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Behavioural lifestyle profiles among students in public higher education: health behaviours, digital engagement, leisure and sociability

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Research Article

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Abstract

Background

Student lifestyles encompass a wide range of interrelated behaviours, yet research has rarely examined conventional health behaviours alongside digital engagement and sociocultural activities. We identified lifestyle profiles among students in Portuguese public higher education and examined their sociodemographic correlates and health, psychosocial, and academic outcomes.

Methods

Data were drawn from the probabilistic ES + Saúde survey of 9611 students in Portuguese public higher education. Latent profile analysis included 8840 students and 27 behavioural indicators spanning sleep, physical activity, sedentary behaviour, diet, leisure, digital use, gaming, and substance use. Multinomial logistic regression assessed sociodemographic correlates; adjusted linear models compared 17 distal outcomes.

Results

Four profiles emerged: *Low-risk and low digital/recreational engagement* (46.5%), *Social alcohol and risk consumption* (19.9%), *Sedentary recreational digital/gaming* (19.2%), and *Active sociocultural and digitally engaged* (14.3%). Profile membership varied by age, gender, residential relocation, field of study, institution type, and subjective social class. All 17 outcomes differed significantly across profiles after adjustment ($p < .001$), although effects were generally modest (partial $\eta^2 = .008–.062$). The sedentary digital/gaming profile showed the least favourable overall health, psychological, social, and academic outcomes. Conversely, the active sociocultural profile combined the highest digital engagement with the highest physical activity and sociocultural participation and generally favourable outcomes. The low-risk profile also showed favourable outcomes.

Conclusions

Student lifestyles reflect distinct behavioural configurations rather than a simple healthy–unhealthy continuum. Digital engagement was not inherently associated with adverse outcomes; its relevance depended on accompanying behaviours. Health promotion may benefit from addressing co-occurring behavioural patterns rather than isolated risks.

Background

The transition to higher education represents an important life-course period for the establishment and consolidation of health-related behaviours (1, 2). During this period, young adults face rapid and profound changes in daily routines, social relationships, sleep patterns, dietary habits, recreational practices, financial responsibilities, and academic demands. For many students, this is the first experience of living independently from their families and without direct parental supervision, requiring them to make autonomous decisions across multiple aspects of daily life (2, 3). These changes create both risks and opportunities: while some students adopt or maintain health-promoting lifestyles, others initiate or intensify patterns of risk behaviour that may persist into adulthood and be associated with subsequent physical and mental health outcomes, as well as academic achievement during the higher education years (2, 4).

Lifestyle is inherently multidimensional. Health-related behaviours rarely occur independently; rather, they tend to co-occur and form recognisable configurations within individuals. In particular, unhealthy behaviours such as poor diet,

physical inactivity, sedentary behaviour, insufficient sleep, excessive alcohol consumption, smoking, and other substance use frequently cluster within individuals (5–7). Problematic or excessive digital media use may also intersect with sedentary behaviour, sleep, physical activity, and other dimensions of lifestyle (8, 9). Reviews of the multiple-health-behaviour literature have consistently documented such clustering and highlighted the limitations of examining individual behaviours in isolation (5–7). This clustering is important because different behavioural configurations have been associated with physical and mental health outcomes (10, 11), while several component behaviours also show prospective associations with academic performance among tertiary education students (4). Consequently, understanding how behaviours combine within individuals has become increasingly relevant for public health research and intervention.

Person-centred approaches provide an alternative framework by shifting the analytical focus from relationships among variables to configurations of characteristics within individuals. Such approaches are particularly useful for studying multidimensional lifestyles, as they allow substantively different combinations of behaviours to be identified within the same population. Research using person-centred approaches among higher education students has provided increasing evidence that health-related behaviours form distinct patterns rather than simply accumulating along a single continuum from healthy to unhealthy. Previous studies have identified subgroups differentiated by combinations of diet, physical activity, sleep, sedentary behaviour, alcohol consumption, smoking, illicit drug use, and other lifestyle characteristics. Laska et al., for example, showed that students with broadly similar levels of overall behavioural risk could nevertheless display markedly different configurations, including patterns characterised by poor lifestyle practices with relatively low substance-related risk and others marked by more extensive risk-taking (12). Kwan et al. likewise identified distinct combinations of multiple modifiable health-risk behaviours among university students (13), while Hutchesson et al. distinguished healthier, moderate, and unhealthy behavioural subgroups that also differed in psychological distress and sociodemographic characteristics (14). Together, these findings show that health-related behavioural patterns in higher education are heterogeneous and that qualitatively different lifestyle configurations may have different implications for student health and well-being.

More recent person-centred studies have broadened this perspective by incorporating behavioural domains such as screen time, sedentary behaviour, and other dimensions of contemporary student lifestyles. Maitiniyazi et al., for example, identified three lifestyle profiles based on diet, sleep, physical activity, screen time, and sedentary behaviour, with clear differences in depression, anxiety, and stress (15). Wang et al. similarly identified distinct healthy-lifestyle profiles and found that profile membership varied according to physical activity and sociodemographic characteristics (16). Although these studies reinforce the value of examining lifestyle configurations rather than isolated behaviours, digital engagement, gaming, and broader recreational and sociocultural activities remain underrepresented in person-centred student research and have rarely been integrated simultaneously with conventional health behaviours within the same analytical framework.

Digital media use and gaming have become important components of contemporary student life and may intersect with sedentary behaviour, sleep, physical activity, and academic functioning (8, 9). Importantly, intensive digital use should not automatically be equated with problematic use. A recent meta-analysis found no significant association between excessive social media use and subjective or psychological well-being, whereas problematic social media use was negatively associated with both outcomes, with effects also varying according to the form of social media use (17). Recent person-centred studies further suggest that different forms of problematic digital engagement are themselves heterogeneous: gaming-, social-media-, and other digital-use patterns show different associations with physical activity and biological rhythms (18, 19). These findings support examining digital behaviour within a broader lifestyle configuration rather than treating total digital exposure as a uniformly adverse characteristic. Likewise, sociability itself can accompany very different health configurations, ranging from active cultural and recreational participation to patterns more strongly associated with alcohol and other substance use. A broader conceptualisation

of lifestyle that integrates digital engagement, gaming, leisure, and sociability with conventional health behaviours may therefore reveal forms of behavioural heterogeneity that narrower models cannot identify.

Understanding these configurations is important because lifestyle profiles may also be socially patterned. Previous person-centred studies have reported differences in profile membership according to age, sex or gender, socioeconomic circumstances, and other sociodemographic characteristics (13–15). Within higher education, residential relocation may be especially relevant. Greater residential independence can increase autonomy in everyday decision-making (2), while living away from the family home has been associated with changes in food purchasing and preparation and with less favourable dietary practices (20). Residence away from parents or with peers has also been associated with heavier alcohol use and alcohol-related consequences among university students (21). Its relationship with broader lifestyle configurations, however, is unlikely to be reducible to a single risk pathway, making residential relocation relevant to examine at the profile level. Examining sociodemographic factors as predictors of complete lifestyle profiles, rather than of isolated behaviours, may therefore provide a more nuanced understanding of how students' social circumstances are associated with different ways of organising everyday life.

In Portugal, existing person-centred research has focused primarily on conventional health-risk behaviours among higher education students. Alves identified three classes based on alcohol consumption, smoking, unhealthy eating, sedentary behaviour, risky sexual practices, illicit drug use, and self-medication (22). More recently, Brandão et al. identified three health-behaviour classes that differed in mental health among students at a Portuguese private higher education institution (23). However, neither study examined lifestyle profiles integrating conventional health behaviours with digital engagement, gaming, and the broader leisure and sociocultural dimensions considered here. To our knowledge, no previous study has examined multidimensional lifestyle profiles using LPA among students across Portuguese public higher education, and internationally, person-centred studies combining comparably large samples with such a broad range of behavioural dimensions remain scarce.

The relevance of identifying such profiles extends beyond behavioural description. Different lifestyle configurations may be associated with students' broader health, psychological functioning, and academic experience. Recent systematic and meta-analytic evidence indicates that individuals characterised by healthier combinations of lifestyle behaviours report lower levels of depression, anxiety, and psychological distress than those displaying less favourable behavioural configurations (11). Among university students specifically, person-centred studies have also linked less healthy behavioural patterns to greater psychological distress and poorer mental health (13–15). Evidence from Portuguese higher education further indicates that students' mental well-being is associated with multiple interrelated domains, including lifestyle, self-esteem and life satisfaction, academic experiences, social relationships, and leisure and cultural activities (24). Academic functioning represents another potentially important outcome. A systematic review of cohort studies among tertiary education students found relatively consistent associations between poorer academic performance and inadequate sleep, higher alcohol consumption, and illicit drug use, while also emphasising the need to investigate the co-occurrence of health behaviours rather than considering them exclusively in isolation (4). However, less is known about whether broad multidimensional lifestyle profiles differentiate not only health and psychological outcomes but also academic performance and planning, life satisfaction, self-esteem, social support, and satisfaction with specific lifestyle domains.

