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Longitudinal patterns of stages of change for exercise and lifestyle intervention outcomes: an application of latent class analysis with distal outcomes

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Abstract

Stages of change measure an individual's readiness to alter a health behavior. This study examined the latent longitudinal patterns of stages of change (SoC) for regular exercise over time among individuals participating in a lifestyle intervention project. It also investigated the association between the longitudinal patterns of SoC and intervention outcomes using a new statistical method to assess the relationship between latent class membership and distal outcomes. We analyzed data from the Special Diabetes Program for Indians Diabetes Prevention Program, a lifestyle intervention program to prevent diabetes among American Indians and Alaska Natives. Latent class analysis (LCA) was conducted to identify the longitudinal patterns of SoC for regular

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COMPLIANCE WITH ETHICAL STANDARDS

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Ethical approval: 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. The SDPI-DP protocol was approved by the institutional review board (IRB) of the University of Colorado Denver and the IHS IRB. When required, grantees obtained approval from other entities charged with overseeing research in their programs (e.g., tribal review boards).

Informed consent. All participants provided written informed consent and Health Insurance Portability and Accountability Act authorization.

exercise reported at three time points. LCA with distal outcomes was performed to investigate the associations between latent class membership and behavioral changes after the intervention. The parameters and standard errors of the LCA with distal outcomes models were estimated using an improved three-step approach. Three latent classes were identified: Pre-action, Transition, and Maintenance classes. The Transition class, where stage progression occurred, had the greatest improvements in physical activity and weight outcomes at both time points post-baseline among female participants. It also had the largest improvements in weight outcomes among male participants. Furthermore, the Pre-action class had more attenuation in the improvements they had achieved initially than the other two classes. These findings suggest the potential importance of motivating participants to modify their readiness for behavioral change in future lifestyle interventions.

Keywords

Latent class analysis; latent class analysis with distal outcomes; physical activity; weight loss; American Indians and Alaska Natives

Accumulated scientific evidence has demonstrated that lack of physical activity is a risk factor for a variety of chronic conditions including hypertension, heart disease, and Type 2 diabetes (Telford, 2007). As a result, lifestyle interventions designed to prevent chronic diseases typically emphasize improving participants' physical activity level. For example, the lifestyle intervention of the Diabetes Prevention Program (DPP), a national randomized clinical trial that demonstrated improving lifestyle can effectively prevent the occurrence of Type 2 diabetes among those at risk, set a goal of 150 minutes of physical activity per week for each participant (Knowler et al., 2002). However, despite the strong evidence for benefits of physical activity, not every participant achieved the physical activity goal at the end of the intervention. In the DPP trial, over a quarter (26%) of the participants in the lifestyle intervention arm failed to achieve this goal (Knowler et al., 2002). Such rates are usually higher in translational projects that attempt to implement the DPP lifestyle intervention in the "real-world" (Absetz et al., 2007; Jiang et al., 2013).

Several social and behavioral science theories inform health-promotion interventions, including those for promoting physical activity. The transtheoretical model (TTM) is one of the most widely applied of these theories. It captures a person's intentional readiness for behavior change (Prochaska & DiClemente, 1983). The model proposes that individuals may move forward or backward through different stages while attempting to adopt and maintain a particular behavior (Prochaska, DiClemente, Velicer, & Rossi, 1993). TTM suggests that people at different stages of readiness need stage-specific interventions and has informed a number of behavioral interventions (Evers et al., 2006; Marcus et al., 1998; Prochaska et al., 1993). Yet, several recent articles (J. Adams & White, 2003, 2005; Casazza et al., 2013; Riemsma et al., 2003; Salmela, Poskiparta, Kasila, Vahasarja, & Vanhala, 2009) regarding TTM-based intervention studies concluded that TTM was not effective in promoting behavioral changes. Some argued that prospective analyses of stage transitions rather than cross-sectional studies are needed to better examine this question (Sutton, 2001). Some contended that stage progression was not always associated with behavioral change (J.

Adams & White, 2005). Yet others suggested the lack of association between self-reported readiness to change and actual behavioral change might be caused by the limited range of readiness among people who are interested in a lifestyle intervention program (Casazza et al., 2013).

To better understand whether and how TTM-based interventions work, it is critical to examine the process by which participants change their willingness to modify their behavior over time. In many previous studies, longitudinal investigations of stages of change (SoC) were limited to reporting that participants were more likely to advance in their readiness to adopt healthy behaviors after the intervention (Greaney et al., 2008; Marcus et al., 1998; Pinto, Frierson, Rabin, Trunzo, & Marcus, 2005). Yet, examining SoC for a behavior over time results in numerous possible patterns of SoC. For example, if one records the SoC for regular exercise at three time points, where each time point has five SoC categories, there are 125 (i.e., $5 \times 5 \times 5$) possible combinations of SoC in total. Some previous studies attempted to subjectively classify the potential patterns into a few categories, such as progress, regression and stable categories (Greaney et al., 2008; Makiko et al., 2012) or define intervention success as being in Action or Maintenance stage at the last time point (Johnson et al., 2008). To date, no study has used statistical methods to objectively determine whether a smaller number of meaningful longitudinal patterns exist among potential SoC patterns across time based on observed data.

