REIPE Revista de Estudios e Investigación en Psicología y Educación

eISSN: 2386-7418

2024, Vol. 11, No. (1)

DOI:https://doi.org/10.17979/reipe.2024.11.1.10028

A latent class analysis of multiple health-risk behaviours among Portuguese college students

Uma análise de classes latentes de múltiplos comportamentos de risco para a saúde entre estudantes universitários/as portugueses/as

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This work was supported by the Foundation for Science and Technology – FCT (Ministry of Education and Science, Portugal) (SFRH/BD/120758/2016).

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Abstract

Traditionally, the prevalence of health-risk behaviours is high among university students. Although these behaviours are often analysed in isolation, there is likely evidence for the co-occurrence of multiple risk behaviours. In this study, a latent class analysis (LCA) was conducted with cross-sectional data from 840 Portuguese students (55.4% female) to explore patterns of multiple risk behaviours across seven behavioural dimensions (alcohol consumption, smoking, unhealthy eating, sedentary behaviour, risky sexual practices, illicit drug use, and self-medication). Additionally, a latent class regression was performed to explore predictors (perceived well-being and sociodemographic and academic characteristics) for each behavioural pattern. A three-class model emerged with different probabilities of risk: Low-risk behaviours (51.4%), Moderate-risk behaviors (14.9%), and High-risk behaviours (33.7%). Students with better perceptions of well-being and health were likelier to be in the healthier class. Students in the low- and moderate-risk classes were more likely to be in their first year of study, not in a romantic relationship and to be full-time students. Students who had not changed residence at the beginning of their studies and were female were more likely to be in the healthiest class. This study provides essential strategies for health promotion among university students, offering crucial insights for the design of effective health promotion interventions, especially targeted at specific groups of students with similar patterns of multiple risk behaviours.

Keywords: university students; health behaviours; well-being.

Resumo

Tradicionalmente, a prevalência de comportamentos de risco para a saúde entre os/as estudantes universitários/as é elevada. Embora estes comportamentos sejam frequentemente analisados isoladamente, é provável a coocorrência de múltiplos comportamentos de risco. Neste estudo, realizou-se uma análise de classes latentes com dados tranversais de 840 estudantes portugueses/as (55.4% do sexo feminino) para explorar os padrões de múltiplos comportamentos de risco inseridos em sete dimensões comportamentais (consumo de álcool, tabagismo, alimentação não saudável, sedentarismo, práticas sexuais de risco, drogas ilícitas e práticas de automedicação). Adicionalmente, realizou-se uma regressão de classe latente para explorar os preditores (perceção de bem-estar e características sociodemográficas e académicas) para cada padrão comportamental. Emergiu um modelo de três classes com diferentes probabilidades de risco: Comportamentos de baixo risco (51.4%), Comportamentos de risco moderado (14.9%) e Comportamentos de elevado risco (33.7%). Os/as estudantes com melhores perceções de bem-estar e saúde apresentaram mais chances de pertencer à classe mais saudável. Os/as estudantes das classes de baixo e moderado risco apresentaram maiores chances de frequentarem o 1º ano, não terem uma relação amorosa e serem estudantes a tempo inteiro. Aqueles/as que não tinham mudado de residência aquando do ingresso no Ensino Superior e do sexo feminino apresentaram mais probabilidades de pertencer à classe mais saudável. Este estudo apresenta estratégias essenciais para a promoção da saúde entre os/as estudantes universitários/as, fornecendo insights cruciais para a concepção de intervenções eficazes de promoção da saúde, especialmente para direccionadas a grupos específicos de estudantes com padrões semelhantes de múltiplos comportamentos de risco.

Palavras-chave: estudantes universitários; comportamentos de saúde; bem-estar.

Emerging adulthood is a critical period in the lives of young people when health-risk behaviours increase significantly. These behaviours correlate positively with the risk of developing chronic diseases (i.e. cardiovascular disease or cancer) that tend to last throughout life. Globally, more attention should be paid to university students, as empirical evidence shows that they are more likely to engage in health-risk behaviours than non-university young adults (Carter et al., 2010). The most highly correlated health-risk behaviours include an unbalanced diet due to low consumption of fruits and vegetables (Alves & Precioso, 2020; Mathur et al., 2014), the use of psychoactive substances such as tobacco, alcohol and illicit drugs (Davoren et al., 2016) and lack of physical activity (Alves et al., 2021). Many factors contribute to health-risk behaviours, especially distance from the family of origin (Alves, 2022b; Nazar et al., 2019) and peer influence (Alves & Precioso, 2022).

Empirical studies typically analyse different health-risk behaviours as isolated measures, although the co-occurrence of multiple risk behaviours is more likely. In this sense, numerous cross-sectional and cohort studies among university students in several countries have relied on latent class analysis (LCA) to show the clustering of health-risk behaviours (Afrashteh et al., 2017; Bennasar-Veny et al., 2020; El Ansari et al., 2018; El Ansari & Berg-Beckhoff, 2017; Kabir et al., 2018; Kang et al., 2014; Laska et al., 2009; Mathur et al., 2014; Nazar et al., 2019; Sanscartier et al., 2018), that is, the likelihood that an individual belongs to a particular class, depending on their response profile and the characteristics that distinguish them from others (Collins & Lanza, 2010). The first study to use LCA was developed in 2009 by Laska et al. with US college students to examine lifestyle patterns of health-risk behaviours. In 2014, a study using NCHA data (n = 39 colleges, n = 30,093 students) was published that identified four classes among the five behaviours examined (smoking, excessive alcohol consumption, unhealthy diet, sedentary lifestyle, and overweight or obesity), with clustering of risk behaviours (i.e. the high prevalence of two or more health-risk behaviours) in three of the classes (Kang et al., 2014). Similarly, Kwan et al. (2016) conducted an LCA of eight risk behaviours (fruit and vegetable consumption, alcohol use, drug use, smoking, marijuana use, sexual health, physical activity and sleep) among Canadian university students. This study found that most students (66%) fell into the 'typical' class (low likelihood of smoking and using illicit drugs and low likelihood of eating enough fruits and vegetables and being physically active), followed by the 'high risk' class (20%; a low likelihood of eating enough fruits and vegetables, getting enough sleep and being physically active and an increased likelihood of using illicit drugs, smoking and binge drinking).