Against this background, the present study used Latent Profile Analysis (LPA) to investigate behavioural lifestyles among students in Portuguese public higher education. LPA is a model-based person-centred method used to identify unobserved subpopulations based on similarities across multiple continuous or continuously treated indicators. Rather than assuming a homogeneous population, LPA estimates latent profiles characterised by distinct multivariate response patterns and provides posterior probabilities of profile membership for each individual (25, 26). LPA is closely related to Latent Class Analysis (LCA), but whereas LCA is generally applied to categorical indicators, LPA is typically

used with continuous indicators. Using data from a large, multi-institutional study of students enrolled in Portuguese public universities, polytechnic institutes, and non-integrated higher education schools, the analysis incorporated 27 behavioural indicators spanning sleep, physical activity, sedentary behaviour, diet, leisure and sociability, digital use, gaming, alcohol, tobacco, and psychoactive/risk substance use. The study pursued three objectives: (1) to identify distinct latent behavioural lifestyle profiles across these multiple domains; (2) to examine sociodemographic predictors of profile membership, including age, gender, residential relocation, institution type, field of study, and subjective social class; and (3) to determine whether the resulting profiles differed across health and lifestyle perceptions, psychological and social outcomes, academic outcomes, and satisfaction with key behavioural domains. Given the exploratory nature of LPA, no assumptions were made regarding the number or precise composition of the profiles. By integrating conventional health behaviours with digital, recreational, and social dimensions of student life, the study aims to provide a more comprehensive account of how health-related behaviours are organised within the higher education population and to provide an empirical basis for interventions directed at co-occurring behavioural patterns rather than isolated risk factors.

Methods

Participants and data collection

The study drew on data from the ES + Saúde survey, which yielded 9611 valid questionnaires from students enrolled in Portuguese public higher education during the 2021/2022 academic year. The survey covered 30 institutions – 13 universities and 17 polytechnic institutes or non-integrated higher education schools – and was designed to represent a reference population of 283542 bachelor's and master's students. A probabilistic stratified cluster sampling strategy was used (27, 28). The overall sampling error was 0.98% at the 95% confidence level; corresponding errors were 1.47% for universities and 1.32% for polytechnic and non-integrated institutions. The initial sampling design encompassed all 35 Portuguese public higher education institutions; however, five institutions – two universities and three non-integrated schools – were unable to participate because of organisational constraints or difficulties in implementing the survey within the available fieldwork period. A detailed account of the sampling design and data collection procedures is provided in Silva et al. (29).

Curricular units served as the primary sampling clusters. Each participating institution provided exhaustive lists of curricular units operating during the second semester of the 2021/2022 academic year, covering both bachelor's and master's programmes. Curricular units were then randomly and sequentially selected within each institution. The number required was determined according to institutional enrolment, using a reference target corresponding to approximately 4% of the student population of each institution. The sampling procedure also incorporated controls intended to minimise potential sources of bias, including overlapping classes, repeated participation, timetable constraints, and non-response. Overall, teaching staff from 865 curricular units were contacted; 518 units were initially pre-scheduled, 477 were subsequently scheduled, and data collection was ultimately completed in 452 curricular units.

The use of curricular units as sampling clusters provided a feasible means of implementing probability-based sampling without requiring access to individual-level lists containing students' personal and contact information. Such access would have been incompatible with the practical and data-protection constraints applying to higher education institutions under the European Union General Data Protection Regulation (EU Regulation 2016/679). Institutional-level collaboration was therefore central to the sampling process. Rectorates, presidencies of polytechnic institutes and non-integrated schools, and designated institutional representatives supported access to the information required for sample construction and facilitated coordination between the research team, teaching staff, and participating students.

Fieldwork was conducted between 4 April and 30 June 2022. The self-administered questionnaire was distributed and supervised in classroom settings by interviewers specifically trained for the study by GfK. Participants could complete the questionnaire digitally through Qualtrics using a smartphone, tablet, or computer; a paper version was also available when required. Average completion time was approximately 30 minutes.

The study protocol was approved by the Ethics Committee of the Institute of Social Sciences of the University of Lisbon (26/2021). Where required, the study was also submitted to the ethics committees or designated representatives of the participating higher education institutions. Participation was voluntary and conditional on prior informed consent. Before accessing the questionnaire, students were provided with information about the aims of the study and the procedures adopted to safeguard anonymity, confidentiality, and data protection. The research was conducted in accordance with the ethical and deontological principles applicable to scientific research, with particular attention to informed consent, anonymity, confidentiality, and data security throughout data collection and processing. In accordance with EU Regulation 2016/679 and Portuguese Law 58/2019, data collection was limited to the information required for the purposes of the study, and all data were processed and protected in compliance with the applicable legal framework.

Measures

a) The LPA incorporated 27 behavioural indicators across 12 behavioural dimensions, selected to capture the broad spectrum of lifestyle behaviours.

Sleep duration: Assessed separately for weekdays and weekends by asking students to report their average nightly sleep duration (in hours, ranging from less than 3 to more than 12 hours).

Sleep difficulties: Measured with two items assessing the (1) frequency of difficulty falling asleep and (2) waking repeatedly during the night (from 1 = *Never* to 4 = *Daily or almost daily*).

Physical activity: Two composite indices were derived from a battery of items assessing frequency of engagement in different physical activity modalities: (1) a general physical activity index aggregating fitness maintenance activities (gym-based activities, mind–body activities, and physical maintenance activities), and (2) a sports modalities index aggregating team sports, individual sports, extreme/adventure sports, and combat sports (both indices were scored from 0 = *never* to 3 = *3 or more times per week*). (3) In addition, students reported how much time per day they spent walking or cycling as part of daily activities (1 = *less than 15 minutes per day* to 4 = *more than 1 hour per day*).

Sedentary behaviour: Two items assessed time (in minutes) spent seated during a typical day: (a) during study-related activities (lectures, seminars, or studying; capped at 600 minutes) and (b) at home using a television, video content, or a computer for leisure or study (capped at 480 minutes).

Diet: Two dietary indicators were included. (1) Healthy eating practices were captured by a composite indicator based on the average frequency of consuming organic foods, preparing one's own meals, taking home-prepared food for lunch, dinner or snacks, and consuming low-fat or light products. The resulting mean was categorised into four frequency levels (1 = *never* to 4 = *3 or more times per week*). (2) Health-conscious food purchasing assessed whether students considered whether foods were healthy when buying food (1 = *never or very rarely* to 3 = *frequently*).

Dietary risk practices: Were captured by a composite indicator based on the average frequency of skipping breakfast, skipping lunch or dinner, consuming fast food, and eating pre-prepared meals, likewise categorised into four frequency levels (1 = *never* to 4 = *3 or more times per week*).

Leisure and sociability: Leisure activities were assessed using a battery of items rated from 1 = *never* to 5 = *always*. Principal component analysis with Varimax rotation identified five components (KMO = 0.848), explaining 54.65% of the total variance. The components represented (1) convivial activities (social and outdoor leisure practices; α = 0.74), (2) self-expression activities (creative and artistic practices; α = 0.62), (3) cultural activities (cultural participation and information-oriented activities; α = 0.68), (4) civic participation (associational and volunteering activities; α = 0.74), and (5) media consumption (screen-based and consumption-oriented leisure; α = 0.51). Composite scores were calculated for each component and used as five indicators in the LPA.

Digital use: Online activities were assessed by asking students to report the average time spent on different types of online activity on a typical day during the previous month, using a scale from 0 = *no time at all* to 5 = *6 or more hours*. Principal component analysis with Varimax rotation identified three components (KMO = 0.766), explaining 48.31% of the total variance: (1) specific online entertainment activities (e.g., online forums, gaming, dating platforms and other niche content; α = 0.56), (2) streaming and social networking (e.g., audiovisual streaming, messaging and social networking; α = 0.61), and (3) utilitarian and informational online activities (e.g., email, information seeking and study/work-related use; α = 0.55). Mean composite scores were calculated for each component and included as separate LPA indicators. (4) An overall mean daily online activity score was additionally included as an indicator of general digital engagement.

