Journal of Clinical Epidemiology 67 (2014) 947−951

Journal of Clinical Epidemiology

Latent class growth analysis successfully identified subgroups of participants during a weight loss intervention trial

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Accepted 18 March 2014; Published online 26 April 2014

Abstract

Introduction: Weight loss interventions often present small mean weight changes over time, despite the fact that a substantial proportion of the participants lost more weight. This effect is often leveled out by the substantial proportion of participants who gained weight during the trial. The aim of this study is to identify and describe distinct subgroups of participants with different weight change trajectories during and after a weight loss intervention.

Methods: We used data from a weight loss intervention that was part of a randomized controlled trial on the preventive effect of a tailor-made weight loss intervention and oral glucosamine sulfate on the incidence of knee osteoarthritis in 407 overweight women aged 50 to 60 years. Latent class growth analysis (LCGA) was used to identify subgroups of participants with different weight change trajectories over time.

Results: Using LCGA, we identified three subgroups with different trajectories of weight change, one large group (n = 298) with almost no change over time, and two smaller groups (both n = 48), of which one represents participants who steadily gained weight over time, whereas the other represents participants who steadily lost weight over time. Participants that had relatively low body weight around their 40th year of life and that gained weight in the year preceding the study were most likely to belong to the group that lost weight.

Conclusion: LCGA was a suitable method to identify three distinct groups of participants with different trajectories of weight change. Low body weight at age 40 and weight gain in the year preceding the study were associated with a higher chance of membership of the group that lost weight. It seems weight loss that occurred during this weight loss intervention was mostly recently gained weight.

Keywords: Latent class growth analysis; Weight loss intervention; Obesity; Diet; Physical Exercise; Methodology

1. Introduction

Numerous studies on weight loss interventions have proved efficacy of interventions that consist of diet and exercise [1]. Longitudinal trajectories of weight data within such trials often show high heterogeneity, making the results hard to interpret.

When assessing mean body weight changes, often the overall mean of the study population is relatively low [1], despite the fact that a substantial proportion of participants did lose weight. This is often leveled out by the proportion of participants that gained weight during the study. As a solution to this problem, studies often present the proportion of people that lost 5% of their baseline weight, an amount of weight loss that has been associated with clinically significant improvement in cardiovascular risk factors, including lipid levels, glycemic and blood pressure control and reduced risk of incident diabetes and hypertension [1−4]. This way, a distinction is made between participants who lost a clinically significant amount of weight and participants who did not or even gained weight. However, there is no distinction between participants who remained stable or who gained weight this way, despite the fact that this could have important clinical consequences. In addition, in many weight loss intervention trials participants that lost 5% of their baseline weight at the end of the follow-up period were considered to be compliant, regardless of their weight changes preceding the end of the follow-up period. This way, participants with widely varying weight changes are not distinguished from participants who steadily lost weight during the entire follow-up period [5,6].

Funding: This study was financed by ZonMw, the Netherlands Organisation for Health Research and Development.

Conflict of interest: The authors declare no conflict of interest.

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0895-4356/$ - see front matter
http://dx.doi.org/10.1016/j.jclinepi.2014.03.007

What is new?

- To our knowledge, this is the first study to apply latent class analysis to weight data from a weight loss intervention trial.
- This way, we based our subgroups on the actual weight changes in reaction to the intervention, instead of basing subgroups on baseline characteristics.

In a study aiming to identify patterns of weight loss strategies in a sample of 197 women, using latent class analysis, Lanza et al. classified participants into four subgroups based on self-reported strategies they had used [7]. With this approach, variation within groups is smaller than between groups [8]. This method yields more reliable results than simply choosing subgroups based on self-selected parameters, because this method allows for testing the reliability of different models based on objective parameters [8]. Literature refers to this method as a 'person-centred' approach, instead of a 'variable-centred' approach, which means the focus is on relationships among individuals, instead of how variables are related to one another [8].

Identifying subgroups of participants with different longitudinal trajectories of body weight changes during weight loss interventions would be useful to identify patients who are likely to follow a particular trajectory. This way, a tailor-made strategy could be offered to overweight and obese patients prone to certain trajectories. Therefore, the present study aimed to identify distinct subgroups of participants with different longitudinal trajectories of body weight changes during and after a weight reduction intervention, using latent class growth analysis (LCGA), and to describe relations between participant's characteristics, compliance to the intervention and subgroup assignment.