Furthermore, as pointed out by several review articles that challenged the TTM (J. Adams & White, 2005; Casazza et al., 2013; Sutton, 2001), positive stage progression is not always associated with improvements in corresponding behaviors. Stronger evidence for actual behavior changes following stage progression is needed to demonstrate the effectiveness of TTM-based interventions. Therefore, to delineate the mechanisms through which TTM-based interventions work, it is important to investigate the association between longitudinal patterns of SoC and the corresponding behavioral outcomes. Such relationships are still underexplored in the existing literature.

Latent Class Analysis (LCA) is a commonly used data reduction tool for analyzing multivariate categorical data (Collins & Lanza, 2010). It assists investigators in identifying simple and meaningful latent class patterns within complicated observed categorical indicators. LCA is typically used to analyze cross-sectional data; but it also can be used for categorical indicators collected longitudinally (Collins & Lanza, 2010; Silverwood, Nitsch, Pierce, Kuh, & Mishra, 2011). Seeking to better understand transition patterns in SoC across time, this study used LCA to analyze data from Special Diabetes Program for Indians Diabetes Prevention (SDPI-DP) Program, a lifestyle intervention project to prevent diabetes among American Indian and Alaska Native (AI/AN) participants with pre-diabetes (Jiang et al., 2013). Although not a TTM-based intervention, the SDPI-DP collected data on both SoC and corresponding health behaviors at multiple time points, providing a unique data source for us to investigate the research questions of the current study in a minority population that bears a disproportionate burden of lifestyle-related chronic diseases. Specifically, we attempted to identify longitudinal patterns of SoC for regular exercise across three time points over a year. We also aimed to examine the relationship between the longitudinal patterns and lifestyle intervention outcomes using LCA with distal outcomes based on an

improved three-step approach, a new statistical method to assess the relationship between latent class membership and distal outcomes (Asparouhov & Muthén, 2014). Because gender differences in physical activity are well known, we investigated whether the patterns and relationships of interest differed for males and females.

MATERIALS AND METHODS

SDPI-DP

The SDPI-DP Program is a congressionally mandated demonstration project designed to reduce diabetes incidence among AI/ANs with pre-diabetes through the implementation of a translational version of the DPP lifestyle intervention. The details of this project are described elsewhere (Jiang et al., 2013). Briefly, 36 health care programs serving 80 tribes in 18 states and 11 Indian Health Service (IHS) administrative areas participated in the SDPI-DP. The participating programs implemented the 16-session *Lifestyle Balance Curriculum* adopted from the DPP (The Diabetes Prevention Program, 2002) and evaluated the effectiveness of the prevention activities over a three-year period. After a baseline assessment, participants participated in the lifestyle curriculum consisting of diet, exercise, and behavior modification sessions to help each reach and maintain a goal of 7% weight loss. The curriculum was provided in group settings (8-12 participants per group) within 16-24 weeks after baseline and typically taught by the program dietitian and/or health educator.

Participants

Participants were recruited locally by each grant program. Eligibility criteria included being AI/AN (based on their eligibility to receive IHS services), at least 18 years of age, no previous diagnosis of diabetes, and having either impaired fasting glucose (a fasting blood glucose level of 100 to 125 mg/dl) and/or impaired glucose tolerance (IGT, i.e., an oral glucose-tolerance test result of 140 to 199 mg/dl 2 hours after a 75-g oral glucose load). Enrollment began in January 2006 and is ongoing. However, in consideration of respondent burden as well as fiscal and workload issues, an abbreviated participant questionnaire, which did not include all of the items needed for this work, was implemented in August 2009. The current study included 1,344 participants who completed the original participant questionnaires at baseline, post-curriculum, and one-year assessments.

Measures

At baseline, within one month of completing the last lifestyle class (usually 4-6 months after baseline, hereafter called the post-curriculum assessment), and annually thereafter, participants underwent a comprehensive clinical assessment to evaluate their diabetes risk and incidence. At the same time, each participant completed a questionnaire including questions regarding sociodemographics, health-related behaviors, and a range of psychosocial factors.

Sociodemographics—Age, gender, educational attainment, employment status, marital status, and annual household income were collected using participant questionnaires.

Stages of change for exercise—Based on questions about their intentions for doing regular exercise (150 minutes planned physical activity per week), participants were assigned to one of the following five stages: 1 = precontemplation (no intention to exercise in the next six months), 2 = contemplation (plan to do regular exercise in the next six months), 3 = preparation (intended to exercise regularly in the next 30 days), 4 = action (had been exercising for less than six months), and 5 = maintenance (had been exercising regularly for more than six months) (Marcus et al., 1992).

Exercise—Five physical activity levels were determined based on the first 7 items from Rapid Assessment of Physical Activity (RAPA) instrument (9 items) (Topolski et al., 2006): 1 = sedentary, 2 = underactive, 3 = regular underactive (light activities), 4 = regular underactive, and 5 = regular active. Responses to the last 2 items of this instrument (the strength training and flexibility items) were scored separately, where 0 = engaged in neither, 1 = engaged in strength training or flexibility, 2 = engaged in both.