Gaming: Time spent playing video games or online games was assessed separately for weekdays and weekends and averaged into a composite daily gaming time variable (0 = *no time at all* to 5 = *6 or more hours*).

Alcohol use: Three indicators were used. (1) Beer consumption frequency and (2) consumption of other alcoholic beverages (distilled spirits, wine, mixed drinks) (0 = *never* to 4 = *daily*), covering the preceding 30 days. (3) Heavy episodic drinking was measured by asking how often students had consumed five or more drinks on a single occasion in the past 30 days (0 = *never* to 4 = *daily*).

Tobacco use: Assessed by asking how often in the past 30 days students had smoked tobacco (excluding e-cigarettes) (0 = *never* to 6 = *more than 20 cigarettes per day*).

Psychoactive and risk substance use: A composite indicator was constructed from three measures: cannabis use, use of other psychoactive substances (amphetamines, methamphetamines, cocaine, ecstasy, LSD and other hallucinogens, hallucinogenic mushrooms, heroin, GHB, ketamine, anabolic steroids, and new psychoactive substances), and nootropic/cognitive enhancer use (with or without prescription). Cannabis and other psychoactive substance use were coded from 0 (*no use*) to 4 (*daily use*), with intermediate categories representing increasing weekly frequency. Nootropic use was coded from 0 (*never*) to 3 (*use in the past 30 days*). The composite indicator was defined as the maximum score across the three measures, yielding an overall range from 0 to 4 and reflecting the highest level of substance involvement recorded for each participant.

b) The following variables were examined as distal outcomes in linear models comparing the latent profiles, adjusted for sociodemographic covariates.

Self-rated health: Assessed with a single item asking students to compare their overall health with that of other people their age (1 = *Very poor* to 5 = *Excellent*).

Perceived lifestyle healthiness: Assessed with a single item asking students to evaluate their current lifestyle (1 = *Not healthy at all* to 5 = *Very healthy*).

Perceived lifestyle change since entering higher education: Assessed with a single item asking students to compare their current lifestyle with the period before entering higher education (1 = *Much less healthy than before* to 5 = *Much*

healthier than before).

Psychological well-being: Measured with the WHO-5 Well-Being Index (30, 31), comprising five positively worded items covering the past two weeks (e.g., *I have felt cheerful and in good spirits*; *I have felt calm and relaxed*; *My daily life has been filled with things that interest me*). Each item is rated from 0 (*At no time*) to 5 (*All of the time*), and summed to produce a raw score ranging from 0 to 25, with higher scores indicating greater psychological well-being (α = 0.85).

General life satisfaction: Assessed with a single item asking students to rate their overall life satisfaction (0 = *Strongly dissatisfied* to 10 = *Strongly satisfied*) (32, 33).

Self-esteem: Measured with the Rosenberg Self-Esteem Scale (34), comprising 10 items rated on a seven-point agreement scale. Items 2, 5, 6, 8, and 9 were reverse-scored, and the items were summed to produce a global self-esteem score ranging from 0 to 60, with higher scores indicating greater self-esteem (α = 0.88).

Perceived social support: Assessed with three items adapted from the Multidimensional Scale of Perceived Social Support (35), measuring the perceived availability of a special person when needed, the reliability of friends in difficult situations, and the ability to discuss problems with family members (1 = *Strongly disagree* to 7 = *Strongly agree*) (α = 0.63).

Career future expectations: Assessed with the 10-item Work Hope Scale (36, 37), rated from 1 (*Strongly disagree*) to 5 (*Strongly agree*). Items 2, 5, and 9 were reverse-scored, and the items formed a unidimensional scale (α = 0.80). Scores were summed to yield a total ranging from 10 to 50, with higher scores indicating more optimistic expectations regarding future professional success.

Academic grade average: Obtained by asking students to report their grade average for the most recently completed semester (0–20 Portuguese grading scale).

Perceived academic success: Assessed with a single item asking students to compare their academic performance with their expectations (1 = *Worse than expected* to 3 = *Better than expected*).

Academic time management and attitudes toward time management: Items from the Time Management Questionnaire (38, 39) were rated from 1 (*never*) to 6 (*always*). After reverse-scoring negatively worded items, principal component analysis with Varimax rotation identified three components (KMO = 0.889), explaining 55.97% of the total variance: short-term study planning (six items; α = 0.88), reflecting the organisation of daily academic tasks; attitudes toward time management (four items; α = 0.75), reflecting perceived control, effectiveness and satisfaction with time use; and long-term study planning (four items; α = 0.65), reflecting strategic and anticipatory planning across longer periods. Composite scores were calculated for each dimension, with higher scores indicating more favourable study-related planning or attitudes.

Behavioural domain satisfactions: Four items assessed satisfaction with specific self-care behaviours on a scale from 0 (*Strongly dissatisfied*) to 10 (*Strongly satisfied*): (a) satisfaction with planned and regular physical exercise practice; (b) satisfaction with planned and regular leisure and break times; (c) satisfaction with sleep quality; and (d) satisfaction with care regarding nutrition (40, 41).

c) The following sociodemographic variables were included as predictors of profile membership in the multinomial logistic regression and as adjustment variables in the distal outcome models.

Gender: Operationalised as a binary variable (male; female), based on participants' self-reported gender. Non-binary and other gender identities were excluded from this variable due to insufficient cell sizes for modelling purposes.

Age: was included as a continuous variable in years (range: 16–65).

Type of institution: Coded as a binary variable distinguishing (1) university institutions from (2) polytechnic higher education institutes and non-integrated schools.

Field of study: Categorised into four groups: (1) social sciences; (2) arts and humanities; (3) life and health sciences; and (4) exact and natural sciences and engineering.

Subjective social class: Assessed with a single item asking students to place themselves on a 0–10 scale relative to the general population (0 = *Lower than people in general* to 10 = *Higher than people in general*).

Relocated from permanent residence: Assessed with a single item asking whether the student was living away from their permanent place of residence during the academic year (Yes; No).

Analysis procedure

All analyses were conducted in R (version 4.6.1), using the *mclust*, *nnet*, and *emmeans* packages. The analytic strategy comprised three stages: (1) latent profile analysis (LPA) to identify behavioural lifestyle profiles; (2) multinomial logistic regression to examine sociodemographic predictors of profile membership; and (3) adjusted linear models to compare profiles across distal health, psychological, social, academic, and lifestyle-related outcomes.

Latent profile analysis: LPA was conducted using the *Mclust()* function from the *mclust* package. The 27 behavioural indicators were standardised to z-scores to place them on a common metric. The analytic sample comprised 8,840 students retained following missing-data screening during indicator development. For the final set of 27 indicators, participants were required to have no more than 20% missing data (≤ 5 of 27). Remaining missing values were imputed using the variable-specific median on the standardised scale.

Models followed the EII parameterisation, which specifies spherical equal-volume covariance matrices, corresponding to equal variances across indicators and profiles and zero within-profile covariances (42). This parsimonious specification was considered appropriate given the relatively large number of indicators. Solutions with three to five profiles were compared. Model selection considered the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (SABIC), entropy, average posterior classification probabilities, profile size, parsimony, and substantive interpretability (26, 43, 44). Participants were assigned to the profile for which they had the highest posterior probability of membership. The resulting profiles were labelled based on their characteristic patterns across the twelve behavioural dimensions.

Sociodemographic predictors of profile membership: Multinomial logistic regression was used to examine associations between profile membership and age, gender, relocated from permanent residence, institution type, field of study, and subjective social class. The *Low-risk and low digital/recreational engagement* profile was used as the reference category; female gender, non-relocated, university attendance, and social sciences were the corresponding categorical reference groups. All predictors were entered simultaneously, and the model was estimated using complete cases. Overall model fit was evaluated using the likelihood-ratio test and McFadden's pseudo-R^2. Associations are reported as odds ratios (ORs) with 95% confidence intervals.

Distal outcome models: Differences between profiles across 17 health, psychological, social, academic, and lifestyle-related outcomes were examined using separate linear regression models adjusted for the same six sociodemographic variables. Models were estimated using complete cases for each outcome and covariate set. Adjusted marginal means and 95% confidence intervals were estimated for each profile using the *emmeans* package. The overall effect of profile membership was evaluated by comparing each full model with a corresponding reduced model containing only the

sociodemographic covariates. Partial eta-squared (η^2p) was used to quantify the magnitude of the profile effect after adjustment for these covariates.

