ISSN 2282-0930 • Epidemiology Biostatistics and Public Health - XIII[th] SISMEC Congress - Vol. 20 Suppl. 1

Assessing Lifestyle Risk Profiles in Older Adults via Latent Class Analysis: A Cross-Sectional Analysis of the Association with Metabolic Biomarkers Using ELSA Data

Das Aditi[(1)], Victoria Lee Hampel[(1)], Paola Zaninotto[(2)], Palla Luigi[(1)]

(1) Department of Public Health and Infectious Diseases, University of Rome La Sapienza, Italy
(2) Department of Epidemiology and Public Health, University College London, UK

CORRESPONDING AUTHOR: *Palla Luigi, luigi.palla@uniroma1.it*

INTRODUCTION

The global prevalence of metabolic diseases such as diabetes continues to rise, particularly among aging populations [1]. Among risk factors, lifestyle behaviors are modifiable and play a central role in the prevention and progression of metabolic diseases [2]. These risks do not act alone, making it important to examine how lifestyle behaviors cluster and interact with one another and how their joint classification is associated with biological markers of metabolic diseases. ELSA [3] is a longitudinal study of over-50 years old subjects, specifically designed to study ageing population in Britain.

OBJECTIVES

The main objective was to identify distinct behaviorally defined subgroups among older adults from Wave 4 (2008/2009) of the ELSA through latent class analysis and characterize their associated biomarker profiles[4]. By linking these lifestyle patterns to early biological risk markers, this study seeks to enhance understanding of the mechanisms connecting lifestyle behaviors to metabolic health, ultimately informing more targeted interventions for the prevention of diabetes and related metabolic conditions in later life.

METHODS

This study utilized data from ELSA Wave 4 specifically for its inclusion of extensive biomarker data, which are critical for analyzing metabolic and diabetes-related health risks.

For downstream analysis, several data transformations and recoding steps were performed. Each blood biomarker (white blood cells, haemoglobin, insulin growth factor 1, HbA1c, fasting glucose, triglycerides, DHEAS) was recoded into a binary variable using cutoff values defined through clinical practice/literature specific to the British population. The initial sample size including data on these biomarkers was n= 3147.

Latent Class Analysis (LCA) was performed using the poLCA package in R, incorporating categorized lifestyle factors such as sleep quality, comorbidities, smoking habits, nutrition (fruit and vegetable intake), alcohol consumption, physical activity, and obesity as manifest variables. To determine the optimal number of latent classes, multiple models were estimated and compared using model fit indices, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and significance of predicted class memberships, to ensure meaningful interpretation. A complete case LCA approach was chosen as this resulted the best model fit compared to analysis with inclusion of missing values.

Depending on the nature of each biomarker, appropriate regression methods were applied: linear regression for continuous biomarkers, binary logistic regression for those with strict cutoff thresholds, and multinomial regression for biomarkers with multiple healthy/unhealthy categories. All regression models were adjusted stepwise, starting with unadjusted models and progressing to fully adjusted ones, incorporating confounders grouped as demographic/biological (age, sex, ethnicity), socioeconomic (education, net worth, deprivation score), health-related (comorbidities, depression), and, finally, household composition.

RESULTS

Latent Class Analysis identified three distinct lifestyle behavior profiles: Class 1—characterized by overall healthy behaviors; Class 2—marked primarily by poor sleep and Class 3—defined by a combination of poor sleep, unhealthy nutrition, smoking and borderline levels of physical activity (Figure

