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Growth Trajectories of Exercise Self-Efficacy in Older Adults: Influence of Measures and Initial Status

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Abstract

Objective—This study examines differential trajectories of exercise-related self-efficacy beliefs across a 12-month randomized controlled exercise trial.

Methods—Previously inactive older adults (N = 144; M age = 66.5) were randomly assigned to one of two exercise conditions (walking, flexibility-toning-balance) and completed measures of barriers self-efficacy (BARSE), exercise self-efficacy (EXSE), and self-efficacy for walking (SEW) across a 12-month period. Changes in efficacy were examined according to *efficacy type* and *inter-individual differences*. Latent growth curve modeling was employed to (a) examine average levels and change in each type of efficacy for the collapsed sample and by intervention condition, and (b) explore subpopulations (i.e., latent classes) within the sample that differ in their baseline efficacy and trajectory.

Results—Analyses revealed two negative trends in BARSE and EXSE at predicted transition points, in addition to a positive linear trend in SEW. Two subgroups with unique baseline efficacy and trajectory profiles were also identified.

Conclusions—These results shed new light on the relationship between exercise and self-efficacy in older adults, and highlight the need for strategies for increasing and maintaining efficacy within interventions, namely targeting participants who start with a disadvantage (lower efficacy) and integrating efficacy-boosting strategies for all participants prior to program end.

Keywords

exercise; self-efficacy; trajectories of change; aging

Self-efficacy expectations reflect one's beliefs in his or her ability to successfully carry out a course of action (Bandura, 1997). Such perceptions influence the activities in which individuals choose to engage, the amount of effort they will invest in those activities, and the extent to which they will persist when they encounter barriers and/or failures. As the central active agent in Bandura's social cognitive theory, self-efficacy has been consistently identified as a determinant of an array of health behaviors including physical activity (Bandura, 1997; McAuley & Blissmer, 2000). There is evidence that the salience of self-efficacy perceptions may differ depending upon which stage of the exercise process the

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individual is currently in. Bandura (1997) posits that cognitive variables such as self-efficacy have the greatest impact on behavior when the task is physiologically and/or psychologically demanding. The physical activity literature provides evidence to support this position whereby the influence of self-efficacy is considered to be strongest during the initial stages of an exercise program, when the behavior is novel, and barriers such as fatigue and time constraints are likely to augment the perceived difficulty of maintaining an exercise routine (McAuley, Courneya, Rudolph, & Lox, 1994; Oman & King, 1998). Once the behavior becomes more habitual, the role of efficacy cognitions diminishes. However, in exercise trials, it is likely that self-efficacy shifts again as the organized intervention terminates and the individual is faced with the challenge of continuing to exercise regularly without the structured routine to which he or she has become accustomed (McAuley, 1993).

There are multiple sources from which one may derive efficacy, including mastery experiences, social persuasion, social modeling, and the interpretation of physiological and affective responses (Bandura, 1997). In the context of an exercise trial, one might expect self-efficacy to increase as a function of engagement in and exposure to activity, interactions with their exercise leader and peers, and through their affective states. From a social cognitive perspective, self-efficacy might be expected to increase with repeated exposures to physical activity. However, several studies detailing findings from randomized controlled physical activity trials report either no change in efficacy across varying lengths of intervention time or reductions in efficacy from baseline to the end of the interventions and beyond. For example, Moore et al. (2006) employed an eight-week lifestyle modification intervention to improve exercise maintenance in individuals enrolled in a cardiac rehabilitation program. They reported a small decrease in barriers self-efficacy ($d = -.09$) and a moderate decrease in exercise self-efficacy ($d = -.67$) at intervention end. At 12-month follow-up, barriers efficacy remained stable whereas exercise efficacy declined further. McAuley, Jerome, Marquez, Elavsky, and Blissmer (2003) examined the effects of a six-month exercise program on barriers and exercise efficacy in older adults and found a significant decline in both measures across the trial. However, there was a greater reduction in exercise efficacy ($d = -.92$) than in barriers efficacy ($d = -.18$). Finally, Hughes and her colleagues (2004) conducted an eight-week, multi-component, center-based physical activity intervention followed by home-based activity in older adults with lower extremity osteoarthritis. Once again, there were declines in barriers efficacy from baseline at two ($d = -.56$) and six months ($d = -.59$) and smaller declines in exercise efficacy at two ($d = -.16$) and six months ($d = -.36$).

Why would self-efficacy decline with continued participation in an exercise intervention? We believe that there may be three issues to consider here. First, as McAuley and Mihalko (1998) have suggested, in the context of relatively *inactive* older adults, participants may simply not have the appropriate previous experiences upon which to form accurate efficacy expectations and, therefore, over-estimate their capabilities at baseline. In essence, as they become exposed to the intervention they recalibrate their personal efficacy. Second, in the event that recalibration takes place and the true baseline self-efficacy is lower than measured, one might expect to see increases throughout the program (i.e., at mid-point), and then a reduction at program end as individuals consider the challenges associated with exercising independently. A third possible explanation is that not all exercise self-efficacy measures might be expected to have similar trajectories. For example, barriers efficacy measures and measures which assess efficacy for adherence to exercise prescriptions over time may not fare as well as those measures which assess gradations of task (e.g., walking further or longer). This may be particularly true when participants have performance-based tests on a frequent basis. This supposition was evidenced in a study by Rejeski et al. (2008) whereby efficacy for a 400 meter walk (i.e., a task-related measure) increased at six months but reverted to baseline at 12 months.