Use of generative AI

Generative AI tools were used during manuscript preparation to assist with the development and debugging of R code. All statistical analyses were performed by the author, who critically reviewed and verified the code and outputs. AI tools were also used to support proofreading of the manuscript. The author takes full responsibility for the accuracy, integrity, and originality of the final manuscript.

Results

Participants had a mean age of 21.73 years (*SD* = 5.11), 63.5% were female, and 52.3% were living away from their permanent residence during the academic year. Mean subjective social class was 5.18 (*SD* = 1.46) on a 0–10 scale. Slightly more than half attended a polytechnic institute or non-integrated higher education school (54.8%), and social sciences was the largest field of study (40.9%).

Across the behavioural indicators used in the latent profile analysis, students reported an average of 6.93 hours of sleep on weekdays (*SD* = 1.17) and 8.40 hours on weekends (*SD* = 1.47). Mean scores indicated relatively low levels of physical activity (physical activity index: *M* = 1.06, *SD* = 0.76) and sports participation (*M* = 0.52, *SD* = 0.66), alongside moderate levels of active commuting (*M* = 2.50, *SD* = 0.94). Average sedentary time was 293.73 minutes per day for study-related activities and 171.17 minutes for television, video, or computer use at home. Moderate scores were also observed for healthy eating, leisure engagement, and online activities, whereas mean frequencies of alcohol, tobacco, and psychoactive substance use were generally low.

Regarding distal outcomes, participants reported generally favourable self-rated health (*M* = 3.85, *SD* = 0.73), perceived healthy lifestyle (*M* = 3.23, *SD* = 0.71), psychological well-being (*M* = 13.58, *SD* = 4.66), life satisfaction (*M* = 6.67, *SD* = 1.95), self-esteem (*M* = 39.54, *SD* = 12.03), and perceived social support (*M* = 5.79, *SD* = 1.22). The mean grade average in the previous semester was 14.08 (*SD* = 2.07), and students also reported moderate to high levels of study planning, positive career expectations, and satisfaction with diet, sleep, leisure, and physical exercise. Descriptive statistics for sociodemographic characteristics, behavioural indicators, and distal outcomes are presented in Table 1.

Table 1
– Descriptive statistics

Variables	n	%	Mean	SD	Minimum	Maximum
Sociodemographic and contextual variables						
Age	8797	99.5	21.73	5.11	16.00	65.00
Gender: Female	5490	63.5	—	—	—	—
Gender: Male	3157	36.5	—	—	—	—
Relocated from permanent residence: No	4177	47.7	—	—	—	—
Relocated from permanent residence: Yes	4576	52.3	—	—	—	—
Subjective social class	8718	98.6	5.18	1.46	0.00	10.00
Type of institution: Polytechnic / non-integrated school	4836	54.8	—	—	—	—
Type of institution: University	3983	45.2	—	—	—	—
Field of study: Arts and humanities	806	9.2	—	—	—	—
Field of study: Exact and natural sciences and engineering	2111	24.1	—	—	—	—
Field of study: Life and health sciences	2273	25.9	—	—	—	—
Field of study: Social sciences	3585	40.9	—	—	—	—
LPA behavioural indicators						
Sleep duration during weekdays	8484	96.0	6.93	1.17	2.50	12.50
Sleep duration during weekends	8579	97.0	8.40	1.47	2.50	12.50
Difficulty falling asleep	8691	98.3	2.40	0.95	1.00	4.00
Waking up during the night	8732	98.8	2.15	0.93	1.00	4.00
Physical activity index	8769	99.2	1.06	0.76	0.00	3.00
Sports modalities index	8784	99.4	0.52	0.66	0.00	3.00
Walking or cycling in daily activities	8678	98.2	2.50	0.94	1.00	4.00
Sedentary time in study activities	6887	77.9	293.73	142.67	30.00	600.00
Sedentary time at home using TV/video/computer	6729	76.1	171.17	106.14	30.00	480.00
Healthy eating category	8711	98.5	2.59	0.68	1.00	4.00
Health-conscious food purchasing	8683	98.2	2.39	0.65	1.00	3.00
Dietary risk category	8719	98.6	2.12	0.66	1.00	4.00
Leisure: convivial activities	8836	100.0	2.71	0.76	1.00	5.00
Leisure: self-expression activities	8828	99.9	1.81	0.74	1.00	5.00
Leisure: cultural activities	8835	99.9	2.17	0.71	1.00	5.00
Leisure: civic participation	8784	99.4	2.03	1.07	1.00	5.00

Variables	n	%	Mean	SD	Minimum	Maximum
Sociodemographic and contextual variables						
Leisure: media consumption	8837	100.0	2.99	0.77	1.00	5.00
Online entertainment activities	8822	99.8	0.57	0.74	0.00	5.00
Online social networking	8826	99.8	2.89	0.96	0.00	5.00
Online utility/information activities	8830	99.9	1.43	0.76	0.00	5.00
Mean online activity	8834	99.9	1.51	0.62	0.00	5.00
Video gaming time	8387	94.9	1.21	1.34	0.00	5.00
Beer consumption frequency	8840	100.0	0.93	1.10	0.00	4.00
Other alcoholic drinks consumption	8840	100.0	1.04	1.03	0.00	4.00
Heavy episodic drinking	8720	98.6	0.72	0.94	0.00	4.00
Tobacco use frequency	8840	100.0	0.62	1.32	0.00	6.00
Psychoactive/risk substance use	8840	100.0	0.35	0.85	0.00	4.00
Distal outcomes						
Self-rated health	8838	100.0	3.85	0.73	1.00	5.00
Perceived healthy lifestyle	8826	99.8	3.23	0.71	1.00	5.00
Lifestyle compared with before higher education	8839	100.0	2.67	0.91	1.00	5.00
Psychological well-being	8629	97.6	13.58	4.66	0.00	25.00
General life satisfaction	8766	99.2	6.67	1.95	0.00	10.00
Global self-esteem	8269	93.5	39.54	12.03	0.00	60.00
Perceived social support	8809	99.6	5.79	1.22	1.00	7.00
Last semester grade average	6820	77.1	14.08	2.07	0.00	20.00
Short-term study planning	8788	99.4	2.82	1.17	1.00	6.00
Long-term study planning	8797	99.5	3.21	0.96	1.00	6.00
Attitudes toward time management	8796	99.5	3.30	1.00	1.00	6.00
Perceived academic success	8514	96.3	1.84	0.69	1.00	3.00
Work hope / career future expectations	7200	81.4	34.97	6.36	10.00	50.00
Satisfaction with diet	8703	98.5	5.56	2.18	0.00	10.00
Satisfaction with sleep quality	8761	99.1	5.22	2.55	0.00	10.00
Satisfaction with physical exercise	8678	98.2	4.14	2.90	0.00	10.00
Satisfaction with leisure	8653	97.9	5.57	2.41	0.00	10.00

Model fit statistics for the three- to five-profile solutions are presented in Table 2. Information criteria decreased progressively from the three- to the five-profile solution. However, the five-profile solution yielded a very small profile

comprising 3.3% of the sample and a slightly lower minimum average posterior classification probability (.831) than the four-profile solution (.844). The four-profile solution was therefore retained as a more parsimonious and substantively interpretable representation of the data, with all profiles comprising at least 14.3% of the analytic sample. Its entropy was .789 and the minimum average posterior classification probability was .844.

Table 2
– Model fit statistics for latent profile solutions with three to five profiles

Number of profiles	AIC	BIC	SABIC	Entropy	Minimum average posterior probability	Smallest profile, n (%)
3	653,667	654,262	653,995	.811	.865	1607 (18.2)
4	**649,076**	**649,870**	**649,514**	**.789**	**.844**	**1267 (14.3)**
5	646,239	647,231	646,786	.797	.831	291 (3.3)

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = sample-size adjusted Bayesian Information Criterion. Lower AIC, BIC, and SABIC values indicate better relative fit, whereas higher entropy and average posterior probabilities indicate better classification quality. The four-profile solution was retained based on parsimony, substantive interpretability, adequate classification quality, and the emergence of a very small profile in the five-profile solution (3.3% of the sample).

