional selection or lapses in self-regulatory skills. Moreover, attention is critical for successful inhibition, and vice versa.

These data indicate that performance on inhibition and task-switching tasks indirectly influence physical activity behavior via self-efficacy beliefs. Inhibitory control is critical to any type of goal-directed behavior (49). From an early age, humans are surrounded by numerous cues related to potential reward (21). Reward anticipation is so strong that it is likely that the dominant type of self-control in daily life is impulse control (21). Inhibition is arguably the most central executive function (50) and behavioral inhibition is critical to successful behavior change. Impairments in cognitive flexibility, or task-switching ability, may significantly disrupt individual ability to self-regulate at a conscious, goal-directed level. In human behavior, there is a duality of goal-directed action and stimulus-based responding (51) as both motivate and activate behavior. Task-switching ability may be important for switching adaptively between goal-directed plans and stimulus-based responses.

Future directions & Integrated Interventions

These results provide supporting evidence for McAuley et al.'s (22) perspective that physical activity adherence relies on both cognitive functioning and self-regulatory strategy use. It is possible that individuals who experience cognitive function impairment, even to a mild degree, might find physical activity adherence more difficult. More research is necessary to develop interventions specifically targeting social cognitive constructs and cognitive function to establish best practices for improving behavioral adherence and remediating disease complications. The findings from this trial support a multi-faceted approach to increasing physical activity in older adults with T2D. Interventions combining social-cognitive based intervention with cognitive remediation focusing on updating (and maintaining) relevant information in working memory, shifting between task sets or flexibility, and inhibiting pre-potent responses may improve physical activity adherence. This study, as a pilot study, did not incorporate testing of automatic or non-conscious self-regulatory processes. A complete conceptualization of self-regulatory capacity must include more basic, automatic aspects of self-control (52,53).

Strengths & Limitations

Several study limitations warrant acknowledgement. It is important to note that this study was not experimental in nature rather a longitudinal analysis with path modeling, thus true causality is not possible to determine. The study sample was homogeneous, particularly in regard to socioeconomic status. Individuals who participate in on-site trials tend to be healthier and have more resources (enabling them to drive to campus, etc.) compared to the general population. Additionally, analyses revealed that participants who completed the trial had higher income, lower BMI, and lower glycosylated hemoglobin compared to those who dropped out. The sample size was relatively small, given the covariance modeling analyses conducted. Modeling was limited in power, preventing the inclusion of cognitive function as

latent constructs. Moreover, statistical power was insufficient to replicate analyses separately by group.

It is important to note that due to the temporal positioning of cognitive function and self-regulatory strategy use at baseline, it is impossible to determine causality from these data. It is possible that individuals with high working memory, inhibitory, attention and flexibility functions were naturally inclined towards self-regulatory activities such as goal-setting, planning, and incentivizing, and self-efficacy. However, it could also be that self-regulatory behaviors, or engagement in activities that require regular self-regulatory strategy use (such as work or physical activity), may improve, or sustain, brain function in older adulthood.

Conclusions

Overall, the results of this study provide preliminary support for an integrated perspective self-regulatory capacity and physical activity behavior in older adults with metabolic disease. The results indicate that specific cognitive functions (i.e. working memory, inhibition, attention, and cognitive flexibility) are important to physical activity behavior change. These results underscore the importance of self-regulatory capacity and self-efficacy for successful physical activity adherence in older adults with metabolic disease.

Improving physical activity adherence is an important public health priority as physical activity is an effective first-line therapy for preventing disease, alleviating symptoms, slowing disease progression and even occasionally reversing glucose dysregulation altogether. As the population continues to age, translatable interventions targeting physical activity in older adults will be crucial to easing the personal and societal impact of metabolic disease. It may appear ironic to intervene targeting cognitive functioning before an exercise program, given the evidence that physical activity improves aspects of cognitive functioning (54). However, it may prove helpful to identify individuals at risk for low adherence before starting a physical activity program and then deliver a brief intervention targeting specific cognitive tasks and relevant self-efficacy. Potential intervention type remains a critical question. However, some success has been observed in interventions consisting of gaming (55), non-invasive brain stimulation (56), and meditation (57). Additionally, pre-interventions could also incorporate physical activity in a more structured way before tapering into an independent adherence driven model.

