

Available online at www.sciencedirect.com



Preventive Medicine

Preventive Medicine 46 (2008) 203-208

www.elsevier.com/locate/ypmed

# Clusters of lifestyle behaviors: Results from the Dutch SMILE study

Hein de Vries<sup>a,\*</sup>, Jonathan van 't Riet<sup>a</sup>, Mark Spigt<sup>b</sup>, Job Metsemakers<sup>b</sup>, Marjan van den Akker<sup>b</sup>, Jeroen K. Vermunt<sup>c</sup>, Stef Kremers<sup>a</sup>

<sup>a</sup> Department of Health Education and Health Promotion, Maastricht University, The Netherlands
<sup>b</sup> Department of General Practice, Maastricht University, The Netherlands
<sup>c</sup> Department of Methodology and Statistics, Tilburg University, The Netherlands

Available online 23 August 2007

#### Abstract

Objective. This study aimed to identify differences and similarities in health behavior clusters for respondents with different educational backgrounds.

*Methods.* A total of 9449 respondents from the 2002 wave of the Dutch SMILE cohort study participated. Latent class analyses were used to identify clusters of people based on their adherence to Dutch recommendations for five important preventive health behaviors: non-smoking, alcohol use, fruit consumption, vegetable consumption and physical exercise.

*Results.* The distribution of these groups of behaviors resulted in three clusters of people: a healthy, an unhealthy and poor nutrition cluster. This pattern was replicated in groups with low, moderate and high educational background. The high educational group scored much better on all health behaviors, whereas the lowest educational group scored the worst on the health behaviors.

*Conclusion.* The same three patterns of health behavior can be found in different educational groups (high, moderate, low). The high educational group scored much better on all health behaviors, whereas the lowest educational group scored the worst on the health behaviors. Tailoring health education messages using a cluster-based approach may be a promising new approach to address multiple behavior change more effectively.

© 2007 Elsevier Inc. All rights reserved.

Keywords: Lifestyle approach; Latent class analysis; Health behavior; Prevention

# Introduction

Smoking, unhealthy diet, excessive alcohol consumption and poor physical activity levels are important determinants of disease and mortality (WHO, 2000). Approximately three quarters of the Dutch population eat too little fruit and vegetables. Moreover, nearly half of the population does not meet the recommendation for physical activity (Schuit, 2004), nearly one third smokes (Willemsen, 2004) and 14% drinks too much alcohol (Van Dijck and Knibbe, 2005). Although some behaviors are explicitly linked to certain health problems (e.g. smoking to lung cancer), the interaction of multiple behaviors determines whether or not many health problems related to cancer and CVD develop (Doll and Peto, 1981; WHO, 2003). Studies suggests that smoking is accountable for 4.1% of the global burden of disease, while alcohol, inactivity and poor nutrition attribute 4%, 1.3% and 1.8%, respectively (Ezzati et al., 2003). Additionally, data suggest that the adverse health risks such as physical inactivity, obesity and smoking status, translate into higher health care costs. This makes it relevant for health insurance companies to consider strategic investments in preventing these risks (Pronk et al., 1999).

Some studies have failed to show a relationship between health-related behaviors (Kronenfeld et al., 1988; Coulson et al., 1997; Wilcox et al., 2000) whereas others suggested associations between physical activity and healthy eating habits (Simoes et al., 1995; Johnson et al., 1998; Schuit et al., 2002;De Vries et al., in press; Kremers et al., 2004), smoking and eating habits (Larkin et al., 1990; Bolton-Smith et al., 1991; Palaniappan et al., 2001), smoking and physical exercise (Emmons et al., 1994; King et al., 1996) and smoking and alcohol consumption (Perkins et al., 1993; Rust et al., 2001; Ruidavets et al., 2004).

<sup>\*</sup> Corresponding author. Peter Debyeplein 1, 6229 HA Maastricht, The Netherlands. Fax: +31 43 3671032.

E-mail address: hein.devries@gvo.unimaas.nl (H. de Vries).

Studies on the association between alcohol consumption and physical activity have shown mixed results (Smothers and Bertolucci, 2001; Westerterp et al., 2004). Although strong relationships may exist between two behaviors (e.g. smoking and alcohol consumption), the evidence for associations between multiple health behaviors is still mixed and may be dependent on the choice of behaviors included (Langlie, 1979; Van Assema et al., 1993; Wirfalt et al., 2000; Reedy et al., 2005).