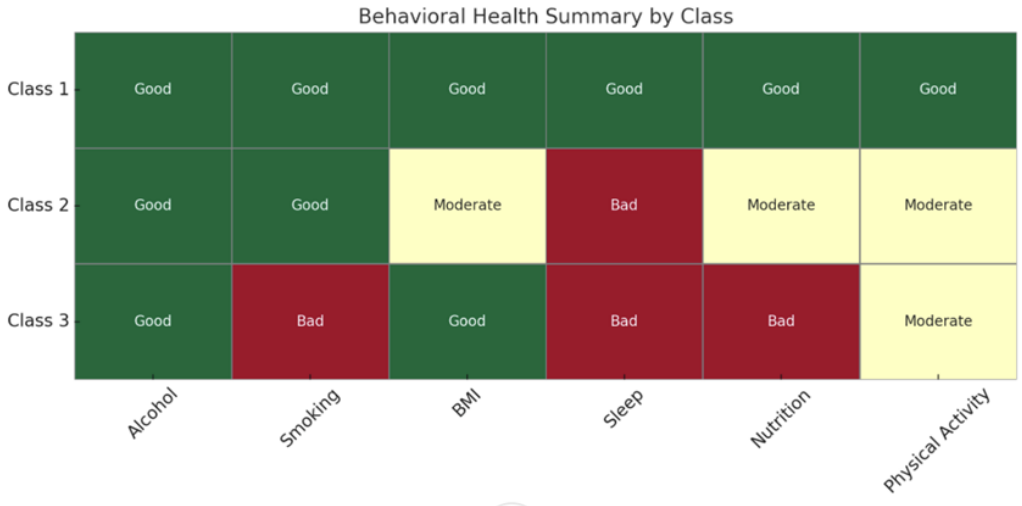
DOI: 10.54103/2282-0930/29247

1). Compared to individuals with healthy behaviors (Class 1), those in Class 2 had higher odds of elevated triglycerides (OR = 1.73; 95% CI: 1.43-2.08), and very similar odds for Class 3 (OR = 1.74; 95% CI: 1.31-2.29). Elevated triglycerides were also significantly associated with male sex. These findings were supported by linear regression results, which showed that Classes 2 and 3 had significantly higher average triglyceride levels—an increase of 0.17 mmol/L (95% CI: 0.09 to 0.24) and 0.25 mmol/L (95% CI: 0.13 to 0.36), respectively—approaching borderline unhealthy levels.

For HbA1c, individuals in Class 2 and Class 3 had higher odds of elevated levels (OR = 1.30; 95% CI: 1.11-1.60 and OR = 1.87; 95% CI: 1.41-2.51, respectively), compared to Class 1. In linear regression, the baseline HbA1c level (intercept) was 5.64 (95% CI: 5.57 to 5.70), and both Class 2 (+0.11, 95% CI: 0.06 to 0.15) and Class 3 (+0.09, 95% CI: 0.03 to 0.16) showed significant increases—pushing average levels to or just above the 5.7% threshold. Elevated HbA1c was also significantly associated with older age, particularly higher in those in their 70s.

In the fully adjusted multinomial regression, participants in Class 2 had significantly higher odds of low DHEAS levels compared to Class 1 (OR = 2.02, 95% CI: 1.51 to 2.70), suggesting a strong association between poor sleep and reduced DHEAS.

1. Sinclair, A., Saeedi, P., Kaundal, A., et al., Diabetes and global ageing among 65–99-year-old adults: Findings from the International Diabetes Federation Diabetes Atlas, 9th edition, (2020), Diabetes Research and Clinical Practice, 162, 108078
2. Schulze, M. B., Hoffmann, K., Boeing, H., et al., An accurate risk score based on anthropometric, dietary, and lifestyle factors to predict the development of type 2 diabetes. Diabetes Care, (2007), 30(3), 510–515
3. English Longitudinal Study of Ageing (ELSA). (n.d.). About ELSA. Retrieved May 23, 2025, from
4. https://www.elsa-project.ac.uk/about-elsa
5. Collins, L. M., & Lanza, S. T. (2010). Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences. Wiley. https://doi.org/10.1002/9780470567333
6. Maggio M., Colizzi E., Fisichella A., Valenti G., Ceresini G., Dall'Aglio E., Ruffini L., Lauretani F., Parrino L., Ceda G.P.Stress hormones, sleep deprivation and cognition in older adults. Maturitas, 2013; 76(1): 22-44



CONCLUSIONS

This study highlights that poor sleep alone (Class 2) is associated with significant increases in metabolic risk markers such as HbA1c and triglycerides, pushing levels toward borderline or unhealthy ranges. When combined with other unhealthy lifestyle factors such as unhealthy diet and smoking (Class 3), there is an additional negative effect for several biomarkers. Furthermore, poor sleep was also strongly related to low DHEAS, which is in turn a known factor linked to the hormonal processes of aging[5]. Overall, these findings highlight the importance of addressing specific patterns of behavior in order to increase awareness of and protection against early metabolic dysregulation and enhance healthy aging.

Figure 1. Behavioral profiles of latent classes using a ≥0.50 probability cutoff for unhealthy behaviors (red) and a 0.35–0.49 range to denote moderate probability of unhealthy behaviour (yellow); <0.35 indicates lower probability of unhealthy behaviour

REFERENCES

DOI: 10.54103/2282-0930/29247