Further, it is often assumed that individuals in health-related interventions are drawn from a single population and have similar trajectories across these interventions. This assumption is the basis of linear growth curve modeling (Bollen & Curran, 2006). However, a more realistic assumption may be that different sub-groups (e.g., combinations of demographic factors, health status, or adherence to an intervention) exist within intervention studies. It is wholly possible that such groups display different trajectories of growth across time. The notion of the existence of “latent classes” or subgroups who exhibit heterogeneity in their behavior is an assumption of growth mixture modeling (McLachlan & Peel, 2000) and such an approach has been gaining popularity, particularly in the study of health behavior (e.g., Barnett, Guavin, Craig, Katzmarzyk, 2008; Jackson & Sher, 2005). Identifying sub-groups within clinical trials that evidence different trajectories of growth across time could have significant implications for treatment outcomes, identification of determinants of these trajectories, and for the implementation of different intervention strategies for different sub-groups. Here, our focus was on sub-groups dually-defined by baseline efficacy scores and efficacy trajectories.

We report data examining the differential effects of a 12-month randomized controlled exercise trial on three measures of self-efficacy in a sample of older men and women. In doing so, we attempt to answer several questions. First, do individuals recalibrate their efficacy expectations in a downward trajectory after being exposed to the exercise intervention? We hypothesized that barriers and exercise self-efficacy would be overestimated at baseline, be reduced with exposure to the intervention (i.e., a true baseline), increase at six months and then decline at program termination. Statistically speaking, for each of these measures we compared a linear growth curve (i.e., single growth process) with a piecewise growth model (i.e., three growth processes accounting for hypothesized transition points). Second, we were interested in whether task-related efficacy measures behave differently than barriers/adherence type measures in terms of growth. We hypothesized that the task-related measure (i.e. self-efficacy for walking) would increase across the trial, as a function of personal assessments of progress and physical testing (i.e., treadmill testing and 1-mile walk test). Finally, an exploratory question focused upon whether there were different sub-groups within our sample (i.e., classes) relative to self-efficacy and whether the trajectory of growth for these classes was different.

Methods

Participants

The flow of subjects through the program can be seen in the CONSORT diagram in Figure 1. Participants (n=179) were community-dwelling older adults who volunteered to participate in a 12-month exercise intervention. They were recruited via local media outlets, including television, radio and print media advertisements. In order to participate in the exercise program, individuals had to be between 60 and 80 years old, report being inactive for at least the previous six months, have no medical conditions exacerbated by physical activity participation, obtain permission from a physician, and be willing to be randomized into one of two exercise programs. In addition, as the primary outcomes of this trial included neurocognitive and brain structure variables, participants had to be right-handed, be screened to rule out possible neurological pathology (MMSE > 51; Stern, Sano, Paulson, & Mayeux, 1987), have normal color vision and normal or adjusted visual acuity, and not be clinically depressed or suffer from claustrophobia. Following initial contact by telephone, participants completed a pre-screening interview to determine whether they met inclusion criteria and consented to have their physician contacted for approval to participate in exercise testing. Participants were excluded from participation if they did not meet the above criteria or their physician refused to provide approval for participation.

Measures

Demographic Characteristics—A brief questionnaire assessed basic demographic information, including age, sex, race, education, income, and marital status.

Self-efficacy—Three measures of self-efficacy were administered in the present study. For all measures of self-efficacy, participants responded to each item by indicating their confidence to execute the given behavior on a 100-point percentage scale ranging from 0% (*not at all confident*) to 100% (*highly confident*). Total strength for each measure of self-efficacy was then calculated by summing the confidence ratings and dividing by the total number of items in the scale, resulting in a maximum possible efficacy score of 100. However, efficacy scores were rescaled by dividing by 10 to assure that residual variances would fit within the recommended range of 1–10 (see Muthén & Muthén, 1998–2009). The *barriers self-efficacy scale* (BARSE; McAuley, 1992) is a 13-item measure designed to tap subjects' perceived capabilities to exercise three times per week over the next three months in the face of commonly identified barriers to participation (e.g., bad weather, boredom, vacation). Internal consistency for BARSE in the present study was excellent (α=.92–.94). The *exercise self-efficacy scale* (EXSE; McAuley, 1993) is a six-item scale that assesses individuals' beliefs in their ability to continue exercising at a moderate intensity three times per week for 40+ minutes per session in the future (e.g. for the next month, next two months, etc.). Internal consistency for EXSE in the present study was excellent (α=.98–.99). The *self-efficacy for walking scale* (SEW; McAuley, Courneya, & Lettunich, 1991) is used to determine participants' beliefs in their physical capability to successfully walk at a moderately fast pace for a specified duration and reflects a task-specific measure of self-efficacy. The scale consisted of eight items, with each item representing an incrementally longer duration ranging from 5 to 40 minutes. Internal consistency for SEW in the present study was excellent (α=.97–.98).