Body weight and Body Mass Index (BMI)—At each time point, every participant's body weight and height were measured with participants wearing light clothing and no shoes. BMI was then calculated using his/her weight and height.

Statistical Analysis

Data analyses were performed using Mplus (Muthén & Muthén, 2012). LCA procedures were used to identify latent subgroups (i.e., latent classes) of participants who exhibited distinct longitudinal patterns of stages of change for regular exercise. LCA is a statistical model to find latent subgroups from a set of observed categorical variables (Collins & Lanza, 2010). The categorical indicators in this study were participant-reported SoC for regular exercise at three time points (baseline, post-curriculum, and year 1 assessment). Our research interest here was to identify subgroups characterized by common longitudinal patterns of SoC across three time points and to estimate the prevalence rates for those subgroups. Following previous examples with similar research purpose (Lanza & Collins, 2006; Silverwood et al., 2011), we decided to use LCA instead of latent transition analysis, which is more suitable to examine transition probabilities between any pair of latent states between adjacent time points (Collins & Lanza, 2010). We began with a one-class model and proceeded to test models with successively larger numbers of classes. The choice of the optimal number of classes was based on the comparison of various class-size models using 3 information criteria: (1) Schwarz's Bayesian Information Criteria (BIC), (2) the sample-size-adjusted BIC, and (3) Akaike Information Criteria (AIC), where a smaller BIC or AIC value indicates a better fitted model. Further, we assessed the entropy of each model as an indicator for class separation and performed bootstrap likelihood ratio tests to test the significance of the difference in likelihoods of two models. The size of the latent classes and investigators' judgment of model interpretability were also considered in the final decision.

Once the optimal number of classes was determined, LCA with distal outcomes, a method allowing latent class membership to predict the level of observed variables, was used to describe the relationships between latent classes and participants' intervention outcomes, including changes in physical activity and body weight at the post-curriculum and first

annual assessments. Recently, an improved three-step method has been proposed and refined by several investigators to estimate the parameters in LCA with covariates models (Bolck, Croon, & Hagenaars, 2004; Vermunt, 2010) and has been extended to LCA with distal outcomes (Asparouhov & Muthén, 2014). The first step of this method fits a LCA model with the categorical indicators only. At the second step, the most likely class memberships are assigned to the participants based on maximum posterior probabilities from the LCA model. Meanwhile, the classification uncertainty rates (i.e., measurement errors) are calculated. In the last step, the most likely class variable is analyzed as a predictor variable for distal outcomes while accounting for misclassification rates obtained in step two. This approach has been implemented in Mplus 7 (Muthén & Muthén, 2012) and is the method we adopted in the current study for LCA with distal outcome models.

RESULTS

Sample Characteristics

Table 1 presents the baseline characteristics of the study sample. A total of 1,344 participants completed the participant questionnaires at all three time points and hence were included in this study. Almost three quarters of these participants (75.4%) were female; 19.1% of the participants were 60 years or older. Approximately 13% of the participants did not graduate from high school, and nearly 17% of the participants were not employed. Thirty-nine percent of the participants reported an annual household income less than \$30,000. The majority of participants were overweight or obese, with an average BMI of 35.5. Compared to males, female participants were more likely to be separated, divorced, or widowed and had lower physical activity level and lower body weight at baseline.

Figure 1 summarizes the distribution of the SoC for exercise variable at three time points. At baseline, of those who were included, about 60% of the participants were in the preparation or earlier stages; 22% in action stage, and 17% in maintenance stage. The percentages of action and maintenance stage increased to 43% and 29%, respectively, at the post-curriculum assessment. At the first annual assessment, the participants in action and maintenance stage were 24% and 38%, respectively. At all three time points, male participants were more likely to be at the maintenance stage than were female participants.

Compared to those who were included in this study (Appendix 1), participants who did not complete all three assessments were significantly younger, less well educated, less likely to be employed, and had lower household income. They also had lower baseline level of physical activity and higher body weight. In addition, they were less likely to be in the action or maintenance stage at baseline than those who completed all the participant questionnaires.

LCA

Because the distributions of SoC for exercise by gender were very different, as shown in Table 1, we first fit LCA models for males and females separately. Table 2 presents the model fit statistics for models with one to five latent classes. Among males, AIC and sample-size-adjusted BIC suggested the three-class model fits the data best, while BIC

suggested the two-class model was the best fit. However, the three-class model had significantly higher entropy. In consideration of entropy and model interpretability, we chose the three-class model as the final model for males. Among female participants, the fit statistics were not consistent in terms of the best fitted model. AIC suggested the four-class model best fits the data; sample-size-adjusted BIC suggested the three-class model; while BIC suggested the two-class model. In reviewing the latent class compositions of various models, we found that two latent classes in the four-class model had similar class profiles, whereas the two-class model seemed to be over-simplified. Therefore, the three-class model was also determined to be the final model for females.

Next we ran a multiple-group three-class LCA with and without assuming measurement invariance. The model assuming invariance in item-response probabilities across gender had a lower AIC and BIC than the model allowing all the parameters to be freely estimated (AIC: 11298.54 vs. 11329.14; BIC: 11511.85 vs. 11729.74). Further, the likelihood ratio test comparing these two models was not statistically significant (χ^2 statistic = 41.4; $P = 0.25$), indicating the measurement invariance assumption is reasonable. As a result, our final model for SoC at three time points was a multiple-group LCA by gender with three latent classes and measurement invariance.