Table 3 presents the four latent lifestyle profiles and their standardised mean scores across the twelve behavioural dimensions. The largest profile, *Low-risk and low digital/recreational engagement* (46.5%), showed below-average scores on alcohol, tobacco, psychoactive/risk substance use, dietary risk, digital use, gaming, and sedentary behaviour, alongside relatively healthier eating. The *Social alcohol and risk consumption* profile (19.9%) was primarily characterised by markedly elevated alcohol consumption, tobacco use, and psychoactive/risk substance use, together with higher dietary risk and lower healthy eating. The *Sedentary recreational digital/gaming* profile (19.2%) was characterised by markedly elevated gaming, above-average digital use and sedentary behaviour, poorer healthy eating, and lower leisure/sociability and physical activity. In contrast, the *Active sociocultural and digitally engaged* profile (14.3%) showed the highest levels of digital use, leisure/sociability, and physical activity, together with relatively healthy eating and generally low or near-average substance use.

Alcohol use, tobacco use, psychoactive/risk substance use, digital engagement, gaming, healthy eating, and leisure/sociability showed the most pronounced variation across profiles. In contrast, sleep duration showed very limited between-profile variation, with standardised means close to zero across all four profiles. Sleep difficulties also showed comparatively modest differentiation, although they were somewhat higher in the *Sedentary recreational digital/gaming* profile. Physical activity and dietary risk contributed more selectively to profile differentiation, with physical activity primarily distinguishing the *Active sociocultural and digitally engaged* and *Sedentary recreational digital/gaming* profiles, and dietary risk primarily distinguishing the *Social alcohol and risk consumption* and *Low-risk and low digital/recreational engagement* profiles.

Table 3
– Latent lifestyle profiles: profile sizes and standardised mean scores by behavioural dimension

Behavioural dimension	Low-risk and low digital/recreational engagement (n = 4115; 46.5%)	Social alcohol and risk consumption (n = 1760; 19.9%)	Sedentary recreational digital/gaming (n = 1698; 19.2%)	Active sociocultural and digitally engaged (n = 1267; 14.3%)
Alcohol use	-0.338	1.250	-0.485	-0.006
Dietary risk	-0.339	0.404	0.250	0.187
Digital use	-0.424	0.011	0.276	0.986
Gaming	-0.440	0.121	0.788	0.150
Healthy eating	0.245	-0.263	-0.528	0.271
Leisure/sociability	-0.062	0.071	-0.505	0.778
Physical activity	-0.044	0.042	-0.307	0.458
Psychoactive/risk substance use	-0.233	0.646	-0.118	0.017
Sedentary behaviour	-0.170	-0.082	0.239	-0.021
Sleep difficulties	-0.101	0.019	0.168	0.047
Sleep duration	0.028	-0.071	-0.003	0.027
Tobacco use	-0.272	0.976	-0.273	-0.107

Note: Values are standardised mean scores within each latent profile. Positive values indicate above-sample-average scores and negative values indicate below-sample-average scores on each behavioural dimension. Model fit: *n* = 8840; AIC = 649076; BIC = 649870; SABIC = 649514; entropy = 0.789; minimum average posterior classification probability = 0.844.

Table 4 presents the multinomial logistic regression examining sociodemographic predictors of latent lifestyle profile membership, using the *Low-risk and low digital/recreational engagement* profile as the reference category. Younger age was consistently associated with greater odds of belonging to all three alternative profiles. Male students had substantially higher odds than female students of belonging to the *Social alcohol and risk consumption* (OR = 3.14, 95% CI [2.76–3.57]) and *Sedentary recreational digital/gaming* (OR = 3.08, 95% CI [2.71–3.51]) profiles, and higher odds of belonging to the *Active sociocultural and digitally engaged* profile (OR = 1.49, 95% CI [1.28–1.73]).

Students relocated from their permanent residence had higher odds of belonging to the *Social alcohol and risk consumption* (OR = 1.99, 95% CI [1.76–2.25]) and *Active sociocultural and digitally engaged* (OR = 1.32, 95% CI [1.15–1.51]) profiles, but slightly lower odds of belonging to the *Sedentary recreational digital/gaming* profile (OR = 0.87, 95% CI [0.77–0.98]). Attendance at a polytechnic institute or non-integrated higher education school was associated only with higher odds of membership in the *Social alcohol and risk consumption* profile (OR = 1.18, 95% CI [1.05–1.33]).

Field of study was also associated with profile membership. Compared with students in social sciences, those in arts and humanities had higher odds of belonging to the *Sedentary recreational digital/gaming* (OR = 2.27, 95% CI [1.84–2.81]) and *Active sociocultural and digitally engaged* (OR = 1.36, 95% CI [1.08–1.72]) profiles. Students in life and health sciences had lower odds of belonging to all three alternative profiles. Those in exact and natural sciences and engineering had higher odds of belonging to the *Sedentary recreational digital/gaming* profile (OR = 1.41, 95% CI [1.20–1.64]) but lower odds of belonging to the *Active sociocultural and digitally engaged* profile (OR = 0.65, 95% CI [0.54–

0.78]). Finally, subjective social class was positively associated with membership in the *Active sociocultural and digitally engaged* profile (OR = 1.13, 95% CI [1.08–1.18]) and negatively associated with the *Sedentary recreational digital/gaming* profile (OR = 0.90, 95% CI [0.86–0.94]), with no significant association for the *Social alcohol and risk consumption* profile.

Table 4
– Multinomial logistic regression predicting latent lifestyle profile membership

Predictor	Social alcohol and risk consumption	Sedentary recreational digital/gaming	Active sociocultural and digitally engaged
Age per year	0.95 [0.94–0.97]***	0.93 [0.92–0.95]***	0.97 [0.96–0.98]***
Male gender	3.14 [2.76–3.57]***	3.08 [2.71–3.51]***	1.49 [1.28–1.73]***
Relocated from permanent residence	1.99 [1.76–2.25]***	0.87 [0.77–0.98]*	1.32 [1.15–1.51]***
Polytechnic / non-integrated school	1.18 [1.05–1.33]**	1.03 [0.91–1.16]	1.05 [0.92–1.20]
Arts and humanities	0.91 [0.72–1.16]	2.27 [1.84–2.81]***	1.36 [1.08–1.72]**
Life and health sciences	0.74 [0.64–0.86]***	0.81 [0.69–0.96]*	0.63 [0.53–0.74]***
Exact and natural sciences and engineering	0.88 [0.75–1.03]	1.41 [1.20–1.64]***	0.65 [0.54–0.78]***
Subjective social class per point	1.00 [0.96–1.05]	0.90 [0.86–0.94]***	1.13 [1.08–1.18]***

Note: Values are odds ratios (ORs) with 95% confidence intervals. The reference outcome category was the *Low-risk and low digital/recreational engagement* profile. Predictors were entered simultaneously. Reference categories were female gender, not relocated from permanent residence, university, and social sciences. Age was entered continuously in years and subjective social class as a continuous 0–10 measure. Model fit: $n = 8351$; LR $\chi^2(24) = 1054$, $p < .001$; McFadden's pseudo-$R^2 = .050$. *$p < .05$; **$p < .01$; ***$p < .001$.

Table 5 presents adjusted distal outcomes across the four latent lifestyle profiles after controlling for age, gender, relocation from permanent residence, type of institution, field of study, and subjective social class. Significant profile differences were observed across all 17 outcomes (all $p < .001$), with partial η^2 values ranging from .008 to .062.

The *Active sociocultural and digitally engaged* profile showed the most favourable adjusted means for several outcomes, including perceived healthy lifestyle, lifestyle improvement since entering higher education, psychological well-being, short- and long-term study planning, perceived academic success, work hope/career future expectations, perceived social support, and satisfaction with diet, physical exercise, and leisure. It also showed high levels of self-rated health and general life satisfaction.

The *Low-risk and low digital/recreational engagement* profile also displayed a broadly favourable outcome pattern. It had the highest adjusted means for self-rated health, global self-esteem, last-semester grade average, attitudes toward time management, and satisfaction with sleep quality, while showing values close to those of the *Active sociocultural and digitally engaged* profile for several other health, psychological, social, and lifestyle-related outcomes.

In contrast, the *Sedentary recreational digital/gaming* profile showed the least favourable adjusted means for most outcomes, including self-rated health, perceived healthy lifestyle, psychological well-being, general life satisfaction, global self-esteem, perceived social support, short- and long-term study planning, attitudes toward time management, perceived academic success, work hope/career future expectations, and satisfaction with diet, sleep quality, physical exercise, and leisure. The *Social alcohol and risk consumption* profile generally occupied an intermediate position,

although it showed the lowest adjusted mean for lifestyle change since entering higher education and last-semester grade average. Satisfaction with leisure followed a somewhat different pattern, with the *Active sociocultural and digitally engaged* profile showing the highest adjusted mean, followed by the *Social alcohol and risk consumption* profile.

