DOI: 10.1590/1413-81232023287.05622022

Lifestyle behaviors and associated factors among individuals with diabetes in Brazil: a latent class analysis approach

Comportamentos de estilo de vida e fatores associados entre indivíduos portadores de diabetes no Brasil: uma abordagem com análise de classes latentes

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Abstract *The purpose of the cross-sectional study was to identify patterns of modifiable lifestyle behaviors and examine the relationship between sociodemographic characteristics and distinct lifestyle behaviors. The data were gathered from the National Health Survey 2019, a study that included adults with diabetes. Four domains of lifestyle behaviors were used to define these behaviors: smoking, alcohol consumption, physical activity, and diet. The association between patterns of lifestyle behaviors and variables of interest was assessed using multinomial regression analysis. The three lifestyle patterns identified were: Class 1, referred to as "unhealthy diet," comprised 17.0% of the sample and was characterized by unhealthy eating habits; Class 2 (less active and insufficient fruit and vegetable intake) represented 71.2% of the sample; Class 3 referred to as "low risk" (11.8%) is characterized by a lower probability of engaging in most risky behaviors. A person over 45 years of age with little or no education and no health care coverage was less likely to be a member of Class 1. Male individuals who do not attend a doctor regularly exhibited more chances of belonging to Class 2. Mixed-race individuals aged 45 years or more with a low level of education have a lower chance of belonging to this class.*

Key words *Health behavior, Latent class analysis, Diabetes mellitus, Health surveys*

Resumo *Neste estudo de caráter transversal objetivou-se identificar os padrões de comportamento de estilo de vida e sua associação com características sociodemográficas. Utilizou-se como base de dados a Pesquisa Nacional de Saúde de 2019, com adultos (≥ 18 anos) diabéticos. Os padrões de saúde foram definidos pela Análise de Classes Latentes em quatro domínios: tabagismo, consumo de bebidas alcoólicas, atividade física e alimentação. Foi aplicada análise de regressão multinominal para identificar a associação entre os padrões de comportamento e as variáveis sociodemográficas de interesse. Identificou-se três padrões de comportamento: a Classe 1 corresponde a 17% da amostra e compreende indivíduos com maior probabilidade de comportamentos de risco ligados à alimentação; a Classe 2 (baixos nível de atividade física e consumo de frutas e hortaliças) compreende 71,2% da amostra; e a Classe 3 (11,8% da população) reúne os indivíduos com menor chance de desenvolver comportamentos de risco. Indivíduos com 45 anos ou mais, com baixa escolaridade e sem plano de saúde têm menos chances de pertencer à Classe 1. Homens, que não fazem visitas regulares ao médico têm maiores chances de pertencer à Classe 2, bem como aqueles com 45 anos ou mais, com baixa escolaridade.*

Palavras-chave *Comportamento de saúde, Análise de classes latentes, Diabetes mellitus, Inquéritos de saúde*

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Introduction

Global health challenges are currently affecting the majority of the population. It is noteworthy that chronic non-communicable diseases (NCDs) are becoming increasingly prevalent, such as diabetes mellitus (DM), cardiovascular disease (CVD), cancer, and respiratory disease, are regarded worldwide as the leading causes of death[1]. There were 451 million diabetics worldwide in 2017, based on the International Diabetes Federation's estimate[2]. These figures are expected to increase to 693 million by 2045[2]. Currently, 70% of those with diabetes live in low- and middle-income countries, and the number of people with diabetes will more than double in these countries over the next 20 years[3,4]. These estimates are worrying as diabetes was responsible for 294,203 deaths in Brazil between 1996 and 2011[5].