This person-centred approach is more useful than a variable-centred approach as it allows the identification of multidimensional behavioural patterns (Lanza et al., 2010) and the provision of personalised interventions after taking into account the characteristics of subgroups categorised on the basis of behavioural patterns (Lanza & Rhoades, 2013).

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

Despite the importance of this type of study, there is a lack of research in Portugal aimed at classifying university students based on patterns of risk behaviours and analysing how perceptions of well-being may vary based on the grouping of health-risk behaviours. To advance the development of relevant intervention strategies for Portuguese university students, the aim of this study is to examine the patterns of multiple health-risk behaviours (physical activity, eating habits, tobacco use, alcohol use, illicit drug use, self-prescribed medication use and risky sexual behaviour) in a sample of Portuguese university students and to determine the predictors associated with each latent class.

Methods

Participants

This cross-sectional study involved 840 students enrolled at a university in northern Portugal during the 2018-2019 academic year. The participants' ages ranged from 18 to 54 years (M = 20.8 ± 4.22), only 3% of students were 30 years or older. The majority of participants were female (55.4%), not in a romantic relationship (58.3%), had not changed residence upon entering higher education (64.9%), had a BMI corresponding to normal weight (73.1%) and were full-time students (88.8%). In addition, approximately one-third of the students surveyed were enrolled in engineering (36.0%) or social sciences and humanities (32.1%) programmes, and most of them were in their first year of study (55.2%) (Table 1).

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

Table 1

Sample characteristics (N = 840)

Characteristics		*n*	%
Year of study	1st year	464	55.2
	3rd year	376	44.8
Scientific area	Engineering sciences	302	36.0
	Exact and natural sciences	136	16.2
	Law and economic sciences	132	15.7
	Human and social sciences	270	32.1
Sex	Male	375	44.6
	Female	465	55.4
Love relationship	Yes	347	41.7
	No	486	58.3
Current residence	Displaced	291	35.1
	Not displaced	537	64.9
BMI	Low weight	58	7.1
	Normal weight	599	73.1
	Overweight	162	19.8
Professional situation	Full time student	739	88.8
	Worker/Student	93	11.2

Instruments

The students completed a self-report questionnaire consisting of three sections: sociodemographic questions, a health-risk behaviour questionnaire and the Well-Being and Health-Perception Scale (WbHPS).

Sociodemographic and academic questions

While maintaining the anonymity of the research instrument, it was essential to collect some sociodemographic data about the students, including gender, age, marital status, current residence, weight and height (to calculate BMI) and professional situation. In addition, the researcher recorded the year of attendance and the subject area of the course attended at the time of data collection.

Health-risk behaviour questionnaire

This section was divided into seven categories, each corresponding to the health-risk behaviours studied. This questionnaire was developed in three stages (scale construction, content validity, psychometric validity), following the procedures outlined by Bowling (Bowling, 1998) and the Guide to Conducting Knowledge, Attitude, and Practice (KAP)

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

Surveys (World Health Organization, 2008). A detailed description can be found in previous studies (Alves, 2022a).

Tobacco consumption was assessed with the question, 'Do you currently smoke?' For the purposes of this study, we dichotomised the 'smoking' responses into 'yes' (2) and 'no' (1).

The alcohol consumption category included the AUDIT-C (frequency of drinking in the past year, amount of alcohol consumed on a typical day and binge drinking) (Barry et al., 2015). The AUDIT-C has a 5-point scale coded from 0 to 4 (range 0-12). A score above 4 points (≥5) for men or above 3 points (≥4) for women is classified as risk consumption: 'yes' (2) and 'no' (1). In addition, the following question on drunkenness was included: 'In the last 12 months, how often did you get drunk?' The response options were 'never', 'once a month or less', '2-4 times a month', '2-3 times a week' and '4 or more times a week'. The answer to the question 'get drunk' was also dichotomised into 'yes' (2) and 'no' (1).

Illicit drug consumption included three questions on the use of cannabis, cocaine and hallucinogens ('In the last 12 months, how often have you used...?'). Users of illicit drugs were categorised as 'yes' (2) and 'no' (1).

The prevalence of self-medication was analysed using the question, 'In the past 12 months, how often have you taken antidepressants, sedatives, relaxants or tranquillisers (without a medical prescription); painkillers or anti-inflammatories (without a medical prescription) or vitamins or food supplements (without a medical prescription)?' Consumers of antidepressants, painkillers and vitamins for self-medication were categorised as 'yes' (2) and 'no' (1).

Sexual risk behaviours were divided into four 'yes' (2) and 'no' (1) response categories: early age (first sexual intercourse at age 16 or younger); multiple partners (two or more sexual partners in the past 12 months); inconsistent condom use (did not use a condom for all sexual intercourse in the past 12 months); and sex, alcohol and drugs (sexual intercourse after alcohol or drug use in the past 12 months).

Healthy eating habits were assessed by the consumption of fruit, vegetables, foods with added sugar and fast food in the last seven days (e.g. 'In the last seven days, how often did you eat fruit (other than natural fruit juices or drinks)?' on a scale from 0 = 'never' to 5 = '3 or more times a day'). In addition, two questions were asked about skipping meals (breakfast, lunch and/or dinner) in the last seven days. For the analyses, the questions were categorised as 1 using a binary method according to the healthy eating guidelines (World Health Organization, 2020), taking into account the following: skipping meals (skipping breakfast and skipping lunch and/or dinner at least once a week); low fruit consumption (two or fewer times a day); low vegetable consumption (two or fewer times a day); higher

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

consumption of sweets (four or more times a week) and higher consumption of fast food (four or more times a week).

The Godin Leisure-Time Exercise Questionnaire (Godin & Shephard, 1997) assessed physical activity, including total time (in minutes) spent walking and doing moderate or vigorous activity in the previous week. The scores followed the information provided by the authors of the questionnaire. Subsequently, 'being sedentary' was classified into 'yes' (2) and 'no' (1) using a binary method. The following question on sedentariness was also included: 'On a normal day, how many hours do you spend sitting?' Again, sitting for more than eight hours per day was classified as high.