Research identifying clusters of health risk behaviors is also relevant because it enables us to analyze whether similar clusters can be identified among respondents with different educational levels. Evidence of socioeconomic differences in health in the Netherlands has been well documented (Mackenbach, 1992; Mackenbach et al., 2001; Van Lenthe et al., 2004). Several international studies also reported on inequalities in health between socioeconomic groups (Franks et al., 2003; Drever et al., 2004; Ferrer and Palmer, 2004) and the contribution of lifestyle factors to these inequalities (Jacobsen and Thelle, 1988; Choiniere et al., 2000; Osler et al., 2000; Kilander et al., 2001).

The first goal of this paper is to explore the existence of clusters in the lifestyle behaviors smoking, alcohol consumption, dietary behavior and physical activity. A second goal was to analyze whether clusters differ within groups with a different educational background. This analysis can identify specific risk groups and thus facilitate targeted primary prevention strategies (Schuit et al., 2002).

# Methods

#### Participants and procedure

The present study is part of the SMILE study, a large ongoing prospective study in the city of Eindhoven in the province of Brabant, the Netherlands. This study is a joint project of Maastricht University and a Corporation of Family Practices in Eindhoven (23 General Practitioners from eight health centers). All patients over 12 years of age are requested to complete self-administered questionnaires at home every 6 months. Addresses of participants were obtained from the General Practitioners. Respondents were eligible for participation after having sent in an informed consent letter. The data from 2002 was used.

# The questionnaire

Fruit consumption, vegetable consumption, smoking, alcohol consumption and physical activity of adult respondents were assessed for this study. A

#### Table 1

Goodness-of-fit measures of the four investigated cluster models (total sample)

dichotomous variable that assessed whether or not respondents adhered to the Dutch norm (0=not adhering to the norm; 1=adhering to the norm) was constructed for each behavior.

Fruit and vegetable consumption were assessed using a food frequency questionnaire of nine items which had been validated and applied in several previous studies (Lechner et al., 1998). Respondents were asked how many times per week they ate a variety of different fruits and vegetables, on a 9-point scale, ranging from 1—'never, or less than once a month' to 9—'7 days a week'. In addition, they were asked to indicate how many of each of these fruits and how many 'small portions' of 50 g, or 'spoonfuls', of these vegetables they ate a day. The average daily intake was computed. People who ate at least two pieces of fruit a day were classified as behaving in accordance with the norm with regards to fruit intake (Van Leent-Loenen and Van Leest, 2005). People who ate at least 200 g of vegetables a day were classified as behaving in accordance with the norm for vegetable consumption (Van Leent-Loenen and Van Leest, 2005).

Physical activity was measured by asking respondents to indicate on how many days a week they engaged in various physical activities for at least 10 min at a time using 15 items on an 8-point scale, ranging from 1—'never, or less than once a week' to 9—'7 days a week' (Wendel-Vos and Schuit, 2002). A single score as an average number of minutes per day was computed. People who engaged in physical activity for at least 30 min, on at least 5 days a week, were classified as adhering to the norm (Schuit, 2004).

Smoking behavior was measured by asking respondents if they smoked daily, smoked occasionally or did not smoke at all (De Vries et al., 1998). Respondents were assured of the confidentiality of their responses, thus optimizing measurement conditions (Murray et al., 1987; Dolcini et al., 1996; Osler et al., 2000). Non-smokers were classified as adhering to the norm (Schuit et al., 2002).

Alcohol consumption was measured by the Dutch Quantity–Frequency– Variability (QFV) Questionnaire (Lemmens et al., 1992). Respondents were asked on how many days a week they drank alcohol and how many glasses they usually consumed on a day when they did drink alcohol. Men who drank three glasses a day or less, and women who drank two glasses a day or less were classified as adhering to the norm (Schuit et al., 2002).

#### Demographic variables

Several questions assessed demographics, such as gender, age and level of education (low—primary school or lower vocational education; middle—secondary school or intermediate vocational education; high—university education or higher vocational training).