Procedures

After participants were approved to participate in the exercise intervention by their physician and passed screening, they completed baseline questionnaire packets that included the demographic questionnaire and the three measures of self-efficacy. At this time they also completed a physician supervised graded maximal exercise test and the Rockport one-mile walk test (Kline et al., 1987). After all baseline data were obtained, participants were randomized into one of two exercise groups: a walking group or a flexibility, toning, and balance (FTB) group. For each group, classes met three days per week for approximately one hour over the 12-month period. BARSE and EXSE were administered a second time three weeks into the exercise intervention. Participants completed all three measures of efficacy and the graded exercise test again at six months into the intervention (midpoint) and at the end of the 12-month intervention (endpoint). They also completed the Rockport 1-mile walk test at 3, 6, 9, and 12 months.

Walking condition—For the walking program, a trained exercise leader supervised all sessions. Participants started by walking for ten minutes and increased walking duration weekly by 5-minute increments until a duration of 40 minutes was achieved at week seven. Participants walked for 40 minutes per session for the remainder of the program. All walking sessions started and ended with approximately five minutes of stretching for the purpose of warming up and cooling down. Participants wore heart rate monitors and were encouraged to walk in their target heart rate zone. This intensity was set at 50–60% of the maximum heart rate reserve for weeks one to seven and 60–75% for the remainder of the program. Following each exercise session, they completed an exercise log, then every four weeks, participants received written feedback forms which summarized the data from their logs. Participants with low attendance and/or exercise heart rate were encouraged to improve their performance in the following month.

Flexibility, toning, and balance (FTB) condition—For the FTB program, exercise sessions were led by a trained exercise leader. All FTB classes started and ended with warm-up and cool-down stretches. During each class, participants engaged in four muscle toning exercises utilizing dumbbells or resistance bands, two exercises designed to improve balance, one yoga sequence, and one exercise of their choice. To maintain interest, a new group of exercises was introduced every three weeks. During the first week, participants focused on becoming familiar with the new exercises, and during the second and third weeks, they were encouraged to increase the intensity by using more weight or adding more repetitions. Participants in the FTB group also completed exercise logs at each exercise session and received monthly feedback forms. They were encouraged to exercise at an appropriate intensity (13–15 on the Borg RPE scale) and attend as many classes as possible.

Data Analytic Strategy

We adopted a systematic approach to testing our hypotheses using *Mplus* (*version* 5.21, Muthén & Muthén, 1998–2009) to analyze the data. Repeated measures were modeled within a general latent variable framework using latent growth curve analyses to examine the trajectories of change in self-efficacy measures across time. For all linear growth models of *BARSE* and *EXSE*, each involving four time points, three latent growth factors were estimated (intercept (i), and two shape factors (s1 and s2)). Factor loadings were fixed at baseline (0), three weeks (.125), six months (1) and 12 months (2), to reflect non-equidistant measurements. Linear models were then compared to piecewise growth models in which intercept loadings were fixed at 1, and three sets of slope loadings (s1=0,1,1,1; s2=0,0,1,1; s3=0,0,0,1) were used to represent hypothesized transition points. In the case of *SEW*, which involved only three data points (0, 6, and 12 months), loadings were fixed with conventional linear loadings (0, 1, 2). Due to the presence of non-normal data, robust maximum likelihood estimation was employed. As noted earlier, all efficacy measures were rescaled (divided by 10) and all values subsequently reported are rescaled values. Goodness of fit tests for these models included the chi-square statistic, Standardized Root Mean Square Residual (SRMR), and Comparative Fit Index (CFI). The SRMR should be less than .08 to indicate good model-data fit (Hu & Bentler, 1999). Values approximating 0.95 or greater for the CFI are indicative of good model-data fit (Hu & Bentler, 1999).

To determine whether there were inter-individual differences in intra-individual change, growth mixture modeling (GMM) using a maximum likelihood estimator was conducted. GMM allows more than one trajectory subgroup or class (k), as well as within-class variation across all variables used to construct the classes. Models were sequentially tested, using k + 1 class, and then compared against multiple model-based indices. Although there is currently no gold standard for selecting the best-fitting model, three criterions (see McLachlan & Peel, 2000) were used, including the Akaike Information Criterion (AIC)), the Bayesian Information Criterion (BIC)), and the adjusted-BIC (ABIC)), with smaller values indicating better fit. Likelihood tests are also available in the MPlus output, including the Lo-Mendell-Rubin Test (LMRT; Lo, Mendell, & Rubin, 2001) and the parametric bootstrap method (BLRT; McLachlan & Peel, 2000). These tests empirically compare the increase in model fit between k class and k-1 class models. A small p value (< .05) indicates that the solution with one fewer class can be rejected. In addition, entropy values and posterior probabilities for most likely class membership were also calculated. These values range from 0 to 1, with 0 corresponding to randomness and 1 to a perfect classification (Celeux & Soromenho, 1996).

Results

The mean age of the sample was 66.5 years (*SD*=5.6; range 59–80 years). Participants were primarily female (66.2%), white (91%), married (58.7%), and well-educated (54.4% with at least a college degree). Mean body mass index (BMI) at baseline was 28.8 kg/m^2 (*SD* = 4.4; range 18.9–42.6). Table 1 details the descriptive statistics for the efficacy measures at each time point by treatment condition and for the total sample. Of 179 participants initially enrolled in the study, 145 (72 walking, 73 FTB) completed the study, and 144 completed all assessments (80.4% retention). Attendance to the group interventions was good with participants in the walking condition attending 80.2% of all activity sessions and those in the FTB condition attending 76.7% of the sessions. These rates were not significantly different from each other and the attendance rate across conditions was 78.42%. *T*-tests comparing participants who completed the study in the walking and FTB conditions indicated that the two conditions did not significantly differ at baseline for BARSE; however, participants in the walking condition scored significantly higher ($p < .05$) on the other two efficacy measures (see Table 1). In addition, males and females did not differ on any of the efficacy measures. There were no significant differences for demographics or efficacy variables ($p > .05$) between individuals who dropped out of the study vs. those who completed the study.