The issue of diabetes is not only one of health but also of economics. People with diabetes are predominantly middle-aged and are at the top of their professional and economic careers[6], and its complications can result in disability and premature death in individuals with diabetes, causing substantial healthcare system costs[7]. Diabetes has a multifactorial etiology involving genetic and modifiable lifestyle factors. The main behavioral risk factors for the onset of NCDs are excessive consumption of alcoholic beverages, smoking, physical inactivity, and an unhealthy diet[8,9]. Studies have also revealed that changes in lifestyle patterns through the adoption of health behaviors can effectively improve an individual's health conditions or alleviate symptoms and complications of chronic diseases, such as diabetes[10].

Health behaviors do not occur in isolation, and there is often synergy between them[11], so it is pertinent to investigate the combined occurrence of these behaviors to better predict an individual's overall healthy lifestyle[12,13]. Research on the clustering of health behaviors has increased recently since it is a potential tool for organizing individuals into mutually exclusive groups by considering similarities in characteristics and behaviors[14-16], allowing the verification of which behaviors coexist among individuals. Researchers have identified clustering patterns and the co-occurrence of negative and positive health-related behaviors through observational studies[16-18]. In order to make interventions more targeted and customized, it is essential to be able to identify subgroups with similar behaviors among people with diabetes.

Nevertheless, evidence from diabetes studies[19,20] indicates that lifestyle behaviors are often examined separately. Additionally, there is a lack of evidence regarding clusters of health-related behaviors among people with diabetes living in low-, lower-middle-, and upper-middle-income countries, and it is assumed that health behavior patterns are closely associated with demographics. We used latent class analysis (LCA) on a nationally representative sample dataset in order to: (1) identify the patterns of modifiable lifestyle behaviors (physical activity, sedentary behavior, diet, smoking, and drinking); (2) assess the relationship between sociodemographic characteristics and distinct patterns, thereby identifying the most vulnerable subgroups of patients.

Methods

Data source and participants

We obtained data from the National Health Survey (PNS – Portuguese acronym for *Pesquisa Nacional de Saúde*), a population-based household survey conducted in Brazil in 2019, by the Brazilian Institute of Geography and Statistics (IBGE – Portuguese acronym for *Instituto Brasileiro de Geografia e Estatística*) in partnership with the Ministry of Health (MH) and the Oswaldo Cruz Foundation (Fiocruz – Portuguese abbreviation for *Fundação Oswaldo Cruz*)[21]. The 2019 PNS included people aged 15 years or older residing in private households throughout the country. Using a three-stage cluster sampling technique, census sectors were used as the primary unit, households were used as the secondary unit, and the adults of each household were selected as tertiary units to complete the PNS questionnaire. There are more details regarding the sample available elsewhere[21].

We included individuals over the age of 18 who answered positively to the question on the survey questionnaire, "Has your doctor already diagnosed you with diabetes?" (n = 7,358), as part of this study (n = 88,531). A total of 7,327 individuals were included in this study after excluding pregnant women (n = 31).

Study variables

We constructed the LCA based on the patterns of lifestyle behaviors that include the following ten modifiable lifestyle risk factors, all of them as dichotomous indicators: (i) current

Ciência & Saúde Coletiva, 28(7):1983-1992, 2023

smoking; (ii) binge drinking (more than five doses on a single occasion)[1]; (iii) physically inactive (< 150 minutes of light or moderate activity/week)[22]; (iv) excessive time spent watching television (> 2 hours/day)[23]; (v) excessive time spent on the computer (> 2 hours/day)[24]; (vi) insufficient intake of fruits/natural juices and vegetables (< 25 times a week/< 5 servings a day)[25]; (vii) regular consumption of sweets (≥ 5 days/week)[26]; (viii) overconsumption of red meat (> 3 times/week)[27]; (ix) regular consumption of soft drinks (≥ 5 times/week); and (x) regular consumption of artificial juices (≥ 5 times/week)[26].

Sociodemographic variables were: sex (male/female), age group (18-24 years; 25-34 years; 35-44 years; 45-54 years; 55-64 years; ≥ 65 years), race/color (white, black, mixed race and others), schooling (illiterate and incomplete elementary school level, complete elementary and incomplete high school level, complete high school and incomplete higher education level, complete higher education level), socioeconomic classification (high: A and B1; middle: B2 and C1; and low: C2, D, and E)[28], self-perceived health (very bad/bad/regular, and good/very good), lives with a partner (yes/no), marital status (married, separated/divorced/widower, and single), regular visits to the doctor (yes/ no) and health care insurance (yes/no).