#### Statistical analysis

Latent class analyses (LCA) were performed using the five dichotomous norm variables as observed indicators. All analyses were performed with the statistical package Latent Gold (Vermunt and Magidson, 2005). In LCA, the observed variables are considered to be indicators of an unobserved, latent variable, with a limited number of mutually exclusive categories. The main assumption of the model is that responses on these observed variables are mutually independent given a person's class membership or, stated differently,

	$N_{\rm par}{}^{\rm a}$	$L^{2 b}$	df <sup>c</sup>	<i>p</i> -value <sup>d</sup>	LL <sup>e</sup>	BIC (LL) <sup>f</sup>	Class. Err <sup>g</sup>
One-cluster model	5	674.7433	26	$1.4e^{-125}$	-23587.4085	47219.6167	0.0000
Two-cluster model	11	112.6383	20	$6.5e^{-15}$	-23306.3560	46711.2714	0.2130
Three-cluster model	17	37.9660	14	0.00053	-23269.0198	46690.3588	0.3355
Four-cluster model	23	12.7657	8	0.12	-23256.4196	46718.9182	0.3501

<sup>a</sup> Numbers of parameters in the model.

<sup>b</sup> Model Fit Likelihood ratio chi-squared statistic.

<sup>c</sup> Degrees of freedom in the model.

<sup>d</sup> *p*-value of the  $L^2$ .

<sup>e</sup> Log likelihood.

<sup>f</sup> Bayesian Information Criterion, based on the log likelihood.

<sup>g</sup> Classification errors.

that the association between the observed responses can be fully explained by the existence of a small number of latent classes or clusters. This assumption is usually referred to as the local independence assumption (Goodman, 1974; Magidson and Vermunt, 2004).

The unknown parameters to be estimated in LCA are two sets of probabilities: a set of unconditional class membership probabilities and a set of class-specific response probabilities. The former indicate the probability that a randomly chosen individual belongs to a particular cluster and can thus be interpreted as cluster prevalences. A class-specific response probability indicates how likely it is that an individual belonging to a particular cluster gives a particular answer to a question. In this case, response probabilities represent the likelihood of adhering to the health norm for a particular behavior. A probability of 0.50 or less will be considered as a low probability, probabilities in the range 0.50–0.75 as moderate probabilities and probabilities of 0.75 or higher as high in order to facilitate interpretation of the results of this study. To avoid local maxima as much as possible, Latent Gold uses an estimation procedure with multiple sets of random starting values.

# Goodness-of-fit measures

The likelihood ratio-goodness-of-fit chi-squared statistic ( $L^2$ ) indicates which part of the observed relationships between the response variables remains unexplained by the model. The smaller the value, the better the model fits the data and the better the observed relationships are described by the specified model. The associated *p*-value yields a formal assessment of the null hypothesis that the specified cluster model is the true population model. Thus, p > 0.05 indicates that the model fits the data (Goodman, 1974; McCutcheon, 1987). The Bayesian Information Criterion (BIC) weights model fit and parsimony by adjusting the log likelihood (LL) value for the number of parameters ( $N_{par}$ ) in the model. The lower the BIC value, the better the model (Vermunt and Magidson, 2004, 2005). Because the present analysis was an exploratory Latent Class analysis, no restrictions were imposed on the forms of the clusters. Therefore, we used the goodness of fit indices to determine the number of clusters and not the forms.

There is no fully automated procedure in LCA for determining the number of clusters based on a single measure. Instead, one usually assesses the goodness-of-fit of the estimated models using the above-mentioned measures, each of which may point in a slightly different direction. Therefore, the interpretability of the clusters plays an important role in the final model selection.

#### Results

#### Respondent characteristics

A total of 9449 respondents participated in this study. The sample consisted of significantly more women (n=5454; 57.7%) than men (n=3995; 42.3%) ( $\chi^2=225.28$ ; p<0.001). Furthermore, 45.4% (n=4286) of the respondents had a low education level, 23.3% (n=2199) had an average level of education and 29.2% (n=2757) of respondents had a high level of education ( $\chi^2=757.93$ ; p<0.001). The education



Fig. 1. Cluster-specific probabilities of adhering to the recommendations for the three-cluster model in the total sample. (A high score indicates a high probability of adhering to the norm.)



Fig. 2. Cluster-specific probabilities of adhering to the recommendations for the three-cluster model in the low education sample. (A high score indicates a high probability of adhering to the norm.)

level could not be assessed for 2.2% (n=207) of the respondents due to missing values. The mean age was 51.11 years (SD=17.7).

