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RESEARCH ARTICLE

Health behaviour profiles in young Australian adults in relation to physical and mental health: The Raine Study

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Abstract

Issues Addressed: We aimed to identify latent health behaviour profiles of young adults and examine their associations with physical and mental health outcomes. We also characterised the profiles by socio-demographic characteristics.

Methods: Data were collected between 2012 and 2014. Participants ($N = 476$) were young adults (M age [SD] = 22.1 [.57] years) from Generation 2 of the Raine Study longitudinal cohort. Health behaviours were measured via ActiGraph GT3X waist monitors (physical activity, sedentary behaviour) and questionnaires (diet quality, alcohol, smoking and sleep). Physical and mental health were measured using clinical health assessments, blood biomarkers, and questionnaires. Latent Profile Analysis using M*plus* (8.2) was employed to identify profiles.

Results: Four latent profiles were identified: 'heavy drinkers with moderately unhealthy eating habits' (high takeaway foods; $n = 135$), 'unhealthy food abstainers' (low takeaway foods; $n = 138$), 'moderately sedentary alcohol abstainers' ($n = 139$) and 'physically active drinkers with unhealthy eating habits' (high takeaway foods and sugary drinks; $n = 64$). 'Physically active drinkers with unhealthy eating habits' had the poorest (physical and mental) health outcomes, yet the lowest insulin resistance. 'Unhealthy food abstainers' had the most favourable health outcomes (adiposity, health perceptions, blood pressure). Sex differed among the profiles.

Conclusions: The profiles identified among young adults are different to profiles with general adult populations. A novel finding was that 'physically active drinkers with unhealthy eating habits' had low insulin resistance. The findings also suggest that future interventions may need to be sex specific.

So What: Our findings suggest that health behaviour interventions for young adults should be targeted to distinct profile characteristics.

KEYWORDS
accelerometry, alcohol, diet, Latent Profile Analysis, physical activity

1 | INTRODUCTION

Adequate levels of physical activity, minimising sitting time, eating the recommended amounts of fruits and vegetables, reducing consumption of high fat and salty take-away foods and sugar sweetened beverages, limiting alcohol intake, and achieving adequate sleep of high quality are all important current public health messages. However, health behaviours are most often considered in isolation, even though they often co-occur on a daily basis. Further, we have little understanding of how several health behaviours cluster *within* individuals; and how different clusters affect health synergistically.[1] Understanding clusters of health behaviours and their effects has several potential benefits. First, it can help identify people at greater risk of poor health and target subsequent interventions to the characteristics of these sub-groups. Second, it may help inform health policy, including advice provided to the public about combinations of health behaviours associated with optimal health. Third, interventions that address several unhealthy behaviours may be more cost-effective than ones targeting single behaviours in isolation.[2]

Several reviews and large-scale population studies have examined how poor health behaviours, often conceptualised as 'poor lifestyle risk factors' in the biomedical literature, cluster in adult populations (18–72 years old). These have tended to focus on combinations of physical activity, diet, alcohol consumption and smoking in general adult populations.[1,3–8] Generally, results of these studies suggest the presence of at least one 'healthy' profile (i.e., a group of individuals with similar characteristics which are dissimilar to those of other groups), one to two 'unhealthy' profiles, and one or more 'mixed' profiles (i.e., a combination of healthy and unhealthy patterns).[3–8] The existing evidence among general populations of adults (generally age 18+) points to the clustering of smoking with problematic alcohol consumption,[4,6] smoking and unhealthy diet[4] and smoking, alcohol consumption, and physical inactivity.[5] However, the pattern in young adults is different. For example, in young adults, heavy drinking tends to cluster with high levels of physical activity,[8,9] a pattern which is not observed in middle-aged and older adults. Young adults (as well as males and single individuals) also appear to engage in more unhealthy behaviours than other groups.[3,6,7] Young adulthood (typically defined as age 18–25) represents a key life transition during which healthy (or unhealthy) lifelong habits are formed.[10] Consequently, it is critical to understand how health behaviours cluster in young adults. However, to our knowledge, only one study has examined health behaviour profiles in young (emerging) adults, using Latent Profile Analysis (LPA).[3] LPA has the advantage over heuristic cluster analysis techniques that they provide model fit statistics.