Latent Growth Curve Models

Overall sample—Initial latent growth curve models were conducted to examine the trajectories of change in the efficacy constructs across the entire sample. The unconditional linear model for BARSE was a reasonable fit to the data, χ^2 (*df* = 6; *N* = 144) = 11.78, p =. 07 CFI = .94, SRMR = .07; however, the piecewise model that tested the down-up-down hypothesis, improved fit indices, χ^2 (*df* = 5; *N* = 144) = 8.95, p =.11 CFI = .97, SRMR = . 05. On average, participants' initial BARSE scores were moderately high (M_i = 7.16, p < . 001), but as hypothesized, they demonstrated a significant negative trend from baseline to 3 weeks (M_{s1} = −.39, $p < .05$) followed by a nonsignificant upward trend (M_{s2} = −.10, p =.55), followed by another significant downturn at program end (M_{s3} = −.85, $p < .001$). Similarly, the linear model for EXSE was a poor fit to the data, χ^2 (*df* = 5; *N* = 144) = 22.27, $p < .01$ CFI = .73, SRMR = .10, whereas the hypothesized model considerably improved fit indices, χ^2 (*df = 5; N* = 144) = 5.31, p =.38, CFI = 1.00, SRMR = .07. Participants' baseline score (M_i = 8.31, $p < .001$) initially showed a negative trend at 3 weeks, (M_{s1} = −.65, $p < .001$) followed by a significant upturn at 6 months, (M_{s2} = .51, $p < .01$), and then a second, steeper downturn (M_{s2} = −1.65, $p < .001$) at program end. For SEW, the conventional linear model provided an excellent fit to the data: χ^2 (*df* = 2, *N* = 144) = .20, p = .90, CFI = 1.00, SRMR = .02. On average, participants' efficacy score at baseline (M_i = 7.38, $p < .001$) showed a significant positive trend over time (M_s = 1.36, $p < .001$) with an increase from baseline to 6 months that was maintained at 12 months.

Group-based Growth Models—Given that this study took place in the context of a 2-arm randomized trial, it was of empirical interest to explore whether intervention groups responded differently across time. To this end, linear growth models were examined across intervention groups to explore change trajectories for each type of efficacy. The linear model for BARSE (χ^2 (*df* = 12; *N* = 144) = 18.53, p = .10 CFI = .93, SRMR = .10) provided a poor fit to the model. Fit indices improved when hypothesized piecewise loadings were employed (χ^2 (*df* = 10; *N* = 144) = 15.40, p = .12 CFI = .96, SRMR = .09). The walking initially showed a negative trend (M_{s1} = −.54, $p < .05$) from baseline to 3 weeks, followed by no significant change at 6 months (M_{s2} = .19, p = .44), and then a second, steeper downturn (M_{s3} = −.88, p = .001) at program end. In contrast, the FTB group initially showed a nonsignificant downward trend (M_{s1} = −.24, p = .32) from baseline followed by no change from 3 weeks to 6 months (M_{s2} = −.39, p = .09), and finally, a third significant downturn

(M_{s3} = −.83, $p < .01$) at program end. Similarly for EXSE, the linear model provided a poor fit (χ^2 (df = 12; N = 144) = 30.65, $p < .01$ CFI = .69, SRMR = .14), and piecewise loadings substantially improved the model (χ^2 (df = 10; N = 144) = 13.30, p = .21, CFI = .96, SRMR = .11). The walking group initially showed a negative trend (M_{s1} = −.85, p = .001) followed by a significant upward trend (M_{s2} = .67, $p < .01$), and then a second, steeper downturn (M_{s3} = −1.67, $p < .001$) at program end. The FTB group showed a downward trend approaching significance (M_{s1} = −.45, p = .07), followed by no change (M_{s2} = .35, p = .24), and then a significant downturn (M_{s3} = −1.62, $p < .001$) at program end. As hypothesized, the linear model for SEW provided an excellent fit to the data (χ^2 (df = 5; N = 144) = 3.24, p = .66 CFI = 1.00, SRMR = .05) with both groups showing a significant positive trend across twelve months (M_s Walking = 1.50, $p < .001$; M_s FTB = 1.22, $p < .001$).

Overall, the pattern of efficacy change was similar across walking and FTB groups, regardless of efficacy type. The piecewise models sufficiently capture a normative growth pattern that in most cases resembled a down-up-down mean trajectory pattern. Our next objective was to explore heterogeneity within the sample that may have exhibited unique growth trajectories that strayed from the norm.

Growth Mixture Models

In conducting the GMM, class solutions were obtained for one, two, and three classes and based on multiple indicators that point to solutions with substantive meaning (see Table 2), two class solutions were selected for all efficacy models. Characteristics of final GMM solutions for each type of efficacy are reported below.