Of all respondents, 43.5% did not adhere to the norm with respect to physical activity, 26.7% smoked, 24.2% drank too much alcohol, 71.6% ate insufficient amounts of fruit and 69.3% ate insufficient amounts of vegetables. Non-adherence rates for respondents with a lower, middle and higher education were 46.2%, 39.8% and 40.2%, respectively, with regards to physical activity, 29.3%, 28.8% and 21.2% for smoking, 23.1%, 30.4% and 21.6% for alcohol consumption, 71.4%, 70.9% and 71.9% for fruit consumption and 72.4%, 69.6% and 63.6% for vegetable consumption.

# Latent class cluster analysis

Models with one to four latent classes were estimated, where the one-cluster model can be seen as a baseline model. It assumes that the five lifestyle behaviors are independent of one another. Goodness-of-fit measures are presented in Table 1.

The goodness-of-fit measures indicated that the three-cluster model represented the most adequate solution for the data. Although the *p*-value corresponding to  $L^2$  should formally be greater than 0.05 to conclude that a model fits the data, in this case a *p*-value of 0.00053 was considered acceptable, given the very large sample size. Furthermore, the three-cluster model had by far the lowest BIC value, which indicates that it is the preferred model according to that criterion.

Fig. 1 shows the estimated probabilities of adhering to the five health recommendations for each of the three clusters.



Fig. 3. Cluster-specific probabilities of adhering to the recommendations for the three-cluster model in the middle education sample. (A high score indicates a high probability of adhering to the norm.)



Fig. 4. Cluster-specific probabilities of adhering to the recommendations for the three-cluster model in the high education sample. (A high score indicates a high probability of adhering to the norm.)

The results show that two groups of behaviors were identified: addictive behaviors (smoking and alcohol consumption) and health promoting behaviors (being physically active and consuming adequate amounts of fruits and vegetables). The distribution of these groups of behaviors resulted in three clusters of people: a healthy, an unhealthy and a poor nutrition cluster. As can be seen from Fig. 1, the group of people pertaining to cluster 1 is characterized by having low probabilities of adhering to the norm for all five behaviors, with low probabilities for physical activity and vegetable and fruit consumption, and moderate probabilities of adhering to the norm for alcohol consumption and smoking. Therefore, cluster 1 can be characterized as an unhealthy cluster. Cluster 2 can be characterized as a healthy cluster. People in this cluster have high probabilities of adhering to the norm for physical activity, and alcohol consumption, and moderate probabilities of adhering to the norm for smoking, and vegetable and fruit consumption. The profile of the respondents of cluster 3 shows a somewhat different pattern, with a low probability of adhering to the norm for physical activity, high probabilities of adhering to the norm for smoking and alcohol consumption and low probabilities of adhering to the norm for vegetable and fruit consumption. Due to the extremely low probabilities for vegetable and fruit consumption, this cluster can thus be characterized as a 'poor nutrition cluster'.

# Latent class analysis per education level

A similar procedure was used in a separate analysis per educational group. As in the overall sample, in each of the three educational groups the three-cluster model represented the most adequate solution, and a healthy, unhealthy and poor nutrition cluster could be identified. Norm adherence probabilities for low, middle and high education are shown in Figs. 2, 3 and 4, respectively.

# Discussion

The first goal of this paper was to explore the existence of clusters of the lifestyle behaviors smoking, alcohol consumption, dietary behavior and physical activity. The results of this study suggest that a healthy, an unhealthy and a poor nutrition cluster can be identified in our general Dutch population.

Our results pertaining to the second goal – the analysis of the cluster structure within educational groups - revealed that the same types of clusters were identified in all three educational groups. However, the higher educated group showed higher adherence levels to the health behavior norms than the lower educated group. These results support findings from other studies (Mackenbach et al., 2001; Louwman et al., 2004; Van Lenthe et al., 2004). Hence, although the adoption pattern of similar behaviors may concur in the same way as for the other groups, their lower adherence levels clearly positions the lower educational group at increased morbidity and mortality risks. Adoption patterns for the high and low educational group were very similar but differed somewhat from the middle educational group. In both groups, the unhealthy cluster was the largest cluster, followed by the poor nutrition and healthy cluster. The poor nutrition group was the largest cluster in the middle education group, with 71% of the respondents of this segment in this cluster, while the unhealthy cluster was the smallest. An interesting finding is that both the low education and high education subgroups show high probabilities of adherence to the norms with respect to alcohol and smoking. More research is needed to detect whether the factors determining this similarity are the same. It is for instance conceivable that price elasticity may have a stronger impact on adults with a lower education because of lack of disposable income to be spent, whereas for higher educated individuals this factor may be of less influence.