Latent class analysis (LCA)

The binary latent class indicators were created to reflect existing health recommendations and included ten items representing multiple dimensions of lifestyle behaviors. As part of the LCA, we first identified heterogeneous groups of health behaviors among individuals with diabetes to examine lifestyle behavior clusters (outcome variable) patterns. We intended to emphasize the importance of health behavior patterns among heterogeneous individuals by analyzing clusters of health behaviors rather than single behaviors[29]. The LCA is used to identify latent classes within a population based on individual responses to discrete manifest variables (observed indicators). This technique has been widely adopted in medical studies and health research. In our study, we derived mutually exclusive groups of individuals whose discrete manifest responses to health behaviors were minimal within groups and whose differences between groups were maximal. LCA examines unobserved heterogeneity, mitigating the possibility of biased estimates due to heterogeneity in conventional regression. A person-centered approach reveals the smallest differences in health behaviors among individuals within the same class. LCA is based on a finite mixture model[30].

To classify the latent classes of patterns of lifestyle behaviors, we used a series of model fit criteria, including the Akaike information criterion (AIC), conditional Akaike information criterion (cAIC), and Bayesian or adjusted Bayesian information criterion (BIC/aBIC). In order to compare the model fit between sequential classes, we used the Vuong–Lo–Mendell–Rubin likelihood ratio test (LMR).

Data analyses

We calculated the relative frequencies and the 95% confidence intervals (CI) for the descriptive analysis, considering the sample's complex design. Using a multinomial logistic regression model with Class 3 as the reference category, we examined the associations between each latent class of lifestyle behaviors (outcome variable), sociodemographic variables, and other variables of interest (independent variables). All sociodemographic variables and the time since the disease diagnosis were considered in the multivariate model. LCA analysis was performed using the Statistical Program R 4.1.1, package poLCA. SAS On-Demand for Academics was used for descriptive analysis and multinomial logistic regression. SAS survey procedures (proc surveyfreq, proc surveymeans, proc surveylogistic) were used to account for the complex sampling design of the study. The significance level of the study was 5%.

The PNS received approval from the National Research Ethics Commission (CONEP – Portuguese abbreviation for *Comissão Nacional de Ética em Pesquisa*) of the National Health Council (CNS – Portuguese acronym for *Conselho Nacional de Saúde*). Respondents who were part of the sample agreed to participate in the study by signing the Term of Free and Informed Consent.

Results

The sociodemographic characteristics of the sample are shown in Table 1. Most respondents were women aged 65 years or older, with white skin color, illiterate or with an incomplete elementary level of education, low socioeconomic status (most belong to classes C2, D, and E), married, or living with a partner. Most individuals with diabetes reported having a negative self-perception of their health, regularly visiting the doctor, not having a private health insurance plan, and not having a private health insurance plan.

Table 1. Sociodemographic characteristics of individuals with diabetes in Brazil. National Health Survey, 2019.