Overall, the profiles were systematically differentiated across health, psychological, social, academic, and lifestyle-related outcomes. The *Active sociocultural and digitally engaged* and *Low-risk and low digital/recreational engagement* profiles generally showed the most favourable outcomes, whereas the *Sedentary recreational digital/gaming* profile showed the least favourable overall pattern.

Table 5
– Adjusted distal outcomes across latent lifestyle profiles

Outcome	n	Low-risk and low digital/recreational engagement	Social alcohol and risk consumption	Sedentary recreational digital/gaming	Active sociocultural and digitally engaged	*p*	Partial η²
Self-rated health	8349	3.95 [3.93–3.98]	3.78 [3.75–3.82]	3.70 [3.67–3.74]	3.93 [3.89–3.97]	< 0.001	0.019
Perceived healthy lifestyle	8339	3.38 [3.35–3.40]	3.05 [3.02–3.09]	2.99 [2.95–3.02]	3.41 [3.37–3.45]	< 0.001	0.062
Lifestyle compared with before higher education	8350	2.75 [2.71–2.78]	2.50 [2.45–2.54]	2.56 [2.52–2.61]	2.85 [2.80–2.90]	< 0.001	0.018
Psychological well-being	8167	14.05 [13.89–14.21]	13.52 [13.30–13.74]	11.87 [11.65–12.10]	15.27 [15.00–15.53]	< 0.001	0.049
General life satisfaction	8301	6.90 [6.83–6.97]	6.44 [6.35–6.54]	6.01 [5.92–6.10]	6.91 [6.80–7.02]	< 0.001	0.034
Global self-esteem	7840	41.21 [40.78–41.64]	38.79 [38.19–39.38]	35.34 [34.74–35.94]	40.03 [39.33–40.72]	< 0.001	0.033
Perceived social support	8328	5.87 [5.83–5.91]	5.65 [5.59–5.71]	5.31 [5.25–5.37]	5.90 [5.83–5.97]	< 0.001	0.032
Last semester grade average	6493	14.39 [14.31–14.47]	13.75 [13.63–13.86]	13.97 [13.85–14.09]	14.17 [14.04–14.30]	< 0.001	0.015
Short-term study planning	8305	2.88 [2.84–2.92]	2.49 [2.43–2.55]	2.47 [2.41–2.52]	3.24 [3.17–3.31]	< 0.001	0.051
Long-term study planning	8312	3.25 [3.22–3.29]	2.94 [2.89–2.98]	2.89 [2.84–2.94]	3.61 [3.55–3.66]	< 0.001	0.060
Attitudes toward time management	8312	3.45 [3.41–3.48]	3.01 [2.96–3.06]	2.96 [2.91–3.01]	3.44 [3.39–3.50]	< 0.001	0.048
Perceived academic success	8063	1.88 [1.86–1.91]	1.77 [1.73–1.80]	1.76 [1.72–1.79]	1.91 [1.87–1.95]	< 0.001	0.008
Work hope / career future expectations	6849	35.28 [35.03–35.52]	34.13 [33.79–34.47]	33.03 [32.68–33.38]	35.50 [35.11–35.89]	< 0.001	0.020

Note: Values are adjusted means with 95% confidence intervals from linear models adjusted for age, gender, relocation from permanent residence, type of institution, field of study, and subjective social class. Higher scores indicate more favourable outcomes for all variables. Partial η² represents the adjusted global effect of latent profile membership on each outcome.

Outcome	n	Low-risk and low digital/recreational engagement	Social alcohol and risk consumption	Sedentary recreational digital/gaming	Active sociocultural and digitally engaged	*p*	Partial η²
Satisfaction with diet	8233	6.04 [5.97–6.12]	5.05 [4.95–5.16]	4.86 [4.75–4.97]	6.05 [5.93–6.18]	< 0.001	0.056
Satisfaction with sleep quality	8283	5.61 [5.52–5.70]	4.80 [4.67–4.92]	4.51 [4.38–4.63]	5.40 [5.25–5.54]	< 0.001	0.030
Satisfaction with physical exercise	8216	4.59 [4.49–4.69]	3.89 [3.75–4.03]	3.26 [3.12–3.40]	5.18 [5.02–5.34]	< 0.001	0.046
Satisfaction with leisure	8191	5.51 [5.43–5.60]	5.78 [5.66–5.90]	5.27 [5.15–5.39]	6.00 [5.87–6.14]	< 0.001	0.010

Note: Values are adjusted means with 95% confidence intervals from linear models adjusted for age, gender, relocation from permanent residence, type of institution, field of study, and subjective social class. Higher scores indicate more favourable outcomes for all variables. Partial η² represents the adjusted global effect of latent profile membership on each outcome.

Discussion

The present study provides evidence that health-related behaviours among higher education students are organised into distinct and substantively meaningful lifestyle configurations rather than distributed along a single continuum from healthy to unhealthy. Using latent profile analysis across 27 indicators spanning sleep, physical activity, sedentary behaviour, diet, leisure and sociability, digital use, gaming, alcohol, tobacco, and psychoactive/risk substance use, four profiles were identified: *Low-risk and low digital/recreational engagement* (46.5%), *Social alcohol and risk consumption* (19.9%), *Sedentary recreational digital/gaming* (19.2%), and *Active sociocultural and digitally engaged* (14.3%). These profiles were not only behaviourally distinct but also socially patterned and consistently differentiated across health, psychological, social, academic, and lifestyle-related outcomes after adjustment for sociodemographic characteristics. Taken together, the findings reinforce the value of a person-centred perspective for understanding student lifestyles and extend previous research by showing that contemporary behavioural heterogeneity involves not only conventional health-risk behaviours but also different combinations of digital, recreational, and sociocultural engagement.

The four-profile solution is consistent with a substantial literature showing that health behaviours cluster in complex configurations within individuals (5–7). Previous person-centred studies among young people and university students have similarly identified healthy, unhealthy, and mixed behavioural configurations across different sociocultural contexts (10, 12–16, 45, 46). Importantly, however, the present profiles do not support a simple distinction between globally “healthy” and “unhealthy” lifestyles. Rather, they show that students with relatively similar levels of conventional behavioural risk may nevertheless differ substantially in digital engagement, gaming, physical activity, and sociocultural participation. Incorporating these domains alongside conventional health behaviours therefore revealed forms of behavioural differentiation that extend beyond a purely cumulative-risk structure.

This is particularly evident in the largest profile, *Low-risk and low digital/recreational engagement*, which comprised almost half of the analytic sample. These students showed relatively low alcohol, tobacco, psychoactive substance, gaming, digital-use, sedentary, and dietary-risk scores and somewhat healthier eating practices. However, they were not characterised by particularly high physical activity or sociocultural engagement. Thus, this profile should not be interpreted as an unequivocally “optimal” lifestyle group. Rather, it represents a relatively low-risk and behaviourally moderate pattern. This distinction is important because an absence of conventional risk behaviours is not equivalent to

high engagement in health-promoting, social, or recreational activities. Similar complexity was observed by Laska et al., who identified low-risk groups that nevertheless displayed suboptimal lifestyle characteristics, and is compatible with broader evidence that mixed behavioural configurations are common (10, 12). The relatively favourable outcomes observed in the present low-risk group nevertheless suggest that lower involvement in substance-related and other behavioural risks is associated with more favourable functioning even in the absence of particularly high physical or sociocultural engagement.

The *Social alcohol and risk consumption* profile represents a qualitatively different form of behavioural risk. Its defining characteristics were markedly elevated alcohol use, tobacco consumption, and psychoactive/risk substance use, accompanied by greater dietary risk and poorer healthy-eating practices. This concentration of substance-related behaviours is highly consistent with previous research. The systematic review by Noble et al. found particularly consistent clustering between risky alcohol consumption and smoking (7), while student studies have identified high-risk groups characterised by the co-occurrence of alcohol, tobacco, illicit substances, and other health-risk practices (12–14). Similar patterns have also been reported in Portugal: Alves identified a high-risk latent class across seven conventional health-risk domains (22), while Brandão et al. identified a distinct unhealthy/substance-use class among Portuguese university students (23). The convergence across studies suggests that substance-related behaviours constitute a particularly coherent dimension of lifestyle patterning during higher education.