Barriers Self-Efficacy—Of the two classes extracted, class 1, the largest class (C1 n = 123, 85.42%; C2 n = 21, 14.58%; see Figure 2) was characterized by those with moderately high efficacy scores at baseline (M_i = 6.98, $p < .001$) that did not significantly change at week three (M_{s1} = −.09, p = .65), 6 months (M_{s2} = −.26, p = .17), or at program end (M_{s3} = −.26, p = .24). Class 2 tended to be individuals with high baseline efficacy (M_i = 8.14, $p < .001$) who showed a significant drop at week three (M_{s1}= −2.07, $p < .01$) followed by a nonsignificant positive trend (M_{s2}= .80, $p < .001$) and a second significant downturn (M_{s3} = −4.15, $p < .001$) at the end of the intervention. Entropy was .80 and posterior probabilities varied from .826 to .963 for the dominant class (.037 to .174 for the cross-probabilities), suggesting that the model could be replicated 80 percent of the time and that class assignment was fairly accurate.

Exercise Self-Efficacy—Class 1 (C1 n = 128, 88.89%; C2 n = 16, 11.11%; see Figure 2), the largest class, tended to be individuals with high exercise self-efficacy at baseline (M_i = 8.81, $p < .001$), whereas individuals in class 2 had low-to-moderate levels at baseline (M_i = 4.23, $p < .001$). Individuals in C1 also showed a significant negative trend at week three (M_{s1} = −1.05, $p < .001$), followed by a significant upturn at 6 months (M_{s2}= .46, $p < .05$), with another significant downturn at program end (M_{s3}= −1.51, $p < .001$), whereas those in C2 showed an initial positive trend (M_{s1} = 2.64, $p < .001$) followed by no change (M_{s2} = .94, p = .22), and then a significant downturn at 12 months (M_{s3} = −2.74, p = .001). Entropy was high (.95) and most likely class membership revealed high probabilities for the dominant class (.927 to .994) and low cross-probabilities (.006 to .073).

Walking Self-Efficacy—The largest class (C1 n = 116, 80.6%; C2 n = 28, 19.4%; see Figure 2), C1, tended to have high baseline walking efficacy (M_i = 8.23, $p < .001$) that trended positively over time (M_s = .58, $p < .001$), whereas those in C2 had moderately high baseline efficacy (M_i = 7.06, $p < .001$) that showed a negative trend across 12 months (M_s = −1.32, p = .001). Note that a second shape factor (e.g., quadratic term) could not be estimated for this linear GMM due to only three data points. Entropy was high (.93) and probabilities for most likely class membership for the dominant class varied from .936 to .989 (.011 to .064 for the cross-probabilities).

Exploratory Analyses Involving Subgroups

We conducted a series of analyses to determine whether the sub-groups or classes described above could be distinguished based upon demographic factors (e.g., sex, age, education, and marital status) or the degree to which participants were adherent to the program. All of these analyses were nonsignificant ($p \geq .28$). Because we have also posited that efficacy trajectories may differ as a function of the type of efficacy measure, we next examined the degree of correlation or "overlap" between class assignment for all measures of efficacy by calculating contingency coefficients. The correlation between EXSE class membership and SEW class membership approached significance (C=.159, p=.053). The relationship between EXSE and BARSE classes was slightly weaker (C=.145, p=.08), and BARSE class membership and SEW class membership were unrelated (C=.046, p=.58). Overall, these analyses indicated a small degree of overlap in class membership for the different measures of efficacy, but a larger degree of variability, such that the individuals in C1 (or C2) for one measure would not be highly likely to be in C1 (or C2) for another measure.

Discussion

We have taken the position that participating in physical activity interventions does not always lead to improvements in older adults' self-efficacy for exercise, as evidenced in several previously reported studies (Hughes et al., 2004; McAuley et al., 2003; Moore et al., 2006). In the context of a 12-month randomized controlled exercise trial with multiple assessment points and efficacy measures, we examined the extent to which this phenomena was a function of the type of measure used and whether different sub-groups of participants evidenced different trajectories of change across the duration of the trial. Our hypothesis that measures of adherence-related efficacy (i.e., barriers efficacy and efficacy to maintain an exercise prescription across time) would initially be over-estimated, rebound above baseline at study mid-point, and then decline at 12 months was generally supported. The overall decline reflects a reduction of approximately 19% (effect size = .61) for barriers efficacy and 22% (effect size = .76) for exercise self-efficacy. In both measures, there was an initial decline in self-efficacy from baseline to three weeks, suggesting that participants do indeed recalibrate their efficacy upon being exposed to the actual exercise experience. As our participants were previously inactive older adults, their exposure to being regularly active was limited and initial efficacy estimations may have been hopeful over-estimations. That is, they lacked an appropriate frame of reference for evaluating their capability to maintain a behavior they have not yet undertaken. This has important implications for exercise trials and programs designed for older adults and other inactive populations. These data suggest that efficacy enhancing experiences should be plentiful and self-efficacy should be assessed frequently in the early stages of an exercise intervention in order to determine strategies for increasing efficacy.