Table 3 shows the estimated item-response probabilities of the SoC for regular exercise variable across three time points in each of the three latent classes. It shows that participants in class 1 had high probabilities in the preparation stage (58.4%, 40.9% and 48.8%, respectively) and substantial probabilities in the contemplation stage (28.4%, 16.5% and 25.3%, respectively) across all three time points. We defined this class as the Pre-action class, implying the majority of the participants in this class was at one of the pre-action stages at baseline and remained in those stages after the intervention. More than half of the participants in class 2 were at a pre-action stage at baseline (56.4%); but two-thirds of them (67.1%) were in the action stage at the post-curriculum assessment, and 81.9% of them were in the action or maintenance stage one year after the intervention started. We named this class the Transition class, indicating participants moved from a pre-action stage at baseline to more advanced stages after the intervention. Class 3 had high probabilities in the maintenance stage at all three time points (65.5%, 76.9% and 86.1%, respectively). We called this class the Maintenance class. The estimated proportions of the three latent classes among female participants were 44.6%, 38.9%, and 16.5% for the Pre-action, Transition, and Maintenance classes, respectively. Those three percentages for male participants were 27.9%, 40.2%, and 31.9%, respectively.

Figure 2 illustrates the expected values of the SoC variable at each time point for each latent class. Expected values were calculated as the sum of the product of the SoC variable (coded as 1-5) and the corresponding item-specific probability for each latent class at each time point. They can be interpreted as the mean scores of SoC for each latent class, where 1 means least advanced and 5 means most advanced. Across the three time points, the Maintenance class had the highest expected value compared with the other two classes. The expected value for the Transition class was relatively low at baseline but increased quickly from baseline to post-curriculum and minimally increased from post-curriculum to year 1.

Finally, the expected value for the Pre-action class was the lowest at baseline and remained relatively low at both the post-curriculum and year 1 assessments.

LCA with Distal Outcomes

The gender-specific associations between latent class membership and changes in intervention outcomes are presented in Table 4. Among male participants, those in the Maintenance class had the highest level of healthy behaviors among the three latent classes at baseline: they reported the highest level of physical activity as reflected by their RAPA scores. They also had the lowest body weight and BMI. Further, participants in the Transition class had healthier behaviors than those in the Pre-action class. No significant difference exists in changes in physical activity from baseline to both follow-up time points among the three latent classes. Yet, those in the Transition class showed the greatest improvement in weight outcomes and had the highest proportion achieving a 5% weight loss at both post-curriculum and year 1. Furthermore, males in the Maintenance class showed more improvements in weight and BMI at year 1 than those in the Pre-action class. Table 4 also reveals that participants' weight loss from baseline to post-curriculum was not completely sustained to 12 months. Compared to the Pre-action class, the Transition and Maintenance classes had less attenuation in the improvements they achieved initially.

Similar to males, the female participants in the Maintenance class had the highest level of healthy behaviors among the three latent classes at baseline, followed by the Transition class. The females in the Transition class also had the greatest improvement in weight outcomes and the highest proportion of achieving a 5% weight loss at both post-baseline assessments and the least attenuation in those improvements. Additionally, the females in the Transition class had the greatest improvement in aerobic physical activity at both follow-up time points.

DISCUSSION

Applying LCA methods to longitudinally measured SoC data, we identified three latent classes based on data collected from the SDPI-DP implemented among a group of AI/ANs with pre-diabetes over a one-year period: Pre-action, Transition, and Maintenance classes. Among the three latent classes identified, the Pre-action class included participants not ready to change their exercise behavior at baseline and who mostly remained in the contemplation or preparation stage after participating in the intervention. Conversely, most of those in the Maintenance class were exercising regularly at baseline and kept or further improved their exercising habit after receiving the intervention. Contrasting with the stability of the Pre-action and Maintenance classes, most of the participants in the Transition class moved from Pre-action stage at baseline to a more advanced stage after the intervention. The LCA model estimated about 40% of the SDPI-DP participants were in the Transition class, demonstrating that the lifestyle intervention was successful at changing the intention for regular exercise among almost half of the SDPI-DP participants. Further, about 20% of the participants were estimated to be in the Maintenance class, in which the participants maintained their relatively high level of physical activity that likely leads to sustained improvements in their weight outcomes.

Although not designed as a TTM-based intervention project, the results of this study partially support the validity of the SoC framework. A recent cross-sectional study revealed that SDPI-DP participants in more advanced SoC latent classes had healthier behaviors (Jiang et al., 2012). Here, SDPI-DP participants in the more advanced longitudinal latent classes also consistently reported healthier behaviors: they exercised more frequently and had lower BMI at all three time points. More importantly, participants in the Transition class were more likely to report behavioral changes: females had the highest increase in their physical activity while both genders experienced the largest weight loss among the three classes. Furthermore, the Transition and Maintenance classes had less attenuation in the improvements they achieved initially. These findings suggest that, rather than initial readiness to change, progress among stages appears to be more closely related to positive behavioral changes. This may explain why previous studies found readiness for weight loss did not predict the magnitude of weight loss or treatment adherence (Casazza et al., 2013). An important next step is to investigate the differences between the Pre-action and Transition classes, most of whom were at a pre-action stage at baseline but diverged in their directions of stage modification after attending the intervention, as well as the underlying reason for their differences. Preliminary analysis indicated the Pre-action and Transition class did not exhibit many significant differences in their baseline socio-demographic characteristics (Appendix 2). A more detailed analysis along this line is warranted to gain further insight regarding how to effectively advance participants' SoC in similar kind of interventions.