2. Methods

2.1. Study design and aim

The present study used data from the PROOF Study (ISRCTN 42823086), a randomized controlled trial that investigated the preventive effect of a weight reduction program and oral glucosamine sulfate vs. placebo on the development of knee osteoarthritis in 407 overweight women in a 2 × 2 factorial design [9]. For this study, only the weight change data were used, the data regarding knee osteoarthritis were disregarded. The follow-up time was 2.5 years; participants body weight was recorded every 6 months. Because the aim of the present study is solely to identify distinct subgroups of a population, undergoing a weight loss intervention, and to describe them, details on the aforementioned study will not be presented here. Obviously, these are published elsewhere [9,10]. To describe the different subgroups, we tested for significant differences between the subgroups in baseline characteristics, as measured in the PROOF Study. Also, we determined the intervention effect on the outcome of assignment to one of the subgroups. Finally, we tested whether baseline characteristics or certain aspects of the intervention had an effect on the outcome, assignment to one of the subgroups.

2.2. Statistical analyses

To identify distinct subgroups of participants with different longitudinal trajectories, LCGA was used. This analysis is capable to identify homogeneous subgroups in a larger heterogeneous population [8,11]. As recommended in literature, several indices of fit of the model were used: the Bayesian information criterion (BIC), the Vuong-Lo-Mendell-Rubin likelihood ratio test (LRT), and entropy indices [8,12]. Improvements of fit of the models were assessed for two to six trajectory classes. Each model was tested with linear, quadratic, and cubic trajectories. In addition to the fit of the model, the usefulness of the latent classes was assessed. Especially, the shape of the trajectories of the different latent classes and the number of participants in each class were evaluated to identify the most optimal model [12].

Characteristics of participants and body weight data in each latent class were presented as means ± standard deviation. Analysis of variance was used to test whether significant differences in these characteristics existed between the groups. Bonferroni and Fisher's least significant difference post hoc tests were used to reveal between which particular groups significant differences existed. The intervention effect on the probability of assignment to one of the latent classes was determined using univariate multinomial regression analysis. Multivariate multinomial regression analysis was used first to test the effect of the baseline characteristics of the participants on the primary outcome, that is, probability of assignment to one of the latent classes, and second to test the effect of characteristics of the intervention, that is, the period of time they were under treatment by the dietician and the amount of goals they met, on the outcome. In the first regression analysis, we adjusted for the intervention effect, as determined in the univariate multinomial regression analysis mentioned previously, because the aim was to determine the effect of the baseline characteristics in itself. In addition, we tested if any of the baseline characteristics showed a significant interaction with the intervention effect, using multivariate multinomial regression analysis, to identify success factors that increased the odds to benefit from the intervention. The second analysis solely included participants that were assigned to the intervention group, because the aim here was to determine the effect of certain aspects of the intervention.

Mplus version 6.12 (sixth edition; Muthén and Muthén, Los Angeles, CA, USA) (1998−2010) was used for the

LCGA. SPSS PASW statistics version 17.0 (SPSS Inc., Chicago, IL, USA) was used for description of characteristics, testing differences and multinomial regression analyses. A significance level of 0.05 was used in all analyses.

3. Results

A detailed description of the randomized participants and their characteristics is published elsewhere [9,10]. For 394 of the 407 participants who entered the original study, weight change data was available. These 394 participants were included in the LCGA.

3.1. Three-group linear model

After evaluating the BIC, LRT, and entropy scores of the models, two models showed the best fit. The first model was a three-group linear model; the second one was a five-group quadratic model. The BIC value of the latter was lower (10,550.628 vs. 10,260.052), and the LRT was more significant ($P = 0.09$ vs. $P = 0.003$), which represents a better fit. In addition, entropy indices showed the five-group model to be the most reliable (0.897 vs. 0.875). However, in the five-group model, two groups consisted each of 10 participants. These two groups had very similar weight change trajectories over time. Our goal was to determine subgroups with different weight change trajectories over time. Therefore, the three-group linear model, which yielded three distinguishable groups, was chosen as the most optimal model. For all participants, the probability of belonging to their subgroup was 88% or higher, suggesting the allocation of the majority of the participants was done correctly. Fig. 1 shows the mean weight change trajectories of the three subgroups.