Following the three-week assessment of the adherence efficacy measures, efficacy was either maintained at this level at six months (i.e., barriers efficacy) or increased (i.e., exercise efficacy). This was then followed by the hypothesized sharp decline at program end. Such declines in efficacy are likely to be related to the impending challenge of maintaining an exercise regimen after the termination of the structured intervention. We believe that such information may prove very useful for behavioral interventionists who are designing physical activity programs with a view to having participants transition from organized, structured, group-based activity to home-based activity. Given the consistent association between self-efficacy and physical activity (McAuley & Blissmer, 2000), planning to include an "intervention within an intervention" may make good sense. That is, interventionists targeting physical activity behavior change should actively plan to address the difficulties of transitioning to maintaining regular exercise beyond the intervention and implement strategies to bolster efficacy and overcome these challenges. Such "mini-interventions" might be woven into the last few weeks of the planned program.

Whereas we found a non-linear pattern of growth trajectories in our measures of adherence efficacy, self-efficacy for walking significantly increased across the trial with growth demonstrated in the first six months of the intervention followed by a small non-significant decline at 12 months. The overall increase was 13.5% (effect size = .41). For most individuals, walking is a familiar behavior in which they engage regularly, whether they are considered physically active or not. Thus, their initial judgments of their ability to engage in a specific, common behavior such as walking for incremental durations may be more accurate than their assessments of their ability to overcome barriers and maintain specific exercise prescriptions. It is somewhat surprising that both the walking and FTB groups evidenced similar increases in self-efficacy for walking, given that only one group was walking regularly during class. One proposed explanation for these findings is that participants assigned to the FTB group may believe it is necessary to walk outside of class in order to reap the benefits of aerobic exercise. An alternative explanation is that engaging in one mode of physical activity may lead to generalized increases in all estimations of exercise self-efficacy, even if the modes differ (McAuley et al., 1999). Additionally, fitness tests requiring participants to walk briskly on a treadmill or indoor track are likely to have acted as a source of efficacy information and were performed by all participants regardless of treatment condition. The increase in task-specific self-efficacy as a result of participation in an exercise intervention is in line with results from previous exercise trials which have led to similar increases (e.g. McAuley et al., 1999).

Our exploratory analyses to determine whether specific sub-groups existed relative to self-efficacy and the extent to which these groups demonstrated differential trajectories of growth produced some intriguing findings. Relative to barriers self-efficacy, the smaller class of individuals demonstrated significant declines at 12 months but the largest class had a relatively flat trajectory which started relatively high and remained that way. As can be seen in Figure 2, individuals who have high barriers efficacy at baseline which drops significantly at three weeks are those individuals most likely to have declines in efficacy at program end. Whether targeting these individuals with efficacy enhancing strategies and increased support during the early part of the program results in elevated efficacy at program end remains to be determined. Two classes of individuals emerged from our mixture models of exercise self-efficacy. Whereas the majority of the sample (~90%) followed the growth pattern that we had hypothesized, a second smaller class emerged composed of individuals who had moderate exercise self-efficacy at baseline and did not experience a recalibration of their exercise self-efficacy. Instead, these individuals experienced an increase in efficacy at both 3 weeks and 6 months and then efficacy levels returned to slightly above baseline at 12 months, highlighting the need for additional strategies to enhance efficacy beliefs at the end of the intervention. Finally, the growth mixture models for walking efficacy revealed a larger class of individuals who started relatively high in their efficacy expectations and continued to follow a positive linear trend across time, as hypothesized. Conversely, the second class of individuals had a moderate level of walking efficacy at baseline, increased a modest amount at six months, then dropped below baseline values at 12 months. Individuals in this latter class may be considered good candidates for the type of efficacy-related "intervention within an intervention" previously suggested.

Our final set of exploratory analyses suggested that although sub-groups of participants exhibited different growth trajectories across the trial these classes could not be differentiated based on demographic characteristics or degree of adherence to the exercise intervention. Moreover, one might expect that there is significant overlap among individuals who compose the smaller class for each of the measures, all of which show sharp declines in efficacy at program end, but our follow-up analyses do not support this assumption. Contingency coefficients suggest individuals with a given baseline score and trajectory profile for one type of efficacy were no more likely to exhibit a similar profile for another type of efficacy. The intriguing question of what underlies the differential patterns reflected in these data demands attention in future endeavors. Additionally, we believe that further investigation into the extent that exercise dose plays a role in sub-group patterns of change may be an important avenue of research. In the present exercise trial both groups had prescribed intensity, frequency, and duration of activity that was identical across conditions. Thus, we were unable to explore this issue.

We believe there are several unique and important facets to this study. First, a novel aspect of this study was the measurement of adherence efficacy at both baseline and three weeks into the intervention. Based on these data, it is clear that although initial self-efficacy judgments may be overestimations, the correction factor operates quickly, given the significant decreases in self-efficacy just three weeks into the exercise intervention. We are not aware of any other intervention studies that have assessed self-efficacy at two such time points. These results help illuminate the relationship between exercise and adherence efficacy, and suggest individuals only need to engage in a behavior for a short time in order to provide a more realistic estimation of their capabilities to continue engaging in the behavior in the future. Second, it is clear that not all measures of efficacy relative to exercise/physical activity operate in the same way following exposure to exercise programs or interventions. Thus, it will be important for researchers designing future exercise intervention trials to make informed decisions on which measures are appropriate and which may be subject to recalibration, and to enact strategies in the early and later stages of the program to ensure realistic estimations of this important determinant of exercise behavior. Additionally, we believe that our use of contemporary statistical methods to determine change across time and differential patterns of change within sub-groups is a strength. There has been increasing interest of late in examining differential trajectories of health behavior among sub-groups or classes of individuals (e.g, Barnett et al., 2008; Laska, Pasch, Lust, Story, & Ehlinger, 2009). To our knowledge this is the first to examine trajectories of a consistent determinant of health behaviors, and to do so in the context of a randomized controlled trial.