A recent study by Makiko et al. (2012) reported findings similar to ours: participants who maintained the action/maintenance stage or moved to more advanced stages lost significantly more weight than did those who remained in the pre-action stages or who regressed to earlier stages. Whereas that study had a relatively small sample size and only included two time points, here we were able to investigate a fuller picture of the longitudinal patterns of SoC in a national sample of AI/ANs measured at three time points. Moreover, instead of subjectively (and arbitrarily) dividing the participants into a few categories in terms of SoC patterns over time, we were able to use a data-driven statistical method to show that the numerous potential longitudinal combinations of SoC measured at three time points can be represented by three latent classes, which were significantly associated with intervention outcomes. In our exploratory data analysis, we found the actual number of different combinations of SoC over time was 83. By performing LCA, an effective data reduction tool, we substantially reduced the complexity of our data to focus only on three latent classes.

The findings of the LCA with distal outcomes analyses reported here, potentially generalizable to other populations, have important implications for AI/ANs who face daunting diabetes disparities. As evidenced previously (Ali, Echouffo-Tcheugui, & Williamson, 2012), lifestyle interventions delivered by lay community members hold great promise as a cost effective way to stem the increasing global diabetes epidemic, especially for underserved populations such as AI/ANs. Our findings revealed that not all AI/AN participants benefited similarly from such intervention, showing substantial population heterogeneity in their readiness to change exercise behaviors. For those classified as Pre-action at baseline, intervention effectiveness might be maximized by focusing initially on

motivating participants to increase their readiness for change. In this regard, it may be particularly valuable to draw upon the unique cultural background of AI/ANs to encourage increased physical activity and weight loss. For example, SDPI-DP grantees incorporated cultural activities such as talking circles, drumming, dancing, and other traditional events into their interventions. These efforts facilitated outreach, offered familiar, non-stigmatized involvement, and encouraged as well as supported the adoption of healthy behaviors. Future inquiry into the relationship of such activities to stage progression promises to inform the translation of lifestyle interventions into the real world of AI/ANs.

It is interesting to note that, although the transition class had the greatest improvements in physical activities among females, no significant difference in physical activity changes among the three latent classes was observed among male participants. One possible explanation for this observation is that male participants had relatively higher levels of physical activity at baseline (Table 4), especially among those in the transition and maintenance classes. Thus, males in those two classes had relatively less room to improve. In addition, although the participants in the Pre-action class tended to improve more with respect to physical activity than those in the Maintenance class, they achieved less weight loss than the maintainers. This may be caused by the fact that maintainers were already at optimal physical activity levels at baseline and hence did not have much room to improve after the intervention started. Conversely, the effect of regular exercise on weight can only be seen after a person has maintained ideal physical activity for several months (i.e., at the maintenance stage). Therefore, those in the Maintenance class lost more weight than the participants in Pre-action class. Indeed, our analysis of the relationship between latent class membership and intervention outcomes, controlling for baseline level of the outcome variable, revealed that participants in the transition or maintenance classes exhibited significantly greater improvements in all the outcome measures across both genders than those in the Pre-action class (data not shown).

As one of the first studies to apply the improved three-step approach in investigating the relationships between latent class membership and distal outcomes (Feingold, Tiberio, & Capaldi, 2014), our findings confirmed the advantages of this newly developed procedure. Traditionally, analyzing the association between a latent class predictor and an observed outcome variable involves three steps: 1) fit a LCA model with categorical indicators only; 2) assign each observation into a latent class based on the posterior probabilities from the LCA model, and 3) treat the latent class membership determined at step 2 as an observed predictor variable to analyze the association of interest using linear regression or logistic regression. This method is usually called the classical three-step analysis, which is straightforward to apply but suffers several drawbacks including underestimation of the strength of associations between latent classes and observed variables (Feingold et al., 2014). Alternatively, a model-based approach that can simultaneously estimate the LCA model and the relationship of latent class membership with distal outcomes may be used (Lanza, Tan, & Bray, 2013). The model-based approach has some advantages over the classical three-step method, such as producing less biased estimates for the relationship of interest. Yet, this approach assumes conditional independence between the categorical indicators and the distal outcome (i.e., conditional independence assumption). When this

assumption is not satisfied, including the distal outcome in the LCA model may affect latent class composition and change the meaning of the latent classes.