Well-being and Health Perception Scale (WbHPS)

Well-being was assessed using the Well-being and Health Perception Scale (WbHPS) (Alves et al., 2020). The WbHPS was answered on a 5-point Likert scale and included the following dimensions: satisfaction with life, satisfaction with oneself, felt happiness, perceived health and satisfaction with physical fitness. The scores for each item were summed, with the highest scores representing a higher level of well-being. The psychometric properties of this scale have been described in detail in previous studies (Alves et al., 2020).

Procedures

The target population consisted of students from a university in northern Portugal enrolled in the first and third years of the undergraduate and integrated master's programmes during the 2018-2019 academic year. The criteria for exclusion were defined as follows: classes from master's or postgraduate programs, as well as classes held in post-working hours, were excluded to limit the population to traditional students; courses without classes in the first and third years were excluded to ensure representation from students across all years of study within the same courses; and classes related to health sciences were excluded due to potential biases, especially concerning their knowledge about health (Hyska et al., 2014).

To create a stratified sample based on the year of study and the scientific area, were considered 5447 university students enrolled in the first- and third-year courses, distributed across 47 courses and four subject areas (as defined by the Foundation for Science and Technology): Engineering, Exact and Natural Sciences, Judicial and Economic Sciences, Social Sciences and Humanities. Considering the number of students in each subject area, 16 courses were identified by simple random selection, resulting in 32 first- and third-year classes.

Using G*Power 3.1.9.2 analysis software, the minimum sample size required for this study was 592 students (margin of error = 5%, confidence level = 99% and distribution of responses = 50%). A total of 873 questionnaires were distributed, reflecting the total number

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

of students who were present in the classroom and had agreed to participate in the study. However, 33 questionnaires were considered invalid due to missing or incongruent responses that could call into question the validity of the information collected. The response rate was 96.2% (95% CI: 94.8-97.6).

Data collection was conducted in the classroom in May 2019. Before the paper questionnaires and the informed consent forms were distributed, the research objectives were presented, confidentiality and anonymity of responses were ensured, the voluntary nature of participation was guaranteed, and the right to decline participation or withdraw at any time was explained. All participants gave their consent before completing the questionnaire, which took about 15 minutes to complete.

This study was approved by the Ethics Committee for Research in the Social Sciences and Humanities of the UMinho Ethics Council under protocol CEICSH 009/2019.

Statistical analyses

In the first step, descriptive analysis was conducted for the different variables by analysing frequencies, means and standard deviations using the Statistical Package for the Social Sciences (SPSS) version 28.0 for Windows. In the second step, LCA was conducted with seven categorical observable variables (risky drinking, smoking, unhealthy diet, sedentarism, risky sexual practices, illicit drugs and self-medication practices) to identify patterns of health-risk behaviour. A range of LCA models with two to five classes was explored to determine the number of classes that best represented patterns of health-risk behaviour (Collins & Lanza, 2010). The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were considered to determine the optimal number of conceptually significant classes (Collins & Lanza, 2010). In addition, the G^2 and log-likelihood (LLIK) values of the estimated model were calculated to select the best-fitting model. Thus, the lowest G^2, AIC and BIC values and the highest LLIK value indicated the best-fitting model (Chan & Shek, 2018).

Entropy was used as an additional criterion to determine the final model. Entropy is a quality criterion for classification, with higher values between 0 and 1 indicating a better fit (Chan & Shek, 2018). However, as these indices are not uniformly indicative of a single model specification (and may overestimate or underestimate the number of latent classes), model-specific estimates for two-, three- and four-class models were examined to select a final model specification based on the interpretability of the results as well as theory and previous results in the literature, as suggested by Nylund-Gibson and Choi (2018). Based on these criteria, we determined that the three-class model was the best fit for the data. All LCA analyses were performed using the GLCA R package in Jamovi software, version 2.3.2. After finalising the model, we performed multinomial logistic regression estimated by odds ratio

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

and the corresponding 95% confidence intervals to analyse the analyses of the predictors (well-being and demographic characteristics) of the classes of health-risk behaviours.

Results

Multiple health-risk behaviours

Table 2 shows the prevalence of the 14 health-risk behaviours in the seven behavioural dimensions under analysis. The prevalence of these behaviours ranged from 7.4% (high consumption of fast food) to 90.4% (insufficient consumption of vegetables), indicating that the prevalence of some risk behaviours (e.g. poor diet and alcohol consumption) was much higher than others. Statistically significant differences were found in the prevalence of certain risk behaviours between male and female students. Drunkenness, use of illicit drugs, early sexual initiation, sexual activity after alcohol and drug use and consumption of sugar products are more common among male students. Conversely, the self-medication with analgesics and sedentary behaviour are more common among female students.

Table 2

Multiple health-risk behaviours by sex (N = 840)

	Total		Male		Female		χ^2
	n	%	n	%	n	%	
Smoking	168	20.0	85	22.7	83	17.8	3.01
Risky alcohol consumption	337	40.1	152	40.5	185	39.8	.05
Getting drunk	368	43.8	186	49.6	182	39.1	9.23**
Use of illegal drugs	178	22.2	114	31.7	64	14.5	33.75***
Self-medication with antidepressants	111	13.9	27	7.5	84	19.0	3.01
Self-medication with analgesics	326	40.8	116	32.2	210	47.7	19.72***
Self-medication with vitamins	211	26.4	92	25.6	119	27.0	.21
Early age	213	25.4	110	29.3	103	22.2	5.66*
Multiple partners	103	12.3	52	13.9	51	11.0	1.62
Inconsistent condom use	329	39.2	148	39.5	181	38.9	.03
Sex, alcohol and drugs	177	21.1	94	25.1	83	17.8	6.50*
Skipping meals	428	51.0	188	50.3	240	51.6	.15
Insufficient fruit consumption	753	89.9	344	92.0	409	88.1	3.34
Insufficient vegetable consumption	784	94.0	354	95.7	430	92.7	3.30
Higher consumption of fast food	62	7.4	29	7.7	33	7.1	.11
Higher consumption of sweets	465	55.5	222	59.4	243	52.4	4.09*
Sedentariness	298	35.7	106	28.3	192	41.7	16.11***
High sitting time	436	51.9	204	54.4	232	49.9	1.69

*$p < .05$; **$p < .01$; ***$p < .001$

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

Latent classes of risk behaviours

Based on the 14 health-risk behaviours analysed, a three-latent-class model was selected after comparing the fit, parsimony and interpretability indices between models with two to five latent classes, as described in the section on statistical analyses and presented in Table 3.