At the same time, the *Social alcohol and risk consumption* profile should not be interpreted as reflecting uniformly adverse functioning. Although students in this profile generally showed less favourable health and psychological outcomes than those in the low-risk group, their satisfaction with leisure was relatively high and was numerically higher than in the low-risk group. This pattern may reflect the social and recreational contexts in which alcohol and other risk behaviours can occur during student life. It also suggests a potential tension between the immediate social or experiential rewards associated with some risk behaviours and their broader associations with health, well-being, and academic functioning. Because the data are cross-sectional, the mechanisms underlying this pattern cannot be established. Nevertheless, these findings suggest that interventions targeting substance use may benefit from considering the social and recreational functions with which alcohol and other substance use may be associated, rather than addressing these behaviours solely as isolated individual choices.

The *Sedentary recreational digital/gaming* profile represents a particularly distinctive behavioural configuration. Students in this profile combined the highest gaming involvement with elevated digital use and sedentary behaviour, markedly poorer healthy eating, and comparatively low physical activity and leisure/sociocultural engagement. At the same time, alcohol, tobacco, and psychoactive substance use were below average. This configuration therefore represents a form of behavioural vulnerability that would be only partially captured by traditional frameworks centred primarily on substance use and other conventional risk indicators. Students may display relatively low levels of alcohol, tobacco, and psychoactive substance involvement while nevertheless belonging to a lifestyle configuration associated with generally less favourable health, psychological, and academic outcomes.

This finding is consistent with growing evidence that digital behaviours constitute an important axis of heterogeneity in contemporary student lifestyles. Maitiniyazi et al. identified a “negative engagement” LPA profile characterised by high screen time and sedentary behaviour and low physical activity (15), which was associated with higher levels of depression, anxiety, and stress. More recent LPA studies focused specifically on digital behaviours have further demonstrated heterogeneity in problematic digital engagement. Peng et al., for example, distinguished low-risk, social-media-dominant, gaming-dominant, and high-risk problematic internet-use profiles among college students (19), while Chen et al. identified distinct biological-rhythm profiles associated with different problematic digital behaviours (18). These studies are not directly equivalent to the present analysis, because the current indicators capture patterns and intensity of digital engagement rather than problematic or addictive use. Nevertheless, they reinforce the importance of

distinguishing different configurations of digital activity rather than treating screen use as a single homogeneous exposure.

The contrast between the *Sedentary recreational digital/gaming* and *Active sociocultural and digitally engaged* profiles is particularly informative. The latter had the highest digital engagement of all four profiles but simultaneously displayed the highest levels of physical activity and leisure/sociocultural participation, relatively healthy eating, and generally low or near-average substance-related risk. It also showed some of the most favourable distal outcomes. Digital engagement therefore did not behave as an intrinsically adverse lifestyle characteristic; its meaning depended on the broader behavioural configuration in which it was embedded. High digital engagement accompanied by physical, social, cultural, and recreational participation was associated with a markedly different pattern of outcomes from digital engagement embedded in gaming, sedentary behaviour, poorer diet, and low offline engagement. More broadly, the *Active sociocultural and digitally engaged* profile suggests that favourable lifestyle configurations may involve behavioural breadth rather than behavioural restriction, with students simultaneously active across physical, sociocultural, and digital domains. This is consistent with evidence that screen-related or sedentary activities can coexist with high physical activity and other favourable behaviours (10), challenging the assumption that engagement in one domain necessarily displaces participation in another. From a health-promotion perspective, interventions aimed indiscriminately at reducing digital activity may therefore overlook students whose digital engagement forms part of an otherwise active and socially connected lifestyle. The broader behavioural configuration surrounding digital use may be more informative than digital exposure considered in isolation.

Not all behavioural domains contributed equally to the four-profile structure. Sleep duration varied relatively little across profiles, with standardised means close to the sample average in all four groups. Sleep difficulties also showed only modest differentiation, although they were somewhat higher in the *Sedentary recreational digital/gaming* profile. Sleep therefore contributed relatively little to distinguishing these particular lifestyle profiles. By contrast, physical activity and dietary risk contributed more selectively to profile differentiation: physical activity was clearly higher in the *Active sociocultural and digitally engaged* profile and lower in the *Sedentary recreational digital/gaming* profile, whereas dietary risk was higher in the *Social alcohol and risk consumption* profile and lower in the *Low-risk and low digital/recreational engagement* profile. Overall, the typology was most clearly differentiated by substance involvement, digital use and gaming, healthy eating, and leisure/sociocultural participation, with more selective contributions from physical activity and dietary risk.

The sociodemographic results further demonstrate that these lifestyle configurations are socially patterned. Male gender was one of the strongest predictors of profile membership, with men having approximately three times the odds of belonging to both the *Social alcohol and risk consumption* and *Sedentary recreational digital/gaming* profiles compared with women, as well as higher odds of belonging to the *Active sociocultural and digitally engaged* profile. The association between male gender and riskier combinations of health behaviours is consistent with the systematic review by Noble et al. (7) and with student-specific person-centred evidence from Hutchesson et al. (14). The particularly strong association with the digital/gaming profile is also consistent with recent evidence from Peng et al., in which male students had more than twice the odds of belonging to a gaming-dominant problematic internet-use profile (19). Importantly, however, male gender in the present study was also associated with the highly active sociocultural profile, again illustrating that sociodemographic characteristics should not be interpreted exclusively through a risk lens.

Younger age was associated with higher odds of belonging to each of the three profiles other than the low-risk reference group. This pattern may reflect age-related differences in autonomy, peer contexts, recreation, and everyday organisation. However, given the cross-sectional design, developmental change cannot be distinguished from cohort or

other age-related differences. The findings nevertheless indicate that age is relevant to the distribution of behavioural lifestyle configurations within the higher education population.

Residential relocation produced an especially informative pattern. Students who had relocated from their permanent residence had almost twice the odds of belonging to the *Social alcohol and risk consumption* profile, but also had higher odds of belonging to the *Active sociocultural and digitally engaged* profile and slightly lower odds of belonging to the *Sedentary recreational digital/gaming* profile. Thus, relocation was not associated with a uniformly more adverse lifestyle configuration. Rather, it was associated with divergent forms of behavioural and social engagement. Greater residential autonomy may provide greater exposure to peer-based drinking and substance-use contexts, consistent with evidence linking independent or peer-based residence to heavier alcohol use among university students (21). Living away from the family home has also been associated with changes in food purchasing, preparation, and dietary practices (20). Although these mechanisms cannot be established from the present data, the contrasting associations suggest that residential transition may be better understood as a context of behavioural reorganisation than as an intrinsically adverse exposure.

Subjective social class showed a similarly differentiated association with profile membership. Higher subjective social class was associated with higher odds of belonging to the *Active sociocultural and digitally engaged* profile and lower odds of belonging to the *Sedentary recreational digital/gaming* profile, but was not significantly associated with membership in the *Social alcohol and risk consumption* profile. The association between higher subjective social class and more favourable behavioural configurations is broadly consistent with previous clustering research (7, 10) and with Maitiniyazi et al., who found lower family income to predict their least favourable lifestyle profile (15). Nevertheless, the absence of an association with the substance-risk profile indicates that alcohol- and substance-related lifestyle configurations in higher education cannot simply be understood in terms of socioeconomic disadvantage.

Field of study also differentiated profile membership. Students in life and health sciences had lower odds of belonging to all three non-reference profiles, whereas those in arts and humanities had substantially higher odds of belonging to the *Sedentary recreational digital/gaming* profile and also had higher odds of belonging to the *Active sociocultural and digitally engaged* profile. Students in exact and natural sciences and engineering had higher odds of belonging to the sedentary digital/gaming profile and lower odds of belonging to the active sociocultural profile. These differences may reflect variation in disciplinary cultures, schedules, workload organisation, or patterns of leisure and technology use, although the present study cannot determine the mechanisms involved. Institution type was considerably less discriminating: attendance at a polytechnic institute or non-integrated higher education school was associated only with modestly higher odds of belonging to the *Social alcohol and risk consumption* profile. More broadly, the sociodemographic model showed relatively modest explanatory power (McFadden's pseudo-R^2 = .050), indicating that demographic and educational characteristics alone provide only limited information about profile membership.