Variables	% (95%CI) Diabetics (n = 7,327)
Sex	
Male	40.4 (38.4 – 42.4)
Female	59.6 (57.6 – 61.6)
Age (in years)	
18-34	4.4 (3.5 – 5.4)
35-44	9.1 (8.0 – 10.3)
45-54	17.9 (16.2 – 19.6)
55-64	28.0 (26.3 – 29.8)
≥ 65	40.5 (38.6 – 42.3)
Race/color	
White	44.8 (42.8 – 46.7)
Black	11.6 (10.4 – 12.8)
Mixed race	41.7 (39.7 – 43.6)
Other§	2.0 (1.4 – 2.6)
Schooling	
Illiterate to incomplete elementary school	56.8 (54.9 – 58.8)
Complete elementary school to incomplete high school	11.9 (10.5 – 13.3)
Complete high school to incomplete higher education	21.4 (19.8 – 23.1)
Complete higher education (graduate)	9.9 (8.8 – 11.0)
Socioeconomic classification£	
High (A – B1)	8.5 (7.2 – 9.8)
Middle (B2 – C1)	33.8 (31.9 – 35.7)
Low (C2/D/E)	57.7 (55.7 – 59.7)
Lives with a partner	
No	37.2 (35.5 – 38.9)
Yes	62.8 (61.1 – 64.5)
Marital status	
Married	52.5 (50.6 – 54.4)
Separated, divorced, or widower	26.1 (24.5 – 27.7)
Single	21.4 (19.9 – 23.0)
Regular visits to the doctor	
No	28.5 (26.6 – 30.5)
Yes	71.5 (69.5 – 73.4)
Health care insurance	
No	72.3 (69.5 – 73.4)
Yes	27.7 (25.9 – 29.5)
Self-perception of health	
Very good/good	33.5 (31.6 – 35.4)
Regular/bad/very bad	66.5 (64.6 – 68.4)

§ Corresponds to the yellow + indigenous race; £ according to ABEP criteria.

Source: Authors.

According to the distribution of individuals with diabetes according to lifestyle variables (Table 2), almost 90% of those with diabetes were non-smokers and did not consume excessive amounts of alcohol. Almost 80% of respondents reported practicing less than 150 minutes of physical activity per week. Approximately half spent more than two hours watching television each day, and only 20% spent more than two hours on the computer each day. Most individuals with diabetes (83.1%) reported consuming less than 25 servings of FVs weekly, eating red meat three times a week or less (65.3%), sweets (cakes, pies, chocolates, candies, cookies, or sweet biscuits) less than five times per week (91.5%), and sweet-

Table 2. Distribution of individuals with diabetes and 95%CI according to lifestyle variables. National Health Survey, 2019.

Variable	% (95%CI) Diabetics (n = 7,327)
Smoking	
Yes	10.1 (8.9 – 11.4)
No	89.9 (88.6 – 91.1)
Excessive alcohol consumption	
Yes	8.3 (7.2 – 9.3)
No	91.7 (90.7 – 92.8)
Leisure-time physical activity	
Active ≥ 150 min./week	20.5 (18.8 – 22.1)
Inactive < 150 min./week	79.5 (77.9 – 81.2)
Time spent watching TV	
> 2 hours/day	51.6 (49.5 – 53.7)
≤ 2 hours/day	48.4 (46.3 – 50.5)
Time spent on the computer	
> 2 hours/day	18.3 (16.7 – 19.9)
≤ 2 hours/day	81.7 (80.1 – 83.3)
Intake of Fruits and vegetables	
≥ 5 portions/day	16.9 (15.4 – 18.4)
< 5 portions/day	83.1 (81.6 – 84.6)
Red meat consumption	
> 3 portions/week	34.7 (33.0 – 36.5)
≤ 3 portions/week	65.3 (63.5 – 67.0)
Consumption of sweets	
≥ 5 portions/week	8.5 (7.4 – 9.7)
< 5 portions/week	91.5 (90.3 – 92.6)
Soft drinks	
≥ 5 times/week	6.4 (4.9 – 7.9)
< 5 times/week	93.6 (92.1 – 95.1)
Artificial juices	
≥ 5 times/week	9.7 (8.5 – 10.9)
< 5 times/week	90.3 (89.1 – 91.5)

Source: Authors

Ciência & Saúde Coletiva, 28(7):1983-1992, 2023

ened beverages (soft drinks and artificial juices, respectively) less than five times per week (93.6% and 90.3%, respectively).