Table 3

Summary of information for selecting number of latent classes of multiple health-risk behaviours (N = 840)

Number of Latent Classes	LLIK	AIC	BIC	Entropy	G2	df	G2 p
2	-7583	15239	15451	.77	4683	802	.08
3 SM	-7516	15144	15409	.84	4549	783	.14
4	-7458	15066	15421	.76	4434	764	.10
5	-7416	15020	15464	.79	4349	745	.16
6	-7385	14996	15531	.77	4258	726	.34

Note: SM = Selected model; LLIK = Log-likelihood; AIC = Akaike Information Criterion; BIC = Bayesian information criterion; G^2 = Likelihood ratio test statistic.

The probabilities of a 'yes' response for each of the 14 risk behaviours are shown in Table 4 for each latent class. The likelihood of a 'no' response can be calculated by subtracting the item response probabilities from 1. These probabilities indicate the possibility that a student in a particular class will engage in a specific risk behaviour and can be used to characterise the three latent classes in the model.

Table 4

Item-response probabilities from the three-latent-class model of multiple health-risk behaviours (N = 840)

Label	1 Low-risk behaviours	2 Moderate-risk behaviours	3 High-risk behaviours
Latent class prevalences	.51	.15	.34
Item-response probabilities			
Corresponding to a 'yes' response	.05	.15	.45
Smoking	.09	**.62**	**.77**
Risky alcohol consumption	.03	**1.00**	**.81**
Getting drunk	.04	.18	**.51**
Use of illegal drugs	.12	.15	.16
Self-medication with antidepressants	.38	.38	.46
Self-medication with analgesics	.23	.13	.36
Self-medication with vitamins	.17	.06	**.46**
Early age	.29	.00	.32
Multiple partners	.29	.17	**.65**
Inconsistent condom use	.02	.00	**.59**
Sex, alcohol and drugs	.44	.43	**.66**
Skipping meals	**.89**	**.96**	**.89**
Insufficient fruit consumption	**.93**	**.99**	**.94**
Insufficient vegetable consumption	.05	.48	.13
Higher consumption of fast food	**.55**	**.52**	**.58**
Higher consumption of sweets	.38	.42	.29
Sedentariness	**.58**	.48	.44

Note: Major probabilities are in bold to highlight the overall pattern.

Class 1 (labelled 'low-risk behaviours') represents the majority of students in the sample (51.4%) and is considered the healthiest class. These students were more likely to be physically active (61.7%), although they were more likely to sit for more than eight hours a day (58.2%) and more likely not to smoke (94.7%), not have risky alcohol consumption (90.0%) and/or not use illicit drugs (96.1%). However, students in this class were not likely to consume the recommended amounts of fruit (88.7%) and vegetables (92.7%).

Class 2 (labelled 'moderate risk behaviours') represents the students (14.9%) at moderate risk of engaging in health-risk behaviours. Students in this class were more likely to have been drunk in the past year (100%), to have consumed too few fruits (96.4%) and vegetables (98.9%), and to have eaten fast food several times a week (48.3%). In addition, students with a high probability of alcohol consumption classified as risky belonged to this class (62.4%). Notwithstanding this, and similar to the 'low-risk behaviour' class, the moderately healthy students were less likely to smoke (14.8%), use illicit drugs (17.6%) and take non-prescribed medications such as antidepressants (14.9%), painkillers (37.7%)

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

and vitamins (13.0%). Of the three classes identified, these students were least likely to engage in the following risky sexual behaviours: early age (6.3%), multiple partners (0.16%), inconsistent condom use (16.6%), sex, alcohol and drugs (< .001%).

Class 3 (labelled 'high-risk behaviours'; 33.7%) exhibited high-risk behaviours in all dimensions except for sedentariness. For example, students in this class were more likely to smoke (44.7%), have risky alcohol consumption (77.4%), get drunk (81.2%) and use illicit drugs (50.8%) but less likely to be physically inactive (29.4%) and sit too long during the day (44.1%). In addition, this class was the most likely to take without prescription medications such as antidepressants (16.4%), painkillers (46.2) and vitamins (36.3%) and engage in the following risky sexual behaviours: early age (46.2%), multiple partners (31.9%), inconsistent condom use (65.2%) and sex, alcohol and drugs (59.1%). In addition, the members of this group reported unhealthy eating habits, such as a high likelihood of skipping meals (65.8%), consuming sugary products (58.1%), and eating too little fruit (88.7%) and vegetables (93.8%).

Sociodemographic and well-being predictors as a function of latent classes of health-risk behaviours

Based on the class with the higher probability of risk behaviours, the probability of belonging to the healthiest class ('low-risk behaviours') increased by 1.06 times for each additional point in the WbHPS. Similarly, being female increased the likelihood of belonging to Class 1 by 24.1% compared to Class 3 and by 10.3% compared to Class 2. Students who had not changed their residence when beginning their university studies were 1.98 and 1.83 times more likely to be in Class 1 than Class 3 and 2, respectively. Being in the first year of study, not being in a romantic relationship and being a full-time student increased the likelihood of being in the healthiest and moderately healthy classes compared to Class 3 ('high-risk behaviours') (Appendix).

Discussion

This study revealed distinct patterns of multiple health-risk behaviours among Portuguese university students, namely the existence of three recognisable classes. These classes included students prone to engaging in health-risk behaviours (33.7%) and students with low (51.4%) and moderate (14.9%) risks of engaging in risky behaviours. These classes were similar to previous studies with university students regarding class division (El Ansari & Berg-Beckhoff, 2017; Hutchesson et al., 2021; Kwan et al., 2016; Laska et al., 2009; Macedo et al., 2020; Nazar et al., 2019). However, this study shows a higher proportion of students in the high-risk class, whereas previous studies showed a higher proportion of students with moderate-risk behaviour patterns.