The improved three-step approach employed in this study takes into account the measurement error in the most likely class. Simulation studies have shown that this procedure can generate less biased estimates and be almost as efficient as the model-based approach in many cases (Asparouhov & Muthen, 2014). Meanwhile, the formation of the latent classes is not influenced by the distal outcome most of the time. Compared with the results from the classical three-step approach (Appendix 3), the improved three-step approach found more significant differences in improvements achieved by SDPI-DP participants across the three latent classes. Furthermore, most differences found among the three classes had higher magnitudes than those revealed by the traditional method. Conversely, using the model-based approach, we found that although the results for the associations between latent classes and weight loss were similar to those using the improved three-step approach, the relationships between latent classes and physical activity changed dramatically from either of the three-step methods (Appendix 4). This was likely caused by the fact that, after introducing the distal outcome into the LCA model, the measurement model of the LCA changed substantially and the resulting latent class variable lost its intended meaning (Appendix 5 illustrates such an example).

The results of this study need to be interpreted in the context of several limitations. First, SoC and physical activity data were self-reported, which are subject to recall bias and measurement error. In particular, social desirability and social approval may play a role in the reported level of those variables (S. A. Adams et al., 2005). For instance, the large improvements in RAPA among those in the Pre-action class might be partially caused by the fact that participants in a lifestyle intervention program were unwilling to report few changes in their physical activity. Yet, the attenuations in those improvements reported by the same group of participants suggest the overall validity of their reports.

Second, participants were all AI/ANs who were interested in and eligible for a lifestyle intervention. This may limit the generalizability of our findings. Due to various reasons, such as family responsibilities, transportation problems as well as the respondent burden of paperwork, the SDPI-DP, as a translational effort, did not achieve an optimal retention rate. This further reduced the generalizability of our study. Only 43% of the participants who started intervention completed the questionnaires at all three time points. Compared to those who were excluded, those with complete data had higher socioeconomic status in general and were more likely to be in the action or maintenance stage at baseline. Use of the expectation-maximization algorithm in LCA allows the inclusion of all participants who responded to at least one indicator of SoC (Collins & Lanza, 2010), however missingness on the distal outcome cannot be accommodated. Our reliance on only the completers may have led to an overestimation of the percentage of people in the Transition or Maintenance classes.

In conclusion, this study offers a novel way to define stage progression by applying LCA method to investigate the SoC data longitudinally. Instead of numerous change patterns, three latent transition patterns were identified to describe the readiness to change exercise

behavior over time among SDPI-DP participants. Furthermore, the findings of the relationships between latent classes and distal outcomes suggest that stage progression is associated with more positive behavioral changes. The findings of the current study expand the current literature on TTM and highlight the importance of motivating participants to advance their readiness for behavioral change in future lifestyle interventions. Investigating the differences between the participants in the Pre-action and Transition classes as well as potential causes for these differences represent important next steps to clarify the mechanisms underlying these intriguing findings. We anticipate that similar patterns of results will be found in other populations and that our findings will provide a basis to maximize the potential benefits of lifestyle intervention more generally.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig 1.
SoC distributions at each time point among SDPI-DP participants

Fig 2.

The expected value of the SoC variable at each time point for each latent class. (Expected value is calculated as the sum of the product of stage of change variable and its corresponding item-specific probability for each latent class at each time point.)

Table 1

Baseline characteristics and SoC distributions among SDPI-DP participants

	All Participants (N = 1344)	Female Participants (N = 1014)	Male Participants (N = 330)	
Sociodemographics	N (%)	N (%)	N (%)	<i>P</i> value^a
Baseline Age Group				0.694
18 to <40	315 (23.4)	239 (23.6)	76 (23.0)	
40 to <50	416 (31.0)	315 (31.1)	101 (30.6)	
50 to <60	357 (26.6)	274 (27.0)	83 (25.2)	
60	256 (19.1)	186 (18.3)	70 (21.2)	
Education Status				0.094
< High School	173 (13.4)	124 (12.7)	49 (15.5)	
High School graduate	268 (20.7)	192 (19.6)	76 (24.1)	
Some college	586 (45.2)	460 (46.9)	126 (39.9)	
college graduate	269 (20.8)	204 (20.8)	65 (20.6)	
Employment Status				0.221
Employed	962 (74.9)	737 (76.1)	225 (71.2)	
Retired	109 (8.5)	79 (8.2)	30 (9.5)	
Unemployed/Student	214 (16.7)	153 (15.8)	61 (19.3)	
Annual Household Income				0.255
\$15 K	192 (17.3)	140 (16.5)	52 (20.0)	
\$15 K to <\$30 k	243 (21.9)	195 (23.0)	48 (18.5)	
\$30 K to <\$50 k	332 (29.9)	258 (30.4)	74 (28.5)	
\$50 K	342 (30.8)	256 (30.2)	86 (33.1)	
Marital Status				<0.001
Married or live together	706 (61.3)	511 (58.6)	195 (69.9)	
Separated, divorced, or widowed	279 (24.2)	242 (27.8)	37 (13.3)	
Never married	166 (14.4)	119 (13.7)	47 (16.9)	
Intervention outcomes	Mean (SD)	Mean (SD)	Mean (SD)	<i>P</i> value^b
RAPA (Aerobic)	3.8 (1.1)	3.7 (1.1)	4.1 (1.0)	<0.001
RAPA (Strength and Flexibility)	0.7 (1.1)	0.7 (1.1)	0.9 (1.1)	0.008
Body Mass Index	35.5 (7.5)	35.7 (7.5)	34.9 (7.7)	0.079
Weight (lbs)	214.7 (52.5)	207.0 (47.7)	238.3 (59.1)	<0.001

Abbreviation: RAPA, Rapid Assessment of Physical Activity.