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References

1. Shaw JE, Sicree RA, Zimmet PZ. Global estimates of the prevalence of diabetes for 2010 and 2030. *Diabetes Res Clin Pract.* 2010; 87(1):4–14. [PubMed: 19896746]
2. Grundy SM. Metabolic syndrome pandemic. *Arterioscler Thromb Vasc Biol.* 2008; 28:629–636. [PubMed: 18174459]

3. CDC. [9/23/2015] National diabetes fact sheet: general information and national estimates on diabetes in the United States, 2012. 2014. Available from: <http://www.cdc.gov/diabetes/library/factsheets.html>
4. Aguilar M, Bhuket T, Torres S, Liu B, Wong RJ. Prevalence of the metabolic syndrome in the United States 2003-2012. *JAMA*. 2015; 313(19):1973–1974. [PubMed: 25988468]
5. Hendrickx H, McEwen BS, van der Ouderaa F. Metabolism, mood, and cognition in aging: The importance of lifestyle and dietary intervention. *Neurobiol Aging*. 2005; 26S:S1–S5.
6. Kumar A, Haroon E, Darwin C, et al. Gray matter prefrontal changes in type 2 diabetes detected using MRI. *JMRI*. 2008; 27:14–19. [PubMed: 18050330]
7. Messier C. Impact of impaired glucose tolerance and Type 2 diabetes on cognitive aging. *Neurobiol Aging*. 2005; 26S:S94–97.
8. Ryan CM. Diabetes, aging, and cognitive decline. *Neurobiol Aging*. 2005; 26S:S21–25.
9. Awad N, Gagnon M, Messier C. The relationship between impaired glucose tolerance, type 2 diabetes, and cognitive function. *J Clin Exp Neuropsych*. 2004; 26:1044–1080.
10. Gold SM, Dziobek I, Sweat V, et al. Hippocampal damage and memory impairments as possible early brain complications of type 2 diabetes. *Diabetologia*. 2007; 50:711–719. [PubMed: 17334649]
11. Hassenstab JJ, Sweat V, Bruehl H, Convit A. Metabolic syndrome is associated with learning and recall impairment in middle age. *Dement Geriatr Cogn*. 2010; 29:356–362.
12. Church TS, Blair SN, Cocreham S, et al. Effects of aerobic and resistance training on hemoglobin A1c levels in patients with type 2 diabetes: A randomized controlled trial. *JAMA*. 2010; 304(20):2253–2262. [PubMed: 21098771]
13. Jeon CY, Looken RP, Hu FB, van Dam RM. Physical activity of moderate intensity and risk of type 2 diabetes: A systematic review. *Diabetes Care*. 2007; 30:744–752. [PubMed: 17327354]
14. Grundy SM, Cleeman JI, Daniels SR, et al. Diagnosis and management of the metabolic syndrome: An American Heart Association/National Heart, Lung, and Blood Institute scientific statement. *Circulation*. 2005; 112:2735–2752. [PubMed: 16157765]
15. Duncan GE, Perri MG, Theriaque DW, Hutson AD, Eckel RH, Stacpoole PW. Exercise training, without weight loss, increases insulin sensitivity and posttherparin plasma lipase activity in previously sedentary adults. *Diabetes Care*. 2003; 26:557–562. [PubMed: 12610001]
16. Balducci S, Iacobellis G, Parisi L, et al. Exercise training can modify the natural history of diabetic peripheral neuropathy. *J Diabetes Complicat*. 2006; 20(4):216–223. [PubMed: 16798472]
17. Sigal RJ, Armstrong MJ, Colby P, et al. Physical activity and diabetes. *Can J Diabetes*. 2013; 37(1):S40–S44. [PubMed: 24070962]
18. ACSM/ADA Joint Position Statement. Exercise and type 2 diabetes. *MSSE*. 2010; 42(12):2282–2303.
19. Nwasuruba CK, Khan M, Egede LE. Racial/ethnic differences in multiples self-care behaviors in adults with diabetes. *J Gen Intern Med*. 2007; 22:115–120. [PubMed: 17351850]
20. McAuley E, Blissmer B. Self-efficacy determinants and consequences of physical activity. *Exerc Sport Sci Rev*. 2000; 28(2):85–88. [PubMed: 10902091]
21. Kelley WM, Wagner DD, Heatherton TF. In search of a human self-regulation system. *Annu Rev Neurosci*. 2015; 38:389–411. [PubMed: 25938728]
22. McAuley E, Mullen SP, Szabo AN, et al. Self-regulatory processes and exercise adherence in older adults: Executive function and self-efficacy effects. *Am J Prev Med*. 2011; 41(3):284–290. [PubMed: 21855742]
23. Bandura, A. Social foundations of thought and action: A social cognitive theory. Englewood Cliffs NJ: Prentice Hall; 1986.
24. Bandura A. Health promotion by social cognitive means. *Health Educ Behav*. 2004; 31:143–164. [PubMed: 15090118]
25. de Jager CA, Budge MM, Clarke R. Utility of TICS-M for the assessment of cognitive function in older adults. *Int J Geriatr Psych*. 2003; 18:318–324.
26. Olson EA, McAuley E. Impact of a brief physical activity intervention in older adults with type 2 diabetes. *J Behav Med*. 2015; 11:1–13.