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

Of concern is that the vast majority of students, regardless of class, were very likely to consume too few fruits and vegetables and too many sugary products. Similarly, in the study conducted by Macedo et al. (2020), nursing students were found to be the most likely to have unhealthy diets across all latent classes. These results demonstrate that while public health has traditionally focused on reducing certain risk behaviours, such as tobacco, alcohol and illicit drugs (Kwan et al., 2016; Wing Kwan et al., 2009), other risk behaviours associated with non-communicable diseases, such as dietary habits, also deserve attention. These behavioural patterns may reflect difficulties such as the cost and accessibility of fruit and vegetables or the difficulty of preparing healthy meals.

Sedentary lifestyles and the amount of time students spend sitting during the week may be related to the number of consecutive lessons and their duration. Therefore, teachers should encourage students to get up and move around after a prolonged sitting period (Torquato et al., 2016). As this is a new phase of life where students have to balance their personal lives with academic, family and social commitments, it is not surprising that students may place less emphasis on physical activity during this stage (Kabir et al., 2018; Nazar et al., 2019).

Regarding alcohol consumption, both 'moderate risk behaviours' and 'higher risk behaviours' were highly likely to involve binge drinking and drunkenness. Other studies have also found that binge drinking is among the highest health-risk classes (Afrashteh et al., 2017). Thus, alcohol consumption should also be discouraged through university health promotion programmes.

The multinomial regression analysis indicated that students in the healthiest class were more likely to be female, in their first year of study, to be full-time students, not to be in a romantic relationship, and not to have moved when they began their studies. Similarly, previous research has shown that male and younger students were likelier to be in unhealthy or moderate lifestyle classes than the healthier ones (Hutchesson et al., 2021; Laska et al., 2009). With this in mind, it is critical to intervene with students in their first year of university study when new experiences significantly influence behavioural choices.

This study also analysed how perceptions of health and well-being were related to patterns of multiple risk behaviours. Overall, the results showed that students with a higher level of well-being were less likely to belong to a class with a high number of risk behaviours. This finding is consistent with other studies showing that higher risk patterns in multiple behaviours are associated with poorer mental health outcomes, namely psychological distress and stress (Hutchesson et al., 2021; Jao et al., 2019; Kwan et al., 2016), with the inverse relationship also demonstrated. In other words, there is a bidirectional effect between health-risk behaviours and mental health indicators (e.g. happiness, life satisfaction and depression) (Ma & Lai, 2018; Molendijk et al., 2018; Schuch et al., 2018).

Strengths and limitations of the study

To our knowledge, this is the first study to analyse complex patterns of health-risk behaviours among Portuguese university students across a wide range of behaviours, focusing on their relationship with perceived well-being and health. Not only do the results provide critical information about students' behavioural patterns and help in the development of health promotion strategies, but this study also demonstrates the usefulness of sophisticated analytical tools such as LCA to understand complex behaviours that would not be possible with statistical approaches such as linear regression.

Although a relatively new statistical analysis was used to analyse the clustering of multiple health-risk behaviours among university students and, because it is a model-based approach, to estimate the actual probability of an outcome as a function of latent class membership (Lanza & Rhoades, 2013), this study has some limitations that should be considered when interpreting the results. First, it should be noted that this is a cross-sectional study whose data were only collected at one Portuguese public university. Therefore, it is not possible to generalise the results to students from other universities or young people in the same age group or to establish causal relationships. Secondly, a self-report questionnaire was used, which might have led to a bias in the responses due to social desirability. However, validated tools were used to minimise this, and confidentiality and anonymity were guaranteed.

Note that health-risk behaviours were assessed on different time scales (e.g. last seven days, last 30 days, last 12 months), and seasonal effects were not captured. Although measures with more extended time scales were intended to capture the less prevalent health-risk behaviours (e.g. illicit drug use), consistency across all behaviours would be ideal. Furthermore, even though data collection was carried out during an academic period that excluded festivities, the described behaviors may not accurately reflect the pattern of behaviors, especially concerning dietary habits in the past seven days. Similarly, specific periods of self-medication were not considered, such as during study and exam preparation. It is noteworthy that the use of electronic cigarettes or heated tobacco products was not considered, as the use of these tobacco products was minimal among university students (Lavado et al., 2020). Another limitation worth mentioning is the exclusion of students from health science courses. This decision was made considering the potential bias that could be introduced (Hyska et al., 2014). It is essential to emphasize that this methodological choice by no means implies a disregard for the importance of investigating the behaviours of students in these fields in future studies. Additionally, it is crucial to acknowledge that a meta-analysis conducted by Xu et al. (2019) identified a significantly higher prevalence of

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

self-medication practices with antibiotics among medical students compared to students in other scientific disciplines.

Even though dichotomising risk variables is common in LCA and contributes to the interpretability and communication of findings, categorising data in this way may lead to some loss of meaning. Finally, while we included several sociodemographic and academic factors in the analysis, others may be relevant to the analysis of health-risk behaviours, such as students' socioeconomic status. Therefore, future studies should include other variables and conduct longitudinal analyses to assess the same students over time.

Practical implications and future studies

This study highlights the need for a reorientation of health services and higher education institutions to ensure that efforts are focused on promoting healthy behaviours that are already commonly targeted, such as smoking and drug use, but also dietary eating habits. In addition, the Healthy Campus 2020 guidelines (ODPHP, 2020) advocate for a greater focus on nutrition and physical activity among young adults. However, higher education institutions need more initiatives to promote healthy, active lifestyles to achieve these goals.

Furthermore, there is a need for continued research on this topic to better understand the patterns of health-risk behaviours and their relationship to well-being among university students. Future research should therefore include longitudinal studies to analyse the behavioural changes in students' profiles and their mental health status throughout their time at university. This further investigation can be used to determine the timing of interventions to support student health and well-being and to target interventions at specific classes of students.