Another important observation was that within the five lifestyle behaviors assessed in our study, we identified clusters with two different sets of behaviors. Two of the behaviors – smoking and alcohol consumption – require restraining, refraining or abstinence, while the other three behaviors – being physically active and consuming adequate amounts of fruits and vegetables – require actively engaging in health promoting activities.

Multiple behavior change interventions are recognized as a promising approach to enhance health, to increase efficiency of health interventions (USDHHS, 2000) and to reduce health costs (Glasgow et al., 2004; Goldstein et al., 2004; Orleans, 2004; Pronk et al., 2004; Prochaska et al., 2005). However, addressing multiple risk factors will put high demands on the participant who may loose attention or interest. Suggestions to change several behaviors may result in discouragement or may reduce a person's motivation and energy, a phenomenon also referred to as ego depletion (Baumeister et al., 1998; Baumeister, 2003). Our findings may imply that a cluster-based approach can have potential because related behaviors are addressed. However, experimental research is needed to find out whether addressing clusters of related behaviors will indeed result in better effects and less demotivation and ego depletion than interventions that focus on changing all risk behaviors simultaneously.

A new approach that has shown to have potential to address large segments of people is computer tailoring in which individuals obtain personalized feedback about their risk profile and how to change the behavior(s). While some computer-tailoring methods have shown promising results, the combination of several behaviors may not always lead to successful multiple behavior change. For instance, a study by Prochaska and colleagues was successful in changing smoking, nutrition, skin cancer and mammography screening behaviors (Prochaska et al., 2005). However, another study – which used previously tested and effective computer-tailored programs on smoking, nutrition and physical activity - did result in changes in nutrition and physical activity but was not successful in changing smoking (Smeets et al., 2007). An implication of the results could – again – be that one generic lifestyle approach targeting all behaviors may not be the best strategy. It might be more effective to use a cluster-tailored approach. A recent cluster analyses approach that focused on colorectal cancer patients found five different clusters (Reedy et al., 2005). In this study, the effectiveness of the computer-tailored approach differed per cluster. These results underline the relevance to target different clusters with different tailored strategies. Our study suggest that a different approach may be needed for people engaging in addictive behaviors such as smoking and alcohol on the one hand and for the poor nutrition group on the other hand.

# Study limitations and strengths

This study is subject to limitations. In general, results of cluster analyses are difficult to compare since they are highly dependent on the inclusion of the set of variables (Prochaska et al., 2005; Reedy et al., 2005). Moreover, the variations in techniques hinder the comparisons between the studies. Clear guidelines for setting up these types of studies for public health research are needed. Finally, body mass index (BMI) was not included separately in our analyses. Further research is needed to analyze whether BMI is encompassed within the product of poor nutrition and inactivity, or whether it deserves to be included in a research model separately.

# Conclusions

First, our results show two groups of addictive behaviors – smoking and alcohol consumption which require restraining, refraining or abstinence and three health promoting behaviors – being physically active and consuming adequate amounts of fruits and vegetables – which require actively engaging in health promoting activities. The distribution of these clusters over people resulted in three groups: a healthy, an unhealthy and poor nutrition cluster; this pattern was replicated in groups with a low, moderate and high educational background. Tailoring health education messages using a cluster-based approach may be a promising new approach to address multiple behavior change more effectively.

# Acknowledgments

The Study of Medical Information and Lifestyles in Eindhoven is funded by the research institute CAPHRI of Maastricht University. The authors would like to thank the Corporation of Family Practices in Eindhoven and their management (E. van Voorst and J. van de Sande) for collaboration, as well as the respondents who filled out the questionnaire. We thank the reviewers for their constructive and useful comments on an earlier version.