The current evidence base remains limited in other important ways. First, there has been a tendency to aggregate analyses across heterogeneous groups of adults which might obscure the above noted differences in clusters between diverse age cohorts. It is therefore important to examine clusters among more age homogenous samples. Second, the omission of sleep as a health behaviour from most studies, including the study by Grant et al., with young adults[3] is an important limitation because sleep is a critical component of health.[11] Sleep is associated with the development of obesity, with evidence suggesting that this association is particularly pronounced in young people.[12] Third, previous studies have *exclusively* relied on self-reported surveys. While self-report surveys are often the only way of assessing perceptions and indicators of mental health, self-reports of health *behaviours* are prone to social desirability and recall bias.[13] Further, relying exclusively on self-report measure to assess all outcomes lead to common-method variance problems. Finally, the number and range of health outcomes associated with cluster profiles have been limited in scope with a lack of studies having examined a range of both physical and psychological health outcomes. Thus, the primary aim of the present study was to identify profiles of health behaviour patterns in young adults and examine differences between these profiles on physical and mental health outcomes. As a secondary aim, we explored how the profiles varied by socio-demographic characteristics (sex, relationship status and education).

2 | METHODS

2.1 | Design

Cross-sectional cohort study. This was due to the fact that the combination of data we used in our study was only available at 1 time point.

2.2 | Procedures and participants

Participants were young adults ($N = 476$; 52.9% female) aged 20.7–24.2 years (M [SD] = 22.1 [.57]) who were part of the Generation 2 cohort of the Raine Study, a prospective multigenerational observational cohort. For the present study, we used the 22-year follow-up data which was collected from 2012 to 2014. Details on the aims and full methodology of the Raine Study are published elsewhere.[14] In brief, 2900 pregnant women enrolled in the study (Generation 1) in May 1989, in Perth, Western Australia; 2730 gave birth to 2868 children (Generation 2) between August 1989 and April 1992.[15,16] Ethics approval for the 22-year follow up was obtained from the University of Western Australia's Human Research Ethics Committee. Written consent was obtained from all participants. Participants underwent physical assessments, bio-sample collection and completed a questionnaire, all of which were administered by trained research assistants. Participants with data on all relevant variables were included in the analysis.

2.3 | Measures

2.3.1 | Health behaviours (independent variables)

Physical activity

Physical activity (moderate to vigorous physical activity [MVPA], light intensity physical activity [LIPA]) and sedentary behaviour was

measured using a tri-axial ActiGraph GT3X+ monitor (Florida, USA). Participants wore the monitor on their right hip for 24 h/day for eight consecutive days. Data from participants with at least one valid day were included in the analysis (i.e., accelerometer worn for at least 10 h on that day). Raw data were collected at a frequency of 30 Hz and processed in 60 s epochs. Vertical axis data in 60 s epochs were processed using a custom automated algorithm[17] to identify waking wear time in SAS (v9.3, SAS Institute, Cary, NC, USA). Common cut-points were used to class each minute as sedentary (<100 counts per minute [cpm]), light intensity (100–1951 cpm), moderate intensity (1952–5724 cpm), or vigorous intensity (>5724 cpm).[18,19] Only participants with a minimum of 10 h waking wear time per day were included in the analysis.

Diet quality

Fruit and vegetable consumption, sugar-sweetened beverages (including fizzy drinks, energy drinks and alcoholic sodas), and take-away foods (including meat pies, pizza, hamburgers, fried fish and chips) were assessed alongside other dietary aspects using the Dietary Questionnaire for Epidemiological Studies (DQES) Version 2 from the Cancer Council (Victoria, Australia). This food frequency questionnaire estimated food and beverage intakes in grams per day from frequency questions that related to the previous 12 months.

Alcohol consumption

Alcohol consumption was also assessed using questions from the validated Cancer Council food frequency questionnaire.[20] Participants were asked how often in the past 12 months they had drunk different alcohol beverages, including beer (low alcohol separately to full strength), red wine, white wine (including sparkling wines) fortified wines and spirits/liqueurs. Participant were also asked to estimate the quantity drunk according to a standard serve size. From this information, average alcohol intake per day (in grams) was calculated.

Cigarette smoking

Participants were classified as either non-smokers or current smokers based on a self-report question on whether or not they currently smoked cigarettes.

Sleep

Self-reported sleep quality and disturbance was measured retrospectively over a 1-month period using the 19-item Pittsburgh Sleep Quality Index (PSQI).[21] Items measured subjective sleep quality, sleep duration and sleep latency. A total score ranging from 0 to 21 was calculated, where higher scores indicated worse sleep quality.