27. Masse L, Fummeler B, Anderson C, et al. Accelerometer data reduction: A comparison of four reduction algorithms on select outcome variables. *MSSE*. 2005; 37(11):S544–S554.
28. Copeland JL. Accelerometer assessment of physical activity in active, healthy older adults. *J Aging Phys Activ*. 2009; 17:17–30.
29. Mailey EL, Gothe NP, Wojcicki TR, et al. Influence of allowable interruption period on estimates of accelerometer wear time and sedentary time in older adults. *J Aging Phys Activ*. 2014; 22(2): 255–260.
30. Freedson PS, Melanson E, Sirand J. Calibration of the computer science and applications, inc. accelerometer. *MSSE*. 1998; 30:777–781.
31. Miyake A, Friedman NP, Emerson MJ, Witzki AH, Howerter A, Wager TD. The unity and diversity of executive functions and their contributions to complex “Frontal Lobe” tasks: A latent variable analysis. *Cognitive Psychol*. 2000; 41(1):49–100.
32. Erickson KI, Colcombe SJ, Wadhwa R, et al. Training-induced plasticity in older adults: Effects of training on hemispheric asymmetry. *Neurobiol Aging*. 2007; 28(2):272–83. [PubMed: 16480789]
33. Milham MP, Erickson KI, Banich MT, et al. Attentional control in the aging brain: insights from an fMRI study of the stroop task. *Brain Cognition*. 2002; 49(3):277–296. [PubMed: 12139955]
34. Kirchner WK. Age differences in short-term retention of rapidly changing information. *J Exp Psychol*. 1958; 55(4):352–358. [PubMed: 13539317]
35. Townsend, JT., Ashby, FG. Methods of modeling capacity in simple processing systems. In: Castellan, J., Restle, F., editors. *Cognitive theory*. Vol. 3. Hillsdale, NJ: Erlbaum; 1978. p. 200-239.
36. Bherer L, Kramer A, Peterson M, Colcombe S, Erickson K, Becic E. Training effects on dual-task performance: Are there age-related differences in plasticity of attentional control? *Psychol Aging*. 2005; 20(4):695. [PubMed: 16420143]
37. McAuley E. The role of efficacy cognitions in the prediction of exercise behavior in middle-aged adults. *J Behav Med*. 1992; 15(1):65–88. [PubMed: 1583674]
38. McAuley E, Lox C, Duncan TE. Long-term maintenance of exercise, self-efficacy, and physiological change in older adults. *J Gerontol B Psychol Sci Soc Sci*. 1993; 48(4):P218–P224.
39. McAuley E, Blissmer B, Marquez DX, Jerome GJ, Kramer AF, Katula J. Social relations, physical activity, and well-being in older adults. *Prev Med*. 2000; 31(5):608–617. [PubMed: 11071843]
40. McAuley E, Hall KS, Motl RW, et al. Trajectory of declines in physical activity in community-dwelling older women: Social cognitive influences. *J Gerontol B Psychol Sci Soc Sci*. 2009; 64B(5):543–550.
41. Umstad MR, Motl R, Wilcox S, Saunders R, Watford M. Measuring physical activity self-regulation strategies in older adults. *J Phys Act Health*. 2009; 6:S105–S112. [PubMed: 19998856]
42. Múthen, LK., Múthen, BO. *Mplus User’s Guide*. Seventh Edition. Los Angeles, CA: Muthen & Múthen; 2012.
43. Hu L, Bentler PM. Cutoff criteria for fit indices in covariance structure analysis: Conventional criteria versus new alternatives. *Struct Equ Modeling*. 1999; 6(1):1–55.
44. Graham, JW., Hofer, SM. Multiple imputation in multivariate research. In: Little, TD, Schnabel, KU., Baumert, J., editors. *Modeling longitudinal and multiple-group data: Practical issues, applied approaches, and specific examples*. Hillsdale, NJ: Erlbaum; 2000.
45. Heatherton TF, Wagner DD. Cognitive neuroscience of self-regulation failure. *Trends Cogn Sci*. 2011; 15(3):132–139. [PubMed: 21273114]
46. Hofmann, W., Friese, M., Schmeichel, BJ., Baddeley, AD. Working memory and self-regulation. In: Vohs, KD., Baumeister, RF., editors. *Handbook of Self-Regulation*. New York, NY: Guilford Press; 2011. p. 206-225.
47. Kent M, Rivers CT, Wrenn G. Goal-directed resilience in training (GRIT): A biopsychosocial model of self-regulation, executive functions, and personal growth (eudaimonia) in evocative contexts of PTSD, obesity, and chronic pain. *Behav Sci*. 2015; 5:264–304. [PubMed: 26039013]
48. Tops M, Boksem MAS, Quirin M, Ijzerman H, Koole SL. Internationally directed cognition and mindfulness: An integrative perspective derived from predictive and reactive control systems theory. *FPSYG*. 2014; 5:1–21.