The largest subgroup ($n = 298$, 73.2%) represented participants who were classified as "steadies" because their weight changes were minimal (0.6 ± 3.4 kg over 30 months) and the slope of this trajectory was close to zero. Participants in the second class ($n = 48$, 11.8%) were classified as "gainers" because their weight changes were mostly positive (7.2 ± 4.1 kg over 30 months) and the slope of this trajectory was positive. Participants in the third class ($n = 48$, 11.8%) were classified as "losers" because their weight changes were mostly negative (−7.7 ± 6.3 kg over 30 months) and the slope of this trajectory was negative. The three groups were significantly different from each other, regarding weight change data on 6, 12, 18, 24, and 30 months, on a significance level of $P < 0.001$.

The intervention effect is estimated by the odds ratio (OR) of 0.4 (95% CI: 0.2, 0.7) for becoming a "gainer" over a "steady". This OR represents that participants in the intervention group, compared with participants in the control group, were less likely to become a "gainer" than to become a "steady". The OR for becoming a "loser"

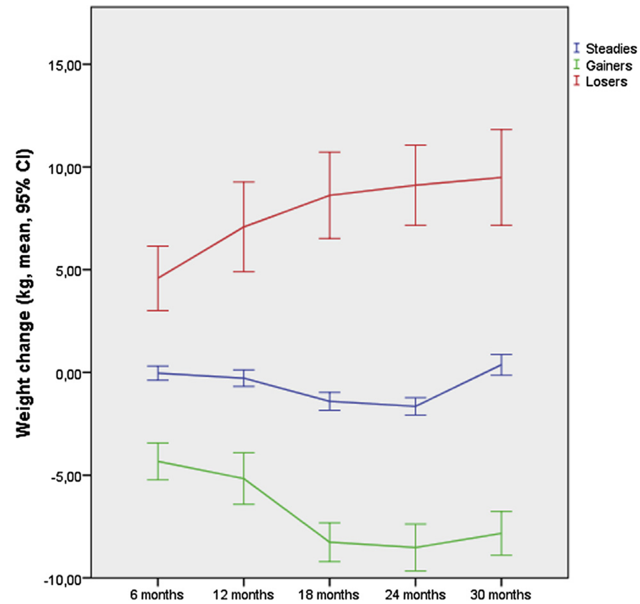

Fig. 1. Mean weight changes during and after the weight loss intervention. Figures presented as mean body weight in kilograms and error bars present 95% confidence intervals. CI, confidence interval.

against becoming a "steady" was 1.2 (95% CI: 0.7, 2.3) for the intervention group compared with the control group. These results are not shown in tables.

3.2. Baseline characteristics

The first multivariate multinomial regression analysis (Table 1) showed that participants with a high baseline body weight were significantly more likely to become a "loser" than to become a "steady". In addition, there is a trend ($P = 0.07$) that participants who gained more weight in the year preceding baseline measurements, are more likely to become a "loser" than to become a "steady". Also, the participants who gained more weight in the year preceding baseline measurements were significantly less likely to become a "gainer" than to become a "steady". Participants that had a high reported body weight around their 40th year of age were significantly less likely

Table 1. Odds ratios from multivariate multinomial regression analysis for effects of baseline characteristics on latent class membership, "steadies" was used as reference class ($n = 394$)

	Losers		Gainers	
Baseline characteristics	**OR**	**95% CI**	**OR**	**95% CI**
Baseline weight, kg	1.06	1.02, 1.09	1.00	0.96, 1.04
Weight change in year preceding baseline, kg	1.06	1.00, 1.13	0.90	0.85, 0.95
Reported body weight around 40th year, kg	0.96	0.92, 1.00	1.00	0.96, 1.04

Abbreviations: CI, confidence interval; OR, odds ratio.

Baseline characteristics that did not show any significant differences between the groups were not included in this analysis. Adjustment for the intervention effect was applied.

to become a ‘‘loser’’ than of becoming a ‘‘steady’’. There were no significant differences found between the three groups in the remaining baseline characteristics, such as age, ethnicity, and educational level. Therefore, we did not adjust for these characteristics. No interactions of any of the baseline characteristics and the intervention effect were found.