2.3.2 | Waking wear time (dependent variable)

Waking wear time was assessed in minutes per day (mean of daily total on valid days).

2.3.3 | Physical health outcomes (dependent variables)

Adiposity-related outcomes

Weight (in kg) was measured via an electronic scale, height (in m) via a stadiometer, and a flexible tape was used to assess waist circumference and hip circumference (in cm). Skinfold thickness was measured at suprailiac, tricep and abdominal locations using Holtain callipers. Each measurement was taken twice, and the average was recorded. The Body Mass Index (BMI) was calculated by dividing weight (kg) by the square of height (m). The waist to hip ratio (i.e., waist circumference/hip circumference) was calculated. Total body fat (in mm) was determined by summing the abdominal skinfold, the suprailiac skinfold and the triceps skinfold.[22]

Health perceptions

Perceptions of physical health were assessed using the Short Form-12 Health Survey Version 2 (SF12).[23] Responses to the physical component of the scale were summed, with higher scores indicating better physical health.

Blood pressure

Systolic and diastolic blood pressure was recorded by a trained research assistant using a Dinamap 8100 semi-automated oscillometric monitor (Critikon, USA). Recordings were obtained from the right arm with the participant seated for at least 5 min. Six measurements were taken 2 min apart. The average of the last five measurements were used to calculate an average for both systolic and diastolic blood pressure.

Cardio-metabolic outcomes

Serum LDL-C (triglycerides), high density lipoprotein cholesterol (HDL-C), total cholesterol, serum insulin and glucose were determined from the results of fasting blood tests. A peripheral blood sample (100 mL) was collected in a tube which contained preservative-free heparin. The sample was processed within 2 h. The plasma was isolated, and the aliquots were stored in a −80°C freezer to allow for the measurement of anti-bodies. Lymhoprep was used to isolate the peripheral mononuclear cells within 18 h of removing the plasma.[14] Insulin resistance (HOMA-IR) was calculated using the formula fasting plasma glucose (mmol/L) × fasting serum insulin (mU/L)/22.5.[24] Low triglyceride and insulin resistance scores are indicative of better health. In a similar vein, a smaller total cholesterol: HDL ratio represents better health.

2.3.4 | Mental health outcomes

Depression, anxiety and stress were measured using the short form of the Depression Anxiety Stress Scale (DASS-21).[25] A score out of 42 was calculated using the scoring manual with higher scores signifying poorer mental health.[25]

2.3.5 | Socio-demographic characteristics

Participants self-reported sex (male, female), relationship status (single, in a relationship but not living together, in a relationship and living together; none were married), and highest levels of education (Primary School, High School, TAFE or college, and University) as part of the questionnaire.

2.4 | Analyses

Prior to the main analysis, we excluded participants who had missing data on any of the independent or dependent variables. We also excluded extreme outlier values for all variables ($N = 19$). We also inspected collinearity statistics among the variables. The only fairly high correlations were between weight/fat related outcomes (r's ranging from .26 to .86) and the mental health outcomes (i.e., depression, stress and anxiety from the DASS which were correlated in the range from .56 to .67). Correlations between the obesity-related measures and the mental health outcomes ranged from <.001 to −.15). The remaining outcomes were not highly correlated (the highest correlation was .38 between insulin resistance and BMI).

We used LPA with a robust maximum likelihood estimator to classify participants who share a common health behaviour pattern into latent profiles. LPA is a probabilistic model-based clustering approach that permits the identification of homogenous subgroups within a mixture distribution of continuous and categorical indicators.[26] Given the exploratory nature of this study, we took an inductive approach whereby we compared a range of models that varied in the number of latent profiles to determine the structure that best represented a balance between model fit and parsimony.[27] Model comparisons were assessed using a combination of relative fix indices (Akaike Information Criteria [AIC]), Bayesian Information Criteria [BIC] and its sample size-adjusted version [ABIC], and consistent AIC [C-AIC]), ratio test (Lo–Mendell–Rubin likelihood [LMR] and Bootstrap likelihood [BLRT] with 200 draws to estimate the *p* value of the test), and an indicator of the precision of profile allocation (entropy). A better fitting model is supported by lower values on the relative fit indexes, a statistically significant ratio test, and entropy values that are closest to one and larger in comparison to other class structures.[27] Aligned with simulation evidence[28,29] and recent empirical examples,[30] we prioritised the BIC, ABIC, C-AIC and BLRT to identify the optimal model. These statistical criteria were complemented by substantive interpretations of the solutions and consideration of sample sizes within each cluster (e.g., profiles <5% of total sample considered potentially spurious).[31–33] We then used multinomial regression within an LPA framework to assess outcomes of latent profile membership; specifically, the BCH command modelled these variables using weights to capture measurement error of the latent class variable.[34,35] With this approach, auxiliary variables are excluded from the classification model, yet they are assessed in relation to the final model and therefore account for most likely class membership and classification error.[26] Finally, we examined the salience of socio-demographic characteristics (sex, relationship status, highest level of education) as correlates of latent profile membership within a multinomial logistic regression framework via the R3STEP function.[36] In these analyses, we reported unstandardised beta coefficients and mutually adjusted odds ratios (ORs). All analyses were performed using M*plus* 8.2[37] using full information maximum likelihood to make use of all available data.