# References

- Baumeister, R.F., 2003. Ego depletion and self-regulation failure: a resource model of self-control. Alcohol Clin. Exp. Res. 27 (2), 281–284.
- Baumeister, R.F., Bratslavsky, E., Muraven, M., Tice, D.M., 1998. Ego depletion: is the active self a limited resource? J. Pers. Soc. Psychol. 74 (5), 1252–1265.
- Bolton-Smith, C., Casey, C.E., Gey, K.F., Smith, W.C., Tunstall Pedoe, H., 1991. Antioxidant vitamin intakes assessed using a food-frequency questionnaire: correlation with biochemical status in smokers and non-smokers. Br. J. Nutr. 65, 337–346.
- Choiniere, R., Lafontaine, P., Edwards, A.C., 2000. Distribution of cardiovascular disease risk factors by socioeconomic status among Canadian adults. Can. Med. Assoc. J. 162, s13–s24.
- Coulson, N.S., Eiser, C., Eiser, J.R., 1997. Diet, smoking and exercise: interrelationships between adolescent health behaviours. Child Care Health Dev. 23, 207–216.
- De Vries, H., Mudde, A.N., Dijkstra, A., Willemsen, M.C., 1998. Differential beliefs, perceived social influences, and self-efficacy expectations among smokers in various motivational phases. Prev. Med. 27, 681–689.
- De Vries, H., Kremers, S.P.J., Smeets, T., Reubsaet, A., in press. Clustering of diet, physical activity and smoking and a general willingness to change. Psychol. Health.
- Dolcini, M.M., Adler, N.E., Ginsberg, D., 1996. Factors influencing agreement between self-reports and biological measures of smoking among adolescents. J. Res. Adolesc. 6, 515–542.
- Doll, R., Peto, R., 1981. The causes of cancer: quantitative estimates of avoidable risks of cancer in the United States today. J. Natl. Cancer Inst. 66, 1191–1308.
- Drever, F., Doran, T., Whitehead, M., 2004. Exploring the relation between class, gender, and self rated general health using the new socioeconomic classfication. A study using data from the 2001 census. J. Epidemiol. Community Health 58, 590–596.
- Emmons, K.M., Marcus, B.H., Linnan, L., Rossi, J.S., Abrams, D.B., 1994. Mechanisms in multiple risk factor interventions: smoking, physical activity, and dietary fat intake among manufacturing workers. Working Well Research Group. Prev. Med. 23, 481–489.
- Ezzati, M., VanderHoorn, S., Rodgers, A., Lopez, A., Mathers, C., Murray, C., 2003. Estimates of global and regional health gains from reducing multiple major risk factors. Lancet 362 (9380), 271–280.
- Ferrer, R.L., Palmer, R., 2004. Variations in health status within and between socioeconomic strata. J. Epidemiol. Community Health 58, 381–387.
- Franks, P., Gold, M.R., Fiscella, K., 2003. Sociodemographics, self-rated health, and mortality in the US. Soc. Sci. Med. 56, 2505–2514.
- Glasgow, R.E., Goldstein, M.G., Ockene, J.K., Pronk, N.P., 2004. Translating what we have learned into practice. Principles and hypotheses for interventions addressing multiple behaviors in primary care. Am. J. Prev. Med. 27, 88–101.
- Goldstein, M.G., Whitlock, E.P., DePue, J., 2004. Multiple behavioral risk factor interventions in primary care. Summary of research evidence. Am. J. Prev. Med. 27, 61–79.
- Goodman, L.A., 1974. Exploratory latent structure analysis using both identifiable and unidentifiable models. Biometrika 61, 215–231.
- Jacobsen, B.K., Thelle, D.S., 1988. Risk factors for coronary heart disease and level of education. The Tromso Heart Study. Am. J. Epidemiol. 127, 923–932.
- Johnson, M.F., Nichols, J.F., Sallis, J.F., Calfas, K.J., Hovell, M.F., 1998. Interrelationships between physical activity and other health behaviors among university women and men. Prev. Med. 27, 536–544.
- Kilander, L., Berglund, L., Boberg, M., Vessby, B., Lithell, H., 2001. Education, lifestyle factors and mortality from cardiovascular disease and cancer. A 25-year follow-up of Swedish 50-year-old men. Int. J. Epidemiol. 30, 1119–1126.