^aTwo-sided *P* Value of χ^2 test.^bTwo-sided *P* Value of ANOVA test.

Table 2

Latent class analysis fit statistics

	Number of latent classes				
	1	2	3	4	5
No. parameters	12	25	38	51	64
Males (N=330)					
Loglikelihood	-1226.55	-1175.40	-1150.95	-1145.14	-1139.48
Information criteria ^a					
AIC	2477.10	2400.79	2377.89	2392.28	2406.96
BIC	2522.69	2495.77	2522.26	2586.03	2650.11
aBIC	2484.63	2416.47	2401.72	2424.26	2447.10
X ² goodness-of-fit tests					
Pearson X ² value	292.29	116.86	71.98	56.92	32.19
Pearson X ² P value	<0.001	0.106	0.860	0.917	0.999
LRT X ² value	206.32	104.02	55.11	43.50	47.28
LRT X ² P value	<0.001	0.345	0.996	0.998	1.000
Smallest class percentage ^b	100.0	44.9	18.8	12.3	11.4
Entropy	1.000	0.563	0.724	0.691	0.701
P-values for bootstrap likelihood-ratio test (bLRT)		<0.001	<0.001	0.842	0.514
Females (N=1014)					
Loglikelihood	-3890.86	-3723.06	-3687.79	-3666.20	-3660.74
Information criteria ^a					
AIC	7805.71	7496.12	7451.58	7434.40	7449.48
BIC	7864.76	7619.14	7638.57	7685.35	7764.41
aBIC	7826.65	7539.74	7517.88	7523.37	7561.14
X ² goodness-of-fit tests					
Pearson X ² value	552.62	206.08	119.67	60.20	44.90
Pearson X ² P value	<0.001	<0.001	0.010	0.858	0.927
LRT X ² value	481.47	170.77	100.23	57.05	46.13
LRT X ² P value	<0.001	<0.001	0.140	0.915	0.906
Smallest class percentage ^b	100.0	37.0	18.6	13.9	9.8
Entropy	1.000	0.609	0.579	0.603	0.656
P-values for bootstrap likelihood-ratio test (bLRT)		<0.001	<0.001	<0.001	0.900

Abbreviation: AIC, Akaike's Information Criterion; BIC, Bayesian Information Criterion; aBIC, sample size-adjusted Bayesian Information Criterion; LRT, likelihood ratio test.

^a Minimum information criteria values are shown in italic type.

^b Based on estimated posterior class membership probabilities.

Table 3

Class-specific item-response probabilities of SoC for regular exercise among female/male participants from the three-Class LCA model

	Class 1 Pre-action class		Class 2 Transition class		Class 3 Maintenance class	
Female	(44.6%)		(38.9%)		(16.5%)	
Male	(27.9%)		(40.2%)		(31.9%)	
	Estimate	SE	Estimate	SE	Estimate	SE
Baseline						
Precontemplation	0.006	0.005	0.014	0.008	0.003	0.009
Contemplation	0.284	0.026	0.157	0.026	0.066	0.033
Preparation	0.584	0.027	0.393	0.040	0.047	0.043
Action	0.086	0.019	0.364	0.037	0.229	0.044
Maintenance	0.040	0.013	0.072	0.028	0.655	0.076
Post-Curriculum						
Precontemplation	0.013	0.005	0.000	0.000	0.008	0.007
Contemplation	0.165	0.023	0.037	0.014	0.000	0.000
Preparation	0.409	0.028	0.051	0.038	0.052	0.022
Action	0.326	0.035	0.671	0.051	0.171	0.047
Maintenance	0.087	0.019	0.241	0.045	0.769	0.051
Year 1						
Precontemplation	0.015	0.007	0.017	0.008	0.000	0.000
Contemplation	0.253	0.033	0.000	0.000	0.004	0.009
Preparation	0.488	0.034	0.165	0.041	0.059	0.024
Action	0.157	0.028	0.397	0.037	0.076	0.032
Maintenance	0.088	0.033	0.422	0.046	0.861	0.042

Table 4
Associations between latent class membership and changes in intervention outcomes among SDPL-DP participants