Current strategies for health promotion for university students are generally most effective for the majority of the university population, such as integrating health promotion activities into curricula. However, the results of this study suggest that at-risk groups need a tailored intervention. This intervention can be health promotion materials that target the different health-risk behaviours together rather than addressing them individually. By simultaneously addressing several target health-risk behaviours, people can transfer their knowledge and experience from one behaviour to another. Although it is not clear which approach is most effective (single behaviour or multi-behaviour) (James et al., 2016), it must always be taken into account that, on the one hand, risk behaviours are interrelated and co-occur, and, on the other hand, separate approaches may be needed for certain risk behaviours, especially in the case of illicit drug use. Finally, any strategies developed to promote health and well-being in higher education should be consistent with the International Charter for Health-Promoting Universities and Colleges guidelines (Black &

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028

Stanton, 2016) and focus on both the academic environment and support for individual students.

Conclusion

This study makes an important contribution to the literature on health-risk behaviours in higher education by identifying three classes of behaviours in a sample of Portuguese university students. Common to all latent classes were unhealthy eating habits and sedentary behaviour. In addition, students who belonged to the classes most likely to engage in risky behaviours were found to experience lower levels of well-being. These findings underscore the need for higher education institutions to implement socio-educational programmes aimed at preventing the adoption of unhealthy habits upon entering higher education. Such programmes would enable students to make informed and responsible choices. There is also a call for psychosocial interventions that facilitate students' reflection on their well-being and happiness, thereby contributing to their holistic development. Furthermore, these findings highlight the need to support and target the development of activities for the classes of students most likely to engage in risky behaviours.

References

AFRASHTEH, Sima; GHAEM, Haleh & ABBASI-GHAHRAMANLOO, Abbas (2017). Clustering and combining pattern of high-risk behaviors among Iranian university students: A latent class analysis. *Journal of Research in Health Sciences, 17*(4), 00398. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7189947/

ALVES, Regina F. (2022a). *Knowledge, attitudes and health-related behaviors among Higher Education students: assessment and monitoring of a socioeducational intervention program in a non-formal context* [Doctoral thesis, University of Minho]. https://hdl.handle.net/1822/75905

ALVES, Regina F. (2022b). The association between subjective well-being and risky behaviours in university students. *Psihologijske Teme, 31*(3), 565-583. https://doi.org/10.31820/pt.31.3.5

ALVES, Regina F. & PRECIOSO, José (2020). Knowledge, attitude and practice on healthy diet among university students in Portugal. *International Journal of Nutrition Sciences, 5*(2), 2-9. https://ijns.sums.ac.ir/article_46568.html

ALVES, Regina F. & PRECIOSO, José (2022). A influência dos pares no consumo de Substâncias Psicoativas entre estudantes universitários/as. *Revista de Estudios e Investigación En Psicología y Educación, 9*, 5-17. https://doi.org/10.17979/reipe.2022.9.0.8912

ALVES, Regina F.; PRECIOSO, José & BECOÑA, Elisardo (2020). Well-being and health perception of university students in Portugal: the influence of parental support and love relationship. *Health Psychology Report, 8*(2), 145-154. https://doi.org/10.5114/hpr.2020.94723

ALVES, Regina F.; PRECIOSO, José & BECOÑA, Elisardo (2021). Physical activity among Portuguese university students and its relation to knowledge and perceived barriers. *Sportis. Scientific*

Journal of School Sport, Physical Education and Psychomotricity, 7(1), 25-42. https://doi.org/10.17979/sportis.2021.7.1.6924

BARRY, Adam E.; CHANEY, Beth H.; STELLEFSON, Michael L. & DODD, Virginia (2015). Evaluating the psychometric properties of the AUDIT-C among college students. *Journal of Substance Use, 20*(1), 1-5. https://doi.org/10.3109/14659891.2013.856479

BENNASAR-VENY, Miquel; YAÑEZ, Aina M.; PERICAS, Jordi; BALLESTER, Lluis; FERNANDEZ-DOMINGUEZ, Juan Carlos; TAULER, Pedro & AGUILO, Antoni (2020). Cluster analysis of health-related lifestyles in university students. *International Journal of Environmental Research and Public Health, 17*(5). https://doi.org/10.3390/IJERPH17051776

BLACK, Tara & STANTON, Alisa (2016, February 4). Final report on the development of the Okanagan Charter: An international charter for health promoting universities & colleges. *International Conference on Health Promoting Universities and Colleges (7th: 2015)*. Kelowna, BC, Canada. https://doi.org/10.14288/1.0372504

BOWLING, Ann. (1998). *Research methods in health: investigating health and health services*. Open University Press.

CARTER, Ashlee C.; BRANDON, Karen Obremski & GOLDMAN, Mark S. (2010). The college and noncollege experience: A review of the factors that influence drinking behavior in young adulthood. *Journal of Studies on Alcohol and Drugs, 71*(5), 742-750. https://doi.org/10.15288/jsad.2010.71.742

CHAN, P., & SHEK, C. (2018). Latent class analysis of student artefacts. *Proceedings of the 10th International Conference on Education Technology and Computers*, 302-307. https://doi.org/10.1145/3290511.3290521

COLLINS, Linda M. & LANZA, Stephanie T. (2010). *Latent class and latent transition analysis with applications in the social, behavioral, and health sciences*. Wiley Series in Probability and Statistics. https://doi.org/10.1002/9780470567333

DAVOREN, Martin P.; DEMANT, Jakob; SHIELY, Frances & PERRY, Ivan J. (2016). Alcohol consumption among university students in Ireland and the United Kingdom from 2002 to 2014: a systematic review. *BMC Public Health, 16*(1), 173. https://doi.org/10.1186/s12889-016-2843-1

El ANSARI, Walid & BERG-BECKHOFF, Gabriele (2017). Country and gender-specific achievement of healthy nutrition and physical activity guidelines: Latent class analysis of 6266 university students in Egypt, Libya, and Palestine. *Nutrients, 9*(7), 738. https://doi.org/10.3390/nu9070738

EL ANSARI, Walid; SSEWANYANA, Derrick & STOCK, Christiane (2018). Behavioral health risk profiles of undergraduate university students in England, Wales, and Northern Ireland: A cluster analysis. *Frontiers in Public Health, 6*. https://doi.org/10.3389/FPUBH.2018.00120