The distal-outcome analyses further support the substantive relevance of the identified profiles. Profile membership was significantly associated with all 17 outcomes after adjustment for age, gender, relocation, institution type, field of study, and subjective social class. This broad pattern is consistent with previous evidence linking less favourable behavioural configurations to poorer mental health. Kwan et al. reported greater stress among students in a high-risk class (13), while Hutchesson et al. found a particularly strong association between an unhealthy behavioural class and psychological distress (14). Jao et al., using a large sample of U.S. college students, similarly found differences in mental health across behavioural clusters (47), and Maitiniyazi et al. reported progressively poorer depression, anxiety, and stress outcomes across less favourable LPA profiles (15). At a broader level, Bourke et al., in a systematic review and meta-analysis of 81 studies involving nearly one million participants, found that membership in the healthiest lifestyle clusters was associated with fewer symptoms of depression, anxiety, and psychological distress (11). The present study extends this evidence beyond symptoms of mental ill-health by showing profile differences in positive

psychological well-being, life satisfaction, self-esteem, social support, and future-oriented expectations. This pattern is also consistent with earlier analyses of the same ES + Saúde dataset, in which mental well-being was associated with lifestyle, self-esteem, academic functioning, social support, and leisure and cultural activities (24).

The contrasting psychological outcomes of the two digitally engaged profiles further illustrate this point. The *Sedentary recreational digital/gaming* profile had the lowest adjusted means for psychological well-being, life satisfaction, self-esteem, and perceived social support, whereas the *Active sociocultural and digitally engaged* profile showed markedly more favourable values across these outcomes. These cross-sectional associations cannot establish directionality: poorer psychological functioning may contribute to more sedentary and gaming-centred routines, these routines may contribute to poorer well-being, or the relationships may be reciprocal.

Academic outcomes showed a related but not identical pattern. The *Active sociocultural and digitally engaged* profile had the highest adjusted means for short- and long-term study planning and perceived academic success, whereas the *Low-risk and low digital/recreational engagement* profile had the highest semester grade average. The *Social alcohol and risk consumption* profile had the lowest grade average, while the *Sedentary recreational digital/gaming* profile showed particularly low study planning, time-management attitudes, perceived academic success, and career expectations. These findings are broadly consistent with the systematic review by Whatnall et al., which found relatively consistent prospective associations between poorer academic performance and inadequate sleep, higher alcohol consumption, and illicit drug use, while highlighting the need to examine the co-occurrence of health behaviours (4). More recent meta-analytic evidence found a significant association between substance use overall and poorer academic achievement among university students, although the pooled alcohol-specific association was smaller and did not reach statistical significance (48). The present findings suggest that different lifestyle configurations may be associated with different dimensions of academic functioning. The *Social alcohol and risk consumption* profile was distinguished particularly by its lower achieved grade average, whereas the *Sedentary recreational digital/gaming* profile showed a broader pattern of poorer planning, time-management attitudes, perceived success, and future orientation. Conversely, the *Active sociocultural and digitally engaged* profile indicates that extensive extracurricular and digital engagement can coexist with strong academic self-regulation, even though its adjusted grade average was lower than that of the low-risk group.

The magnitude of the distal associations also deserves consideration. Although all global profile effects were statistically significant, partial η^2 values ranged from .008 to .062, indicating that the magnitude of profile differences varied considerably and was generally modest. The largest profile effects were observed for perceived lifestyle healthiness, long-term study planning, satisfaction with diet, short-term study planning, psychological well-being, attitudes toward time management, and satisfaction with physical exercise. By contrast, the smallest effects were observed for perceived academic success and satisfaction with leisure. Given the large analytic sample, statistical significance alone should therefore not be interpreted as evidence of substantial practical differences. More informative is the consistency of the pattern across multiple conceptually distinct outcomes, including measures not used to construct the profiles. The convergence across health perceptions, psychological well-being, self-esteem, social support, academic functioning, and future orientation provides stronger evidence of the substantive relevance of the profiles than any single outcome considered in isolation.

Strengths and limitations

The present study has important strengths. The large probabilistic, multi-institutional sample provided broad coverage of Portuguese public higher education, while the LPA incorporated a wide range of behaviours spanning both conventional health domains and contemporary forms of digital and recreational activity. The profiles were examined in

relation to multiple sociodemographic predictors and a broad set of distal outcomes, allowing the identified lifestyle configurations to be evaluated across health, psychological, social, academic, and future-oriented domains. Classification quality was also acceptable, with an entropy of .789 and a minimum average posterior classification probability of .844, and all four profiles represented sizeable subgroups of the analytic sample.

These strengths should be considered alongside some limitations. First, the cross-sectional design limits causal interpretation, as the direction of the associations between lifestyle profiles and distal outcomes cannot be established. Second, all measures were self-reported and may be subject to recall and social-desirability biases. Third, the four-profile solution depends on the selected indicators and modelling assumptions, including the restrictive EII covariance structure. Fourth, the exclusion of participants with substantial missing data and the use of median imputation may have influenced the results, particularly for sedentary behaviour. Fifth, subsequent analyses did not account for uncertainty in profile assignment. Moreover, some distal outcomes were conceptually close to the behaviours used to construct the profiles and should not be considered independent validation. Longitudinal studies using alternative modelling and missing-data approaches, alongside more objective behavioural measures, would help assess the stability and broader relevance of these findings.

Future longitudinal research could examine how behavioural lifestyle configurations evolve throughout higher education and whether students transition between different profiles over time. Particular attention should be given to the temporal relationships between behavioural patterns, residential circumstances, psychological functioning, academic demands, and socioeconomic conditions. Further studies should also distinguish more clearly between functional and problematic forms of digital engagement, considering how its associations with health and well-being may vary according to purpose, timing, social context, and participation in physical and offline social activities. Intervention studies could assess whether strategies addressing co-occurring behavioural patterns offer advantages over approaches targeting individual behaviours.

Conclusions

This study identified four distinct behavioural lifestyle profiles among students in Portuguese public higher education, demonstrating that student lifestyles cannot be adequately represented along a simple continuum from healthy to unhealthy. The profiles reflected different combinations of conventional health behaviours, substance use, digital and gaming activity, physical activity, and leisure and sociocultural engagement, and were systematically differentiated across sociodemographic characteristics and a broad range of health, psychological, social, academic, and lifestyle-related outcomes. Particularly informative was the contrast between the *Sedentary recreational digital/gaming* and *Active sociocultural and digitally engaged* profiles: high digital engagement was associated with markedly different outcomes depending on whether it occurred alongside sedentary and gaming-centred routines or within a physically active and socially and culturally engaged lifestyle. Digital engagement should therefore not be considered an intrinsically adverse lifestyle characteristic independently of its broader behavioural context.

These findings support a more differentiated approach to health promotion in higher education. Substance-related risk may require strategies that recognise the social and recreational contexts of alcohol and other substance use, whereas students characterised by sedentary digital/gaming lifestyles may benefit from approaches addressing physical activity, diet, social connection, time management, and psychological well-being alongside digital habits. At the same time, students with relatively low conventional behavioural risk may still have scope for greater engagement in health-promoting, physical, social, and recreational activities. Overall, the findings suggest that combining universal health-promoting environments with more selective, profile-informed strategies may be more appropriate than interventions focused on isolated behaviours. Longitudinal research is needed to establish how these lifestyle configurations develop over time and how they relate prospectively to student health, well-being, and academic functioning.

Abbreviations

AIC
Akaike Information Criterion
BIC
Bayesian Information Criterion
CI
Confidence interval
EII
Spherical, equal-volume covariance model
KMO
Kaiser–Meyer–Olkin measure of sampling adequacy
LCA
Latent Class Analysis
LPA
Latent Profile Analysis
LR
Likelihood ratio
OR
Odds ratio
PCA
Principal Component Analysis
SABIC
Sample-size adjusted Bayesian Information Criterion
SD
Standard deviation

Declarations

Ethics approval and consent to participate:

The study was conducted in accordance with the Declaration of Helsinki and all relevant national and international ethical guidelines and regulations. The research protocol was approved by the Ethics Committee of the Institute of Social Sciences of the University of Lisbon (26/2021). All participants were informed about the objectives of the study and provided informed consent before completing the questionnaire. Participation was voluntary, and anonymity and confidentiality of the data were guaranteed in accordance with the EU General Data Protection Regulation (GDPR) 2016/679 and Portuguese Law 58/2019.

Consent for publication:

Not applicable.

Competing interests:

The author declares that they have no competing interests.

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Author Contribution

PAS conceived and designed the present study, conducted the statistical analyses, interpreted the findings, and drafted and revised the manuscript. The author read and approved the final manuscript.

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Data Availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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