According to the latent class model fit criterion, small AIC or adjusted BIC values and large entropy values indicate a good model fit index. Also, we used the LMR approach to compare the improvements in model fit between sequential classes; from one up to six classes, we found significant test statistics, indicating that the model with K classes is superior to the model with K-1 latent classes. Based on the model fit indices (Table 3) and parsimony (i.e., interpretability), we identified three latent classes of patterns of lifestyle behaviors, each with notable characteristics (Figure 1). The lifestyle behaviors of Class 1 corresponded to 17.0% of the population (*n* = 1,249 individuals) and comprised individuals with a higher probability of engaging in the five risk behaviors related to eating. There were 5 215 individuals in Class 2 (71.2% of the population) who were more likely to engage in risk behaviors related to their low leisure-time physical activity and low intake of FVs. Class 3 represented 11.8% of the sample (863 individuals) and is characterized by the lower probability of engaging in most risk behaviors, and that is why it was used as a reference for comparisons.

Almost 90% of the respondents in Class 1 reported consuming insufficient FVs, and 18% reported excessive consumption of red meat, artificial juices, soft drinks, and sweets, respectively. In Class 2, 90.7% of respondents reported a low level of leisure-time physical activity, whereas 90.4% reported a low intake of FVs. In Class 3, the probability of adopting all risk behaviors was low compared to the other classes, and none of the respondents reported regular consumption of artificial juices and soft drinks.

Table 4 presents the odds ratio (OR) for the three latent classes of patterns of lifestyle behaviors associated with sociodemographic and other variables of interest estimated by a multinomial logistic model. Comparing Classes 1 and 3, we observed that individuals aged 45 years or over were less likely to adopt risky eating behaviors than those aged between 18 and 24. Similarly, those with a lower level of education (OR: 0.30; 95%CI: 0.19-0.48) and without health care insurance (OR: 0.55; 95%CI: 0.41-0.75) were less likely to adopt an unhealthy diet compared to their counterparts.

Comparing Classes 2 and 3, we identified that male individuals had more chance (OR: 2.03; 95%CI: 1.59-2.58) of being physically inactive with an insufficient intake of FVs than women. Also, the individuals who did not visit a doctor regularly (OR: 1.46; 95%CI: 1.11-1.92) tended to present the same behavior. In contrast, mixed-race individuals aged 35 years or more (OR: 0.75; 95%CI: 0.59-0.96) with a low level of education (OR: 0.54; 95%CI: 0.37-0.79) had fewer chances of belonging to Class 2.

Discussion

This is the first study to identify lifestyle behavior among individuals with diabetes in Latin America, particularly Brazil. The study identifies lifestyle behaviors using the LCA method, an innovative approach to exploratory analysis. The results of our study indicated that three distinct

Table 3. Model fit statistics of LCA models (n = 7,327).

Number of classes	log-likelihood	resid. df	AIC	BIC	aBIC	cAIC	likelihood-ratio	p-value LMR test	Entropy
1		1013	58153.33	58222.32	58190.55	58232.32	1636.394		-
2	-28791.57	1002	57625.15	57770.03	57703.3	57791.03	1086.208	< 0.001	0.315
3	**-28671.43**	**991**	**57406.86**	**57627.63**	**57525.95**	**57659.63**	**845.9182**	< 0.001	**0.316**
4	-28631.56	980	57349.11	57645.78	57509.14	57688.78	766.1756	< 0.001	0.329
5	-28605.3	969	57318.61	57691.17	57519.57	57745.17	713.6674	< 0.001	0.32
6	-28582.78	958	57295.55	57744.01	57537.45	57809.01	668.6152	< 0.001	0.325

Bold font signifies the selected model; df – degrees of freedom; AIC – Akaike's information criterion; BIC – bayesian information criterion; aBIC – sample-size adjusted BIC; cAIC – conditional Akaike's information criterion; LMR Vuong-Lo-Mendell-Rubin likelihood ratio test.

Source: Authors.