GODIN, G. & SHEPHARD, R. J. (1997). Godin leisure-time exercise questionnaire. *Medicine and science in sports and exercise, 29*(6), 36-38. https://doi.org/10.1097/00005768-199706001-00009

HUTCHESSON, Melinda J.; DUNCAN, Mitch J.; OFTEDAL, Stina; ASHTON, Lee M.; OLDMEADOW, Christopher, KAY-LAMBKIN, Frances & WHATNALL, Megan C. (2021). Latent class analysis of multiple health risk behaviors among Australian university students and associations with psychological distress. *Nutrients, 13*(2), 425. https://doi.org/10.3390/nu13020425

HYSKA, Jolanda; MERSINI, Ehadu; MONE, Iris; BUSHI, Entela; SADIKU, Edite & HOTI, Kliti (2014). Assessment of knowledge, attitudes and practices about public health nutrition among students of the University of Medicine in Tirana, Albania. *Southeastern European Journal of Public Health, 88*, 1-8. https://doi.org/10.12908/SEEJPH-2014-01

JAMES, Erica; FREUND, Megan; BOOTH, Angela; DUNCAN, Mitch. J.; JOHNSON, Natalie; SHORT, Camille E.; WOLFENDEN, Luck; STACEY, Fiona G.; KAY-LAMBKIN, Frances & VANDELANOTTE, Corneel (2016). Comparative efficacy of simultaneous versus sequential multiple health behavior change interventions among adults: A systematic review of randomised trials. *Preventive Medicine, 89*, 211-223. https://doi.org/10.1016/j.ypmed.2016.06.012

JAO, Nancy C.; ROBINSON, Laura D.; KELLY, Peter J.; CIECIERSKI, Christina C. & HITSMAN, Brian (2019). Unhealthy behavior clustering and mental health status in United States college students. *Journal of American College Health, 67*(8), 790-800. https://doi.org/10.1080/07448481.2018.1515744

KABIR, Kourosh; BAHARI, Ali; HAJIZADEH, Mohammad; ALLAHVERDIPOUR, Hamid; TARRAHI, Mohammad J.; FAKHARI, Ali; ANSARI, Hossein & MOHAMMADPOORASL, Asghar (2018). Substance abuse behaviors among university freshmen in Iran: a latent class analysis. *Epidemiology and Health, 40*, e2018030. https://doi.org/10.4178/epih.e2018030

KANG, Joseph; CIECIERSKI, Christina Czart; MALIN, Emily L.; CARROLL, Allison J.; GIDEA, Marian; CRAFT, Lynette L.; SPRING, Bonnie & HITSMAN, Brian (2014). A latent class analysis of cancer risk behaviors among U.S. college students. *Preventive Medicine, 64*, 121-125. https://doi.org/10.1016/j.ypmed.2014.03.023

KWAN, Matthew; ARBOUR-NICITOPOULOS, Kelly P.; DUKU, Eric; & FAULKNER, Guy (2016). Patterns of multiple health risk-behaviours in university students and their association with mental health: application of latent class analysis. *Policy and Practice, 36*(8). https://doi.org/10.24095/hpcdp.36.8.03

LANZA, Stephanie T. & RHOADES, Brittany L. (2013). Latent class analysis: An alternative perspective on subgroup analysis in prevention and treatment. *Prevention Science, 14*(2), 157-168. https://doi.org/10.1007/s11121-011-0201-1

LANZA, Stephanie T.; SAVAGE, Jennifer S. & BIRCH, Leann L. (2010). Identification and prediction of latent classes of weight-loss strategies among women. *Obesity, 18*(4), 833-840. https://doi.org/10.1038/oby.2009.275

LAVADO, Elsa; CALADO, Vasco; & FEIJÃO, Fernanda (2020). ECATD-CAD 2019. *Estudo sobre o consumo de álcool, tabaco, drogas e outros comportamentos aditivos e dependências: Portugal 2019*. Serviço de Intervenção nos Comportamentos Aditivos e nas Dependências - SICAD. Disponível em: https://www.sicad.pt/PT/EstatisticaInvestigacao/EstudosConcluidos/Paginas/detalhe.aspx?itemId=221&lista=SICAD_ESTUDOS&bkUrl=/BK/EstatisticaInvestigacao/EstudosConcluidos

LASKA, Melissa Nelson; PASCH, Keryn E.; LUST, Katherine; STORY, Mary & EHLINGER, Ed (2009). Latent class analysis of lifestyle characteristics and health risk behaviors among college youth. *Prevention Science, 10*(4), 376-386. https://doi.org/10.1007/s11121-009-0140-2

MA, Cecilia M. & LAI, Catie C. (2018). Mental health profile and health-related behavior among Hong Kong Chinese university students. *Health Psychology Open, 5*(2), 205510291878686. https://doi.org/10.1177/2055102918786869

MACEDO, Tassia T. S.; MUSSI, Fernanda C.; SHEETS, Debra; CAMPOS, Ana C. P.; PATRÃO, Ana L.; FREITAS, Caren L. M. & PAIM, Melissa A. S. (2020). Lifestyle behaviors among undergraduate nursing students: A latent class analysis. *Research in Nursing & Health, 43*(5), 520-528. https://doi.org/10.1002/nur.22064

MATHUR, Charu; STIGLER, Melissa; LUST, Katherine & LASKA, Melissa (2014). A latent class analysis of weight-related health behaviors among 2- and 4-year college students and associated risk of obesity. *Health Education & Behavior, 41*(6), 663-672. https://doi.org/10.1177/1090198114537062

MOLENDIJK, Marc; MOLERO, Patricio; ORTUÑO SÁNCHEZ-PEDREÑO, Felipe; VAN DER DOES, Willem & ANGEL MARTÍNEZ-GONZÁLEZ, Miguel (2018). Diet quality and depression risk: A systematic review and dose-response meta-analysis of prospective studies. *Journal of Affective Disorders, 226*, 346-354. https://doi.org/10.1016/j.jad.2017.09.022

NAZAR, Gabriela; STIEPOVIC, Jasna & BUSTOS, Claudio (2019). Latent class analysis of lifestyle behavior among Chilean university students. *International Journal of Health Promotion and Education, 57*(2), 98-111. https://doi.org/10.1080/14635240.2018.1552534