Intervention Outcomes	Males				Females			
	Pre-action Mean (SE)	Transition Mean (SE)	Maintenance Mean (SE)	P [*]	Pre-action Mean (SE)	Transition Mean (SE)	Maintenance Mean (SE)	P [*]
RAPA^d (Aerobic)								
Baseline	2.83 (0.33) ^{bc}	4.42 (0.08) ^a	4.62 (0.09) ^a	<.001	3.22 (0.07) ^{bc}	3.90 (0.08) ^{ac}	4.51 (0.06) ^{ab}	<0.001
Post-Curriculum - Baseline ^{\$}	0.77 (0.27)	0.37 (0.17)	0.18 (0.08)	.084	0.55 (0.08)	0.80 (0.09) ^c	0.28 (0.08) ^b	0.001
Year 1 - Baseline ^{&}	0.47 (0.20)	0.13 (0.15)	0.14 (0.11)	.321	0.13 (0.08) ^b	0.58 (0.10) ^{ac}	0.16 (0.10) ^b	0.008
Year 1 - Post-Curriculum [#]	-0.25 (0.16)	-0.28 (0.12)	-0.08 (0.11)	.658	-0.44 (0.08) ^c	-0.21 (0.08)	-0.09 (0.06) ^a	0.047
RAPA^d (Strength and Flexibility)								
Baseline	0.37 (0.10) ^c	0.61 (0.34) ^c	1.63 (0.64) ^{ab}	<.001	0.05 (0.01) ^c	0.11 (0.02) ^c	2.44 (0.03) ^{ab}	<0.001
Post-Curriculum - Baseline ^{\$}	0.70 (0.18)	0.65 (0.18)	0.29 (0.17)	.278	0.65 (0.08)	0.86 (0.11)	0.77 (0.14)	0.388
Year 1 - Baseline ^{&}	0.20 (0.12)	0.26 (0.15)	0.32 (0.19)	.888	0.22 (0.07)	0.58 (0.12)	0.24 (0.19)	0.080
Year 1 - Post-Curriculum [#]	-0.49 (0.18)	-0.38 (0.18)	0.10 (0.19)	.086	-0.41 (0.08)	-0.31 (0.10)	-0.42 (0.13)	0.738
Weight (lbs)								
Baseline	249.64 (10.17) ^c	243.81 (8.71)	221.35 (3.92) ^a	<.001	222.35 (3.12) ^{bc}	199.08 (2.70) ^a	187.18 (2.78) ^{ab}	<0.001
Post-Curriculum - Baseline ^{\$}	-7.82 (1.26) ^b	-14.68 (1.57) ^a	-10.30 (1.30)	<.001	-7.66 (0.57) ^b	-9.20 (0.68) ^a	-8.38 (0.80)	0.007
Year 1 - Baseline ^{&}	-1.16 (1.55) ^{bc}	-10.28 (1.74) ^a	-7.03 (1.56) ^a	<.001	-3.72 (0.75) ^{bc}	-8.16 (1.00) ^a	-6.51 (0.99) ^a	0.000
Year 1 - Post-Curriculum [#]	7.02 (1.58) ^{bc}	4.09 (1.12) ^a	3.27 (1.31) ^a	<.001	3.94 (0.56) ^{bc}	1.07 (0.76) ^a	1.86 (0.72) ^a	<0.001
Body Mass Index								
Baseline	35.93 (1.24) ^c	35.73 (1.05)	32.75 (0.51) ^a	0.012	37.85 (0.48) ^{bc}	34.70 (0.42) ^{ac}	32.68 (0.47) ^{ab}	<0.001
Post-Curriculum - Baseline ^{\$}	-1.16 (0.17) ^b	-2.12 (0.22) ^a	-1.53 (0.18)	0.001	-1.30 (0.10)	-1.61 (0.12)	-1.44 (0.14)	0.145
Year 1 - Baseline ^{&}	-0.14 (0.25) ^{bc}	-1.51 (0.25) ^a	-1.00 (0.22) ^a	<.001	-0.68 (0.14) ^{bc}	-1.42 (0.18) ^a	-1.12 (0.17) ^a	0.000
Year 1 - Post-Curriculum [#]	1.01 (0.26)	0.60 (0.17)	0.52 (0.21)	0.158	0.63 (0.11) ^b	0.20 (0.14) ^a	0.33 (0.13)	0.013

% achieving 5% weight loss

Intervention Outcomes	Males				Females				<i>P</i> *	Range
	Pre-action Mean (SE)	Transition Mean (SE)	Maintenance Mean (SE)		Pre-action Mean (SE)	Transition Mean (SE)	Maintenance Mean (SE)			
Post-Curriculum	35.1 (6.4)	50.2 (6.3)	45.7 (6.2)		35.0 (2.8)	43.3 (3.7)	38.0 (5.1)		0.280	26.301
Year 1	13.6 (4.1) ^{bc}	35.4 (6.3) ^a	31.2 (6.4) ^a		25.6 (2.6) ^c	36.9 (3.7) ^a	35.5 (5.4)		0.001	17.025

Abbreviation: SE, standard error; RAPA, Rapid Assessment of Physical Activity.

* Two-sided *P* Value from LCA with distal outcome model using the improved 3-step approach

[§] Changes in the outcome variable from baseline to post-curriculum (i.e., values at post-curriculum minus values at baseline)

[&] Changes in the outcome variable from baseline to year 1 (i.e., values at Year 1 minus values at baseline)

[#] Changes in the outcome variable from post-curriculum to year 1 (i.e., values at year 1 minus values at post-curriculum)

^a Significantly different from the mean of Pre-action class at $\alpha = 0.017$ level (based on Bonferroni correction for multiple comparisons)

^b Significantly different from the mean of Transition class at $\alpha = 0.017$ level (based on Bonferroni correction for multiple comparisons)

^c Significantly different from the mean of Maintenance class at $\alpha = 0.017$ level (based on Bonferroni correction for multiple comparisons)