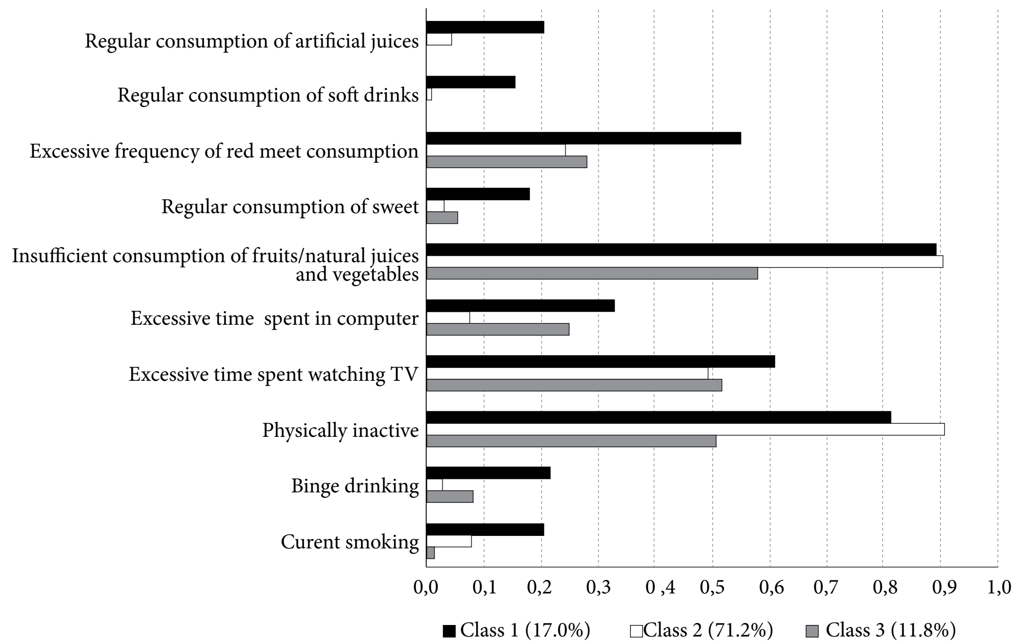

Figure 1. Item-response probabilities of lifestyle behaviors for the three-class model: the probability of endorsing an item given a latent class. Item-response probabilities are the probabilities of participants responding to different items. National Health Survey, 2019.

Source: Authors.

patterns of lifestyle behaviors are associated with risk patterns of lifestyle behaviors. These patterns include sex, education, age, race, and regular doctor visits. Considering these results, it may be possible to design specific intervention strategies for high-risk subgroups.

Class 1 (unhealthy diet) comprised 17% of the sample and showed the highest probability of items for unhealthy eating behaviors than other groups. Although most participants did not adopt this pattern, this result is worrying since individuals classified in this group reported regularly consuming foods rich in sugar, such as sweets and sugar-sweetened beverages (artificial juices and soft drinks). The consumption of FVs, foods considered healthy sources of fiber, was also irregular. Adopting healthy eating habits, including the regular consumption of FVs, whole grains, lean meats, and plant-derived proteins, is essential for preventing, treating, and controlling NCDs[25,31,32]. In the same way, limiting the consumption of sweetened foods is the main recommendation for DM patients, representing a direct relationship with blood glucose control.

Several studies[16-18,20] have analyzed lifestyle behavior patterns among adults in recent years. Nevertheless, these studies are conducted in different populations, use different analytical methods, and employ different lifestyle behaviors, making comparing results across studies difficult. According to our study, individuals over 45 and those with a low level of education were less prevalent in Class 1. A study with American adults[33] who used the LCA to identify behavior patterns has shown that younger adults are more likely to be in the non-healthy groups. As a result, this may significantly impact future generations' health since their children are highly likely to adopt similar lifestyle behaviors. In addition, they are more prone to chronic diseases as well. Efforts should be made to reverse this trend by targeting young adults who have a direct impact on children's health as well as children and adolescents.