49. Hall PA, Fong GT. Temporal self-regulation theory: a neurobiologically informed model for physical activity behavior. *Frontiers Hum Neurosci.* 2015; 9:117.
50. Miyake A, Friedman NP. The nature and organization of individual differences in executive functions: Four general conclusions. *Curr Dir Psychol Sci.* 2012; 21(1):8–14. [PubMed: 22773897]
51. Kent M, Rivers CT, Wrenn G. Goal-directed resilience in training (GRIT): A biopsychosocial model of self-regulation, executive functions, and personal growth (eudaimonia) in evocative contexts of PTSD, obesity, and chronic pain. *Behav Sci.* 2015; 5:264–304. [PubMed: 26039013]
52. Buckley J, Cohen JD, Kramer AF, McAuley E, Mullen SP. Cognitive control in the self-regulation of physical activity and sedentary behavior. *Frontiers Hum Neurosci.* 2014; 29:747.
53. Rebar AL, Loftus AM, Hagger MS. Cognitive control and the non-conscious regulation of health behavior. *Frontiers Hum Neurosci.* 2015; 9:122.
54. Eggermont LHP, Milberg WP, Lipsitz LA, Scherder EJA, Leveille SG. Physical activity and executive function in aging: The MOBILIZE Boston Study. *J Am Geriatr Soc.* 2009; 57(10):1750–1756. [PubMed: 19702618]
55. Baniqued P, Allen CM, Kranz MB, Johnson K, Sipolins A, Dickens C, Ward N, Geyer A, Kramer AF. Working memory, reasoning, and task switching training: Transfer effects, limitations, and great expectations? *PLOS One.* 2015; 10(11):e0142169. [PubMed: 26555341]
56. Fregni F, Boggio PS, Nitsche M, Bermanpohl F, Antal A, Feredoes E, et al. Anodal transcranial direct current stimulation of prefrontal cortex enhances working memory. *Exp Brain Res.* 2005; 166:23–30. [PubMed: 15999258]
57. Zeidan F, Johnson SK, Diamond BJ, David Z, Goolkasian P. Mindfulness meditation improves cognition: Evidence of brief mental training. *Conscious Cogn.* 2010; 19(2):597–605. [PubMed: 20363650]

Figure 1. Participant flow diagram

Note. CONSORT information and flow diagram previously published elsewhere: Olson & McAuley, 2015.

Figure 2. Integrated neuro- and social-cognitive model of physical activity behavior

Note. Dashed line: $p = .055$. All other paths: $p < .05$

Note. LSE = lifestyle self-efficacy; SEW = walking self-efficacy; EXSE = exercise self-efficacy; BARSE = barriers self-efficacy.

Table 1

Baseline values for study assessments

	Mean $\pm$ SD, or %	Range
<i>Demographics</i>		
age (years)	61.9 $\pm$ 6.4	50 – 75
income above \$40K/year	62.9%	--
female	64.7%	--
glycosylated hemoglobin (%)	7.1 $\pm$ 1.4	5.4 – 12
<i>Self-regulation</i>		
self-monitoring	4.9 $\pm$ 2.0	2 – 10
goal setting	4.5 $\pm$ 2.0	2 – 10
eliciting social support	3.4 $\pm$ 1.6	2 – 8
reinforcement	5.6 $\pm$ 1.9	2 – 10
time management	4.1 $\pm$ 1.7	2 – 10
relapse prevention	3.4 $\pm$ 1.6	2 – 10
MVPA/day (minutes)	8.2 $\pm$ 8.9	0 – 45.3

Note: MVPA = moderate-to-vigorous physical activity