- King, T.K., Marcus, B.H., Pinto, B.M., Emmons, K.M., Abrams, D.B., 1996. Cognitive–behavioral mediators of changing multiple behaviors: smoking and a sedentary lifestyle. Prev. Med. 25, 684–691.
- Kremers, S.P.J., De Bruijn, G.J., Schaalma, H., Brug, J., 2004. Clustering of energy balance-related behaviours and their intrapersonal determinants. Psychol. Health 19 (5), 595–606.
- Kronenfeld, J.J., Goodyear, N., Pate, R., et al., 1988. The interrelationship among preventive health habits. Health Educ. Res. 3, 317–323.
- Langlie, J.K., 1979. Interrelationships among preventive health behaviors: a test of competing hypotheses. Public Health Rep. 94, 216–225.
- Larkin, F.A., Basiotis, P.P., Riddick, H.A., Sykes, K.E., Pao, E.M., 1990. Dietary patterns of women smokers and non-smokers. J. Am. Diet. Assoc. 90, 230–237.
- Lechner, L., Brug, J., DeVries, H., vanAssema, P., Mudde, A., 1998. Stages of change for fruit, vegetable and fat intake: consequences of misconception. Health Educ. Res. 13, 1–11.
- Lemmens, P., Tan, E., Knibbe, R., 1992. Measuring quantity and frequency of drinking in a general population survey: a comparison of five indices. J. Stud. Alcohol 53, 476–486.
- Louwman, W.J., van Lenthe, F.J., Coebergh, J.W., Mackenbach, J.P., 2004. Behaviour partly explains educational differences in cancer incidence in the south-eastern Netherlands: the longitudinal GLOBE study. Eur. J. Cancer Prev. 13, 119–125.
- Mackenbach, J.P., 1992. Socio-economic health differences in The Netherlands: a review of recent empirical findings. Soc. Sci. Med. 34, 213–226.
- Mackenbach, J.P., Borsboom, G.J.J.M., Nusselder, W.J., Looman, C.W.N., Schrijvers, C.T.M., 2001. Determinants of levels and changes of physical functioning in chronically ill persons: results from the GLOBE Study. J. Epidemiol. Community Health 55, 631–638.
- Magidson, J., Vermunt, J.K., 2004. Latent class analysis. In: Kaplan, D. (Ed.), The Sage Handbook of Quantitative Methodology for the Social Sciences. Sage Publications, Thousand Oakes, pp. 175–198.
- McCutcheon, A.L., 1987. Latent Class Analysis. Sage Publications, Beverly Hills, CA.
- Murray, D.M., O'Connell, C.M., Schmid, L.A., Perry, C.L., 1987. The validity of smoking self-reports by adolescents: a reexamination of the bogus pipeline procedure. Addict. Behav. 12, 7–15.
- Orleans, C.T., 2004. Addressing multiple behavioral health risks in primary care. Broadening the focus of health behavior change research and practice. Am. J. Prev. Med. 27, 1–3.
- Osler, M., Gerdes, L.U., Davidsen, M., et al., 2000. Socioeconomic status and trends in risk factors for cardiovascular diseases in the Danish MONICA population, 1982–1992. J. Epidemiol. Community Health 54, 108–113.
- Palaniappan, U., Jacobs Starkey, L., O'Loughlin, J., Gray Donald, K., 2001. Fruit and vegetable consumption is lower and saturated fat intake is higher among Canadians reporting smoking. J. Nutr. 131, 1952–1958.
- Perkins, K.A., Rohay, J., Meilahn, E.N., Wing, R.R., Matthews, K.A., Kuller, L.H., 1993. Diet, alcohol, and physical activity as a function of smoking status in middle-aged women. Health Psychol. 12, 410–415.
- Prochaska, J.O., Velicer, W.F., Redding, C., et al., 2005. Stage-based expert systems to guide a population of primary care patients to quit smoking, eat healthier, prevent skin cancer, and receive regular mammograms. Prev. Med. 41, 406–416.
- Pronk, P., Goodman, M., O'Connor, P., Martinson, B., 1999. Relationship between modifiable health risks and short-term health care charges. JAMA 282, 2235–2239.
- Pronk, N.P., Anderson, L.H., Crain, A.L., et al., 2004. Meeting recommendations for multiple healthy lifestyle factors. Prevalence, clustering, and predictors among adolescent, adult, and senior health plan members. Am. J. Prev. Med. 27 (2 Suppl), 25–33.