Some studies[16,33-35] have found that high levels of education facilitate compliance with self-management of diabetes, in contrast to our data. Our results may be explained by the fact that individuals with a low level of education engage in fewer risky eating behaviors. It is because of the difficulty of accessing financial resources since education can be considered a proxy for income. In

Ciência & Saúde Coletiva, 28(7):1983-1992, 2023

Table 4. Association analysis between variables of interest and patterns of lifestyle behaviors among individuals with diabetes. National Health Survey, 2019.

	Class 1 vs. Class 3		Class 2 vs. Class 3	
	OR$^{€}$	**(95%CI)**	**OR$^{€}$**	**(95%CI)**
Sex				
Male	0.88	0.65-1.19	2.04**	1.59-2.61
Female	Ref		Ref	
Age (in years)				
18-34	Ref		Ref	
35-44	0.63	(0.30-1.32)	0.43*	(0.23-0.79)
45-54	0.36*	(0.18-0.73)	0.27*	(0.16-0.48)
55-64	0.19*	(0.11-0.34)	0.19*	(0.10-0.37)
≥65	0.19*	(0.10-0.37)	0.16*	(0.09-0.27)
Race/color§				
White	Ref		Ref	
Black	0.87	(0.53-1.41)	0.89	(0.63-1.26)
Mixed race	1.00	(0.75-1.33)	0.75*	(0.59-0.96)
Schooling				
Illiterate to incomplete elementary school	0.30*	(0.19-0.48)	0.59*	(0.39-0.87)
Complete elementary school to incomplete high school	0.63	(0.37-1.08)	0.87	(0.50-1.53)
Complete high school to incomplete higher education	0.86	(0.56-1.31)	1.03	(0.69-1.54)
Complete higher education (graduate)	Ref		Ref	
Socioeconomic classification$^{£}$				
High (A-B1)	Ref		Ref	
Middle (B2-C1)	0.95	(0.60-1.49)	0.74	(0.45-1.19)
Low (C2/D/E)	0.61	(0.37-1.01)	0.56*	(0.34-0.95)
Self-perception of health				
Very good/good	Ref		Ref	
Regular/bad/very bad	0.89	(0.66-1.20)	0.97	(0.75-1.25)
Lives with a partner				
No	Ref		Ref	
Yes	1.03	(0.69-1.52)	0.97	(0.69-1.36)
Marital status				
Married	Ref		Ref	
Separated, divorced or widower	0.81	(0.51-1.24)	1.12	(0.77-1.64)
Single	0.79	(0.55-1.12)	1.27	(0.88-1.82)
Regular visits to the doctor				
No	0.83	(0.61-1.11)	1.46*	(1.11-1.92)
Yes	Ref		Ref	
Health care insurance				
No	0.56*	(0.41-0.77)	0.76	(0.57-1.02)
Yes	Ref		Ref	

OR$^{€}$: odds ratio adjusted for time since diabetes diagnosis and all table variables; CI: confidence interval; Class 1 unhealthy diet group; Class 2 less active and insufficient FV intake group; Class 3 low-risk group; § yellow + indigenous race were excluded due to minor frequency (n = 123); $^{£}$ according to ABEP criteria; * $p < 0.05$.

Source: Authors.

addition, our findings are consistent with qualitative research among diabetes patients, which found that respondents from low socioeconomic backgrounds followed self-management behavior (SMB) instructions strictly and almost literally. In contrast, those from higher socioeconomic backgrounds interpreted SMB instructions relatively freely.

Class 2, the less active and insufficient FV intake group, was the most prevalent category

(71.2%). Most individuals with diabetes reported not engaging in the recommended level of physical activity. This is a concern since adopting and maintaining physical activity is critical for blood glucose management and overall health in individuals with diabetes and prediabetes[37]. Some authors have observed that exercise improves blood glucose control in type 2 diabetes, reduces cardiovascular risk factors, contributes to weight loss, and improves well-being[38,39]. Furthermore, regular exercise may prevent or delay type 2 diabetes development. Furthermore, optimal consumption of FVs has been identified as a protective factor against diabetes development and control[40,41]. Fiber content, shallow to moderate energy density, and a wide range of nutrients (e.g., potassium and vitamin C) and phytochemicals (e.g., polyphenols and carotenoids) are among the many health benefits provided by FVs[42,43].