3.3. Intervention characteristics

The second multivariate multinomial regression showed that participants who were under treatment by a dietician for a longer period of time were significantly more likely to become a ‘‘loser’’ than to become a ‘‘steady’’. In addition, participants who met more of their goals set by their dietician were significantly more likely to become a ‘‘loser’’ than to become a ‘‘steady’’. Table 2 shows the ORs acquired with this analysis.

4. Discussion

In this study, we classified 394 overweight women who entered a weight reduction trial into three different subgroups based on their weight changes during and after a weight reduction intervention, using an objective method of classifying participants into a number of groups. LCGA revealed three distinct subgroups of individuals. We found that most participants remained relatively stable over time, and there were two smaller groups of which one represented participants who steadily gained weight over time, whereas the other represented participants who steadily lost weight over time. Additionally, we found a significant intervention effect lowering the odds of becoming a ‘‘gainer’’, when assigned to the intervention group. When controlling for the intervention effect, participants with higher baseline weight and with a lower body weight around their 40th year of age were more likely to become a ‘‘loser’’ than to become a ‘‘steady’’. In addition, there is a trend ($P = 0.07$) that participants who gained more weight in the year preceding baseline measurements, are more likely to become a ‘‘loser’’ than to become a ‘‘steady’’. These participants, who gained weight in the year preceding baseline measurements, were significantly less likely to become a ‘‘gainer’’ than to become a ‘‘steady’’. Most ORs are very close to 1.0. This is a consequence of the independent variables in the model, being linear. This means the OR of instance baseline weight in Table 2 represents the change in odds of a 1-kg increase in baseline weight.

Table 2. Odds ratios from multivariate multinomial regression analysis for effects of intervention characteristics on latent class membership, ‘‘steadies’’ is used as reference class ($n = 394$)

	Losers		Gainers	
Intervention characteristics	**OR**	**95% CI**	**OR**	**95% CI**
Period under treatment, months	1.06	1.01, 1.12	0.90	0.79, 1.04
Percentage of achieved goals in dietician's treatment, scale 0–100%	1.02	1.01, 1.04	0.99	0.97, 1.01

Abbreviations: CI, confidence interval; OR, odds ratio.

Intervention characteristics that did not show any significant differences between the groups, were not included in this analysis.

In short, the participants who had low body weight around their 40th year of age, who gained weight in the year preceding baseline measurements, and who had a high baseline weight were most likely to become ‘‘losers’’. It therefore seems that the weight loss recorded during the trial in this group is mostly recently gained weight. In future research, the developments of body weight changes in the years preceding the study should be better assessed, to correctly understand the interaction between these developments and the intervention effect, instead of simply asking participants whether they are currently on a diet or not, which is customary in weight loss trials [6].

To our knowledge, this is the first study to apply latent class analysis to weight data from a weight loss intervention trial. One previous study investigated latent classes of weight loss strategies among women, but based their subgroups on strategies the participants used [7]. We based our subgroups on the actual weight changes in reaction to the intervention, to identify subgroups of patients who are likely to benefit from an intervention as described in this study. When a general practitioner would have a guideline of which intervention is likely to be effective in which subgroups of patients, a tailor-made advice could be given to each patient after assessing a number of characteristics. In this study, we solely found predictors of success, independent of the intervention effect. No interactions of predictors and the intervention effect were found.

This study solely evaluates the effect of a weight loss intervention on weight changes. In addition, subgroups of people that change their nutritional habits or that change their physical activity patterns would be useful too, because either one of these can be a specific goal. Therefore, in addition to the analysis done in the present study, LCGA should be used to recognize patterns in change in nutritional habits or physical activity as well.

In conclusion, LCGA is a useful approach to assess weight loss data in weight loss intervention trials, because it makes it possible to identify patients who are likely to benefit from a particular intervention. In this study, we identified three distinct subgroups of participants with different weight change trajectories during and after a weight loss intervention. Using this model, we found out that a certain amount of the weight loss that occurred during this weight loss intervention was in fact recently put on weight. Success factors that increased the probability to benefit from the intervention were not found, but predictors of success, independent of the intervention effect, were identified. More studies are needed to externally validate these findings.

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