However, we do acknowledge several limitations to our study. First, our sample was relatively homogenous and consisted of primarily well-educated, white women. Whether minority populations demonstrate similar patterns of change and sub-groups as reported herein remains to be determined. Additionally, determining whether such patterns emerge in younger and middle-aged adults is warranted. We further acknowledge the relatively small sample size of our study but submit that this may be mitigated by the increased efficiency and thereby power afforded by repeated measurements and the analytical approach (Duncan, Duncan, & Strycker, 2006). Finally, we note that our analytical strategy may be considered by some as much a limitation as strength. That is, growth mixture models are considered by some to be simply methods of identifying outliers (Bauer & Curran, 2003). Nevertheless, smaller classes of individuals within any health intervention still remain important participants. Identifying them and treating them accordingly may greatly contribute to ensuring fidelity of the intervention.

In conclusion, we believe that the findings from this study shed new light on how one of the most consistent determinants of physical activity behavior, self-efficacy, operates in older adults. Decelerating patterns of adherence related efficacy at program end do not bode well for maintenance beyond program termination. Implementing efficacy-boosting strategies prior to program end may help improve post-intervention adherence to physical activity.

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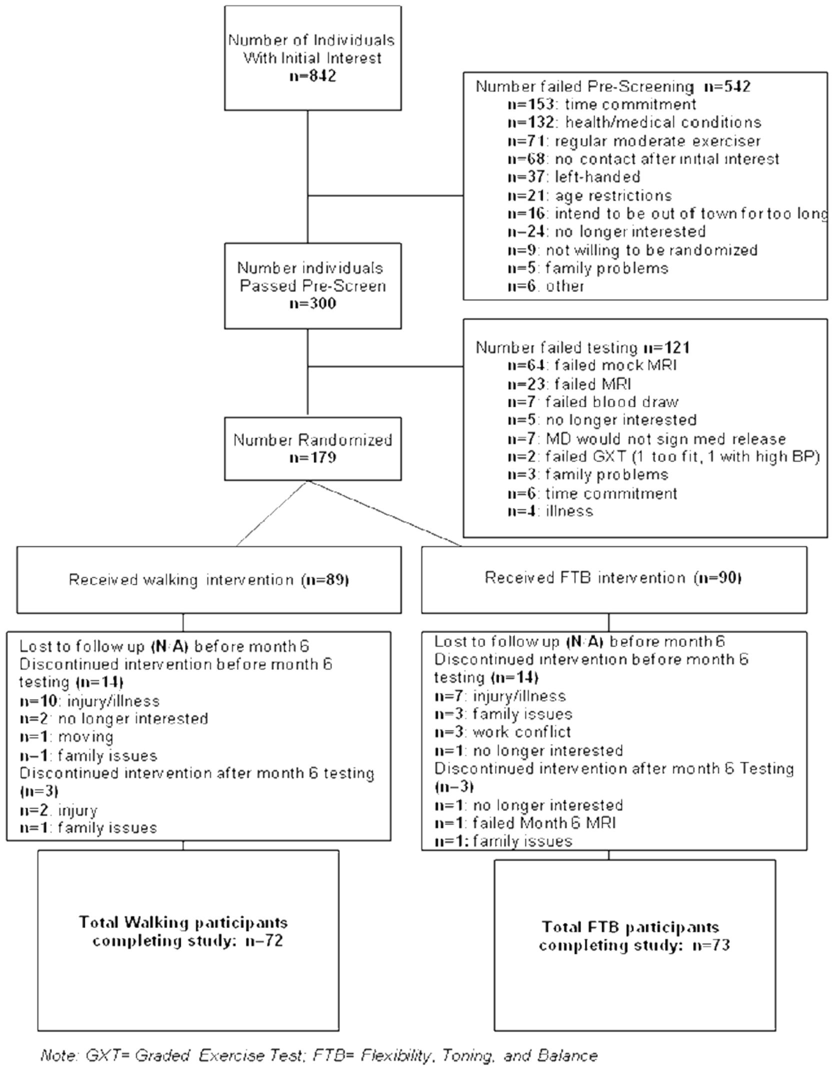

Figure 1.