Men and individuals who do not regularly visit a doctor had more chance of belonging to Class 2 than their counterparts. Other previous studies have also reported higher male prevalence in more unhealthy clusters[44,45]. In fact, men have a different self-care pattern than women. They seek fewer health services and, consequently, receive less guidance regarding the risks and consequences of inappropriate health behaviors related to NCDs[46,47].

A recent study has shown that not making regular doctor visits increases the chance of Brazilians with diabetes not engaging in healthy behaviors independently of sex, age, schooling, and economic status[48]. Similar results were also observed among hypertensive individuals[49]. In contrast, mixed-race individuals aged 35 years or more, with a lower level of education, were less likely to belong to Class 2. There is a difference between our results and those in the literature regarding the educational level and color/race. One possible explanation could be that social desirability bias is present. As a result, participants may respond in a way that does not reflect their reality, adapting to guidance previously received. Additionally, many individuals who receive a diagnosis may begin to adopt healthier behaviors after following the guidelines provided by the health team.

Some limitations of the study should be mentioned. Firstly, all information on health behaviors is self-reported, and the nature of these data introduces the possibility of social desirability bias as the survey content is evident. However, gold standards or objective measures are less feasible and cost-prohibitive to collect in large population studies. Another limitation lies in the cross-sectional design of this study, as we can only provide a snapshot of the association between current lifestyle behaviors and other characteristics in individuals with diabetes. Additionally, we did not consider the complex sampling design in LCA, so results should be interpreted with caution due to possible underestimates of the associations between covariates and class membership[50]. Finally, the behaviors evaluated in this study are not the only ones involved in the lifestyle concept. Behaviors such as hours of sleep, use of other drugs, and differences between types of physical activity, among others, were not considered in this study.

In this study, some limitations should be mentioned. First, all health behavior information was self-reported, and because of the survey content, there is a possibility of social desirability bias. In extensive population studies, however, gold standards and objective measures are less feasible and more expensive to collect. The cross-sectional design of this study presents another limitation since we can only provide a snapshot of the association between current lifestyle behaviors and other characteristics in individuals with diabetes. Moreover, the complex sampling design of LCA was not considered, so the results should be interpreted with caution due to the possibility of an underestimate of the associations between covariates and class membership[50]. Furthermore, lifestyle is not limited to the behaviors examined in this study. We did not consider behaviors such as sleep hours, drug use, and differences between types of physical activity in this study.

Among the strengths of this study are the use of an innovative analysis model and the use of recent extensive population-based data. Future studies that include in their analysis other variables related to lifestyle that prioritize directly measured information and that do not only consider the individual's self-perception may contribute to a better understanding of these patterns.

In a diabetic population, three groups have been identified based on lifestyle behavior factors. Individualized behavioral modification strategies should be tailored to high-risk groups based on their demographic and clinical characteristics. A lot still needs to be done to improve preventive health behaviors for specific high-risk groups. Moreover, disparities across demographic groups suggest that population-level interventions may not be as effective as anticipated and may not reach at-risk groups. As a result, some groups may benefit from more targeted interventions.

Collaborations

GB Peres contributed to the interpretation, discussion of the data and drafted the initial manuscript. LB Nucci contributed to the data analysis, interpretation and writing of the manuscript. ALM Andrade contributed to the interpretation and writing of the manuscript. CC Enes contributed to the conception, design, analysis, interpretation and discussion of the data, and wrote the final version of the manuscript. All authors approved the final version of the manuscript.

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Article submitted 08/04/2022
Approved 21/12/2022
Final version submitted 23/12/2022

Chief editors: Romeu Gomes, Antônio Augusto Moura da Silva