- Reedy, J., Haines, P.S., Campbell, M.K., 2005. The influence of health behavior clusters on dietary change. Prev. Med. 41, 268–275.
- Ruidavets, J.B., Bataille, V., Dallongeville, J., et al., 2004. Alcohol intake and diet in France, the prominent role of lifestyle. Eur. Heart J. 25, 1153–1162.
- Rust, P., Lehner, P., Elmadfa, I., 2001. Relationship between dietary intake, antioxidant status and smoking habits in female Austrian smokers. Eur. J. Nutr. 40, 78–83.
- Schuit, A.J., 2004. Hoeveel mensen zijn onvoldoende lichamelijk actief? (How many people are insufficiently physically active?) Volksgezondheid Toekomst Verkenning. RIVM, Bilthoven.
- Schuit, J.A., Van Loon, J.M., Tijhuis, M., Ocké, M.C., 2002. Clustering of lifestyle risk factors in a general adult population. Prev. Med. 35, 219–224.
- Simoes, E.J., Byers, T., Coates, R.J., et al., 1995. The association between leisure-time physical activity and dietary fat in American adults. Am. J. Public Health 85, 240–244.
- Smeets, T., Kremers, S.P.J., Brug, J., De Vries, H., 2007. Effect of tailored feedback on multiple health behaviors. Ann. Behav. Med. 33 (2), 117–123.
- Smothers, B., Bertolucci, D., 2001. Alcohol consumption and health-promoting behavior in a U.S. household sample: leisure-time physical activity. J. Stud. Alcohol 62, 467–476.
- USDHHS, 2000. Healthy People 2010. Conference Edition. U.S. Department of Health and Human Services, Washington, D.C.
- Van Assema, P., Pieterse, M., Kok, G., Eriksen, M., De Vries, H., 1993. The determinants of four cancer-related risk behaviours. Health Educ. Res. 8, 461–472.
- Van Dijck, D., Knibbe, R.A., 2005. De prevalentie van probleemdrinken in Nederland: Een algemeen bevolkingsonderzoek (The prevalence of problem drinking in the Netherlands. A general screening). Maastricht University, Maastricht.
- Van Leent-Loenen, H.M.J.A., Van Leest, L.A.T.M., 2005. Voeding samengevat (Nutrition summarized). Volksgezondheid Toekomst Verkenning, Nationaal Kompas Volksgezondheid. RIVM, Bilthoven.
- Van Lenthe, F.J., Schrijvers, C.T., Droomers, M., Joung, I.M., Louwman, M.J., Mackenbach, J.P., 2004. Investigating explanations of socio-economic inequalities in health: the Dutch GLOBE study. Eur. J. Public Health 14, 63–70.
- Vermunt, J.K., Magidson, J., 2004. Latent class analysis. In: Lewis-Beck, M., Bryman, A., Liao, T.F. (Eds.), The Sage Encyclopedia of Social Sciences Research Methods. Sage Publications, Thousand Oakes, CA, pp. 549–553.
- Vermunt, J.K., Magidson, J., 2005. Latent Gold 4.0 User's Guide. Statistical Innovations Inc., Belmont, Massachusetts.
- Wendel-Vos, W., Schuit, J.A., 2002. SQUASH. Short QUestionnaire to ASses Health enhancing physical activity. Centrum voor Chronische ziekten Epidemiologie, Bilthoven.
- Westerterp, K.R., Meijer, E.P., Goris, A.H., Kester, A.D., 2004. Alcohol energy intake and habitual physical activity in older adults. Br. J. Nutr. 91, 149–152.
- WHO, 2000. The World Health Report 2000. World Health Organization, Geneva.
- WHO, 2003. Diet, nutrition and the prevention of chronic diseases. WHO technical report series. WHO, Geneva.
- Wilcox, S., King, A.C., Castro, C., Bortz, W., 2000. Do changes in physical activity lead to dietary changes in middle and old age? Am. J. Prev. Med. 18, 276–283.
- Willemsen, M.C., 2004. Hoeveel mensen roken? (How many people smoke?) Volksgezondheid Toekomst Verkenning. RIVM, Bilthoven.
- Wirfalt, E., Mattisson, I., Gullberg, B., Berglund, G., 2000. Food patterns defined by cluster analysis and their utility as dietary exposure variables: a report from the Malmo Diet and Cancer Study. Public Health Nutr. 3, 159–173.