CONSORT Diagram of Participant Flow Through the Study

Note: GXT= Graded Exercise Test; FTB= Flexibility, Toning, and Balance

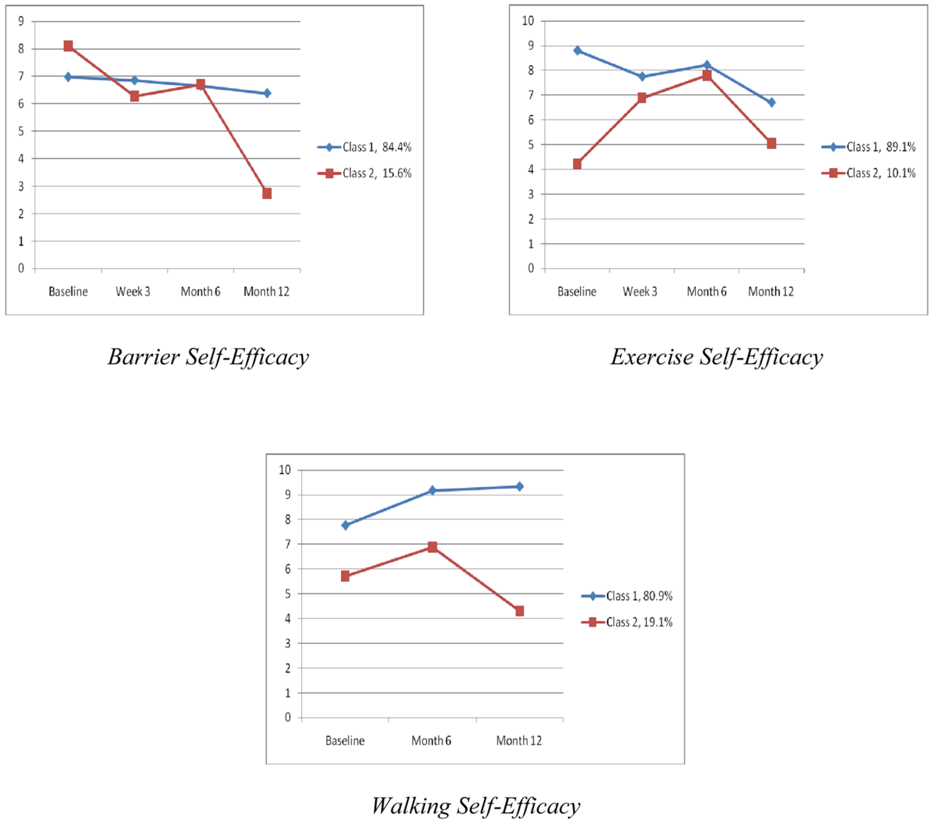

Figure 2.
Plots of Growth Mixture Models

Table 1

Descriptive Statistics for Efficacy Measures at Each Measurement Occasion for Complete Sample and by Condition

Measure	**OVERALL *M (SD) N* = 145**	**WALK *M* (*SD*) *n* = 72**	**FTB *M* (*SD*) *n* = 73**
Barriers Self-Efficacy			
Baseline	7.16 (2.07)	7.26 (2.03)	7.06 (2.10)
3 weeks	6.77 (2.09)	6.72 (1.89)	6.80 (2.30)
6 months	6.67 (2.02)	6.90 (1.80)	6.43 (2.20)
12 months	5.81 (2.36)	6.02 (2.27)	5.60 (2.42)
Exercise Self-Efficacy			
Baseline	8.31 (1.94)	8.66 (1.81)	7.96 (2.00)
3 weeks	7.66 (2.11)	7.81 (1.98)	7.51 (2.23)
6 months	8.17 (2.02)	8.48 (1.63)	7.86 (2.31)
12 months	6.52 (2.74)	6.81 (2.91)	6.24 (2.61)
Walking Efficacy			
Baseline	7.38 (2.62)	7.82 (2.19)	6.95 (2.86)
6 months	8.74 (1.88)	9.32 (1.50)	8.17 (2.03)
12 months	8.38 (2.26)	9.13 (1.62)	7.63 (2.56)

Table 2

Unconditional Growth Mixture Models: Class Solutions Based on Efficacy Trajectories

	1-C	2-C	3-C
BARSE			
H_o	−1182.86	−1171.19	−1163.22
AIC	2383.72	2370.37	2364.44
BIC	2410.45	2411.95	2420.87
ABIC	2381.97	2367.65	2360.75
Entropy	--	.80	.76
LMRT (*p*)	--	22.45 (.08)	15.32 (.38)
BLRT (*p*)	--	23.35 (.00)	15.93 (.11)
N	144	123, 21	81, 38, 25
EXSE			
H_o	−1221.13	−1193.87	−1174.29
AIC	2460.25	2415.73	2386.57
BIC	2486.98	2457.31	2443.00
ABIC	2458.50	2413.01	2382.89
Entropy	--	.95	.98
LMRT (*p*)	--	52.42 (.02)	37.64 (.20)
BLRT (*p*)	--	54.52 (.00)	39.16 (.00)
N	144	128, 16	129, 6, 9
SEW[a]			
H_o	−919.72	−885.57	−847.41
AIC	1851.43	1789.15	1720.81
BIC	1869.25	1815.88	1759.42
ABIC	1850.46	1787.40	1718.28
Entropy	--	.93	.97
LMRT (*p*)	--	63.99 (.12)	30.08 (.37)
BLRT (*p*)	--	68.28 (.00)	32.09 (.00)
N	144	116, 28	114, 21, 9

Note. Larger restricted (H_O) log likelihood values (closer to zero) indicate better fit. Smaller AIC, BIC, and ABIC values indicate better fit. Low *p* values for LMRT and BLRT suggest that the *k*-1 model can be rejected (and the k class model suggests a better fit). Analyses involving only 1 class do not generate output for *k*-1 tests, as 1 class is the lowest and only solution.

[a]SEW models are based on 3 data points (baseline, 6 months, 12 months); other efficacy measures are based on 4 time points

* $p < .05$