NYLUND-GIBSON, Karen & CHOI, Andrew Young (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science, 4*(4), 440-461. https://doi.org/10.1037/tps0000176

ODPHP - Office of Disease Prevention and Health Promotion. (2020). *Healthy People 2020*. Available in: https://wayback.archive-it.org/5774/20220413182850/https://www.healthypeople.gov/2020/

SANSCARTIER, Matthew D.; EDGERTON, Jason D. & ROBERTS, Lance W. (2018). A latent class analysis of gambling activity patterns in a Canadian university sample of emerging adults: Socio-demographic, motivational, and mental health correlates. *Journal of Gambling Studies, 34*(3), 863-880. https://doi.org/10.1007/s10899-017-9734-y

SCHUCH, Felipe B.; VANCAMPFORT, Davy; FIRTH, Joseph; ROSENBAUM, Simon; WARD, Philip B.; SILVA, Edson S.; HALLGREN, Mats; PONCE DE LEON, Antonio; DUNN, Andrea L.; DESLANDES, Andrea C.; FLECK, Marcelo P.; CARVALHO, Andre F., & STUBBS, Brendon (2018). Physical activity and incident depression: A meta-analysis of prospective cohort studies. *American Journal of Psychiatry, 175*(7), 631-648. https://doi.org/10.1176/appi.ajp.2018.17111194

TORQUATO, Sara C. R.; DA SILVA, Emilene F.; RODRIGUES, Aline R.; PIMENTA, Mayara V. T.; MOURA, Jayne R. A. & DA SILVA, Ana Roberta V. (2016). Sedentary lifestyle and metabolic disorders among university study / Sedentarismo e alterações metabólicas entre universitários / Estilo de vida sedentario y trastornos metabólicos entre la universidad. *Revista de Enfermagem Da UFPI, 5*(2), 16. https://doi.org/10.26694/reufpi.v5i2.5244

WING KWAN, Matthew Y.; BRAY, Steven R. & MARTIN GINIS, Kathleen A. (2009). Predicting Physical Activity of First-Year University Students: An Application of the Theory of Planned Behavior. *Journal of American College Health, 58*(1), 45-55. https://doi.org/10.3200/JACH.58.1.45-55

WORLD HEALTH ORGANIZATION. (2008). *Advocacy, communication and social mobilization for TB control: a guide to developing knowledge, attitude and practice surveys*. https://apps.who.int/iris/handle/10665/43790

WORLD HEALTH ORGANIZATION. (2020). *Healthy diet*. https://www.who.int/news-room/fact-sheets/detail/healthy-diet

XU, Rixiang; MU, Tingyu; WANG, Guan; SHI, Jing; WANG, Xin & NI, Xiaoli (2019). Self-medication with antibiotics among university students in LMIC: A systematic review and meta-analysis. *The Journal of Infection in Developing Countries, 13*(08), 678-689. https://doi.org/10.3855/jidc.11359

Receipt date: 02 November 2023
Review date: 17 January 2024
Acceptance date: 25 January 2024
Publication date: 01 July 2024

Appendix

Adjusted odds ra ios (OR) and 95% con idence intervals (CI) from mul inomial logis ic regression model about class on sociodemographic variables and well-being

Class	Predictor	OR	95% CI	
1 - 3	Predictor	0.0852	0.0222	0.328
	Intercept	1.0600*	1.0067*	1.116*
	WbHPS	1.5313*	1.0988*	2.134*
	Year study: 1st year - 3rd year			
	Scientific area:	0.9734	0.5831	1.625
	Exact and natural sciences - Engineering sciences	0.7829	0.4657	1.316
	Law and economic sciences - Engineering sciences	0.9370	0.6054	1.450
	Human and social sciences - Engineering sciences	1.8026*	1.2414*	2.618*
	Sex: Female - Male	1.5356*	1.0972*	2.149*
	Love relationship: No - Yes	2.8107*	1.9788*	3.992*
	Current residence: Not displaced - Displaced	1.7270*	1.0491*	2.843*
	Professional Situation: Full time student - Worker/Student			
	BMI:	0.8723	0.4448	1.711
	Normal weight - Low weight	1.0876	0.5125	2.308
2 - 3	Overweight - Low weight	0.1076	0.0182	0.636
	Intercept	1.0129	0.9474	1.083
	WbHPS	2.1099*	1.3436*	3.313*
	Year study: 1st year - 3rd year			
	Scientific area:	1.3818	0.7362	2.593
	Exact and natural sciences - Engineering sciences	0.9212	0.4651	1.824
	Law and economic sciences - Engineering sciences	0.7707	0.4270	1.391
	Human and social sciences - Engineering sciences	1.0283	0.6321	1.673
	Sex: Female - Male	2.0832*	1.3086*	3.316*
	Love relationship: No - Yes	1.0033	0.6454	1.560
	Current residence: Not displaced - Displaced	2.5167*	1.0657*	5.943*
	Professional Situation: Full time student - Worker/Student			
	BMI:	0.6866	0.3005	1.569
	Normal weight - Low weight	0.5007	0.1899	1.320
1 - 2	Overweight - Low weight	0.792	0.142	4.420
	Intercept	1.047	0.981	1.117
	WbHPS	0.726	0.471	1.118
	Year study: 1st year - 3rd year			
	Scientific area:	0.704	0.392	1.265
	Exact and natural sciences - Engineering sciences	0.850	0.441	1.638
	Law and economic sciences - Engineering sciences	1.216	0.694	2.131
	Human and social sciences - Engineering sciences	1.753*	1.103*	2.786*
	Sex: Female - Male	0.737	0.472	1.151

Class	Predictor	OR	95% CI	
	Love relationship: No - Yes	2.801*	1.828*	4.293*
	Current residence: Not displaced - Displaced	0.686	0.292	1.613
	Professional Situation: Full time student - Worker/Student			
	BMI:	1.271	0.605	2.670
	Normal weight - Low weight	2.173	0.895	5.275

Note: OR: odds ratio; 95% CI: 95% confidence intervals; AIC = 1533; χ^2 (22) = 109
*p < .05

eISSN: 2386-7418 / https://doi.org/10.17979/reipe.2024.11.1.10028