3 | RESULTS

A description of the study sample on all variables is presented in Table 1. The majority were in a relationship (55.7%) with the remaining participants being single. The largest proportion of participants had completed high school (48.5%). On average the sample was fairly physically active but also fairly sedentary. They ate a moderate number of daily fruits and vegetables (3.3–4.2) but consumed fairly high numbers of sugary drinks (2.9), and relatively high amounts of take-away food (98.6 g) and alcohol (15.5 g) on a daily basis. The vast majority of participants were non-smokers (86.3%). Table 1 also includes a break-down of the percentage of participants that had health outcomes in the 'normal' range. For most of the health outcomes, the majority had 'normal' levels when compared to established norms, except most participants (71.2%) did not eat the recommended daily number of fruits and vegetables. However, there were substantial proportions of participants who were overweight or obese (34.7%), had a high systolic blood pressure (41.8%), and/or an unfavourably high total cholesterol: HDL ratio (41.6%).

An overview of the fit indices for the LPA models is provided in Table 2. We tested *k* profiles consecutively starting with a one-profile through to a five-profile solution, at which point we ceased the model building approach here because of increasing BIC and C-AIC values from the 4- to the 5-profile solution. The four-factor profile was chosen as the best fitting solution because of the (i) lower BIC, C-AIC and ABIC values compared with the two-, and three-profile solutions; (ii) significance of the LMR ratio tests; and (iii) on substantive grounds, due to a lack of conceptual distinctions with increasing profiles. Figure 1 presents the chosen solution using *z* scores to facilitate interpretation. The criteria reported by Liu et al.[38] were applied, suggesting that *z* scores of ± .5 are considered high versus low in relation to other profiles. Profiles were labelled according to their key characteristics.

In terms of standardised factor scores (see Figure 1), the largest profile (Profile 3; $n = 139$) included individuals who reported low to moderate levels on all profile indicators except for alcohol consumption which was low; we therefore labelled these individuals 'moderately sedentary alcohol abstainers'. They were 77.5% likely to report as non-smokers. The second largest profile (Profile 2; $n = 138$) represented participants who reported low take-away consumption but low or moderate levels on all other variables; we labelled these individuals 'unhealthy food abstainers'. They were 95.5% likely to report as non-smokers. The third largest profile (Profile 1; $n = 135$) included individuals who reported consuming a relatively high amount of alcohol, with low to moderate scores on the remaining variables; we

TABLE 1 Participant characteristics.

Socio-demographics	%	*n*	% normal/recommended range
Sex (female/male)	52.9/47.1	252/224	N/A
Relationship status			N/A
Single	44.3	211	
In a relationship but not co-habiting	35.3	168	
In a relationship and co-habiting	19.1	91	
Married	1.3	6	
Highest education			N/A
Primary school	1.5	7	
Secondary school (High School)	48.5	231	
TAFE (trade college)	21.2	101	
University	28.2	134	
	M (SD)		
Health behaviours		N/A	N/A
MVPA (minutes/day)	35.8 (26.6)		69.1%[a]
LIPA (minutes/day)	315.7 (90)		
SB (minutes/day)	547.6 (93)		
Waking wear time (minutes per day)[b]	901.4 (89.8)		
Fruits per day (1–6)	3.3 (1.1)		28.8[c]
Different vegetables per day (1–7)	4.2 (1.3)		28.8[c]
Sugary drinks (number/day)	2.9 (2.8)		
Take-away (g/day)	98.6 (76.4)		
Alcohol (g/day)	15.5 (16.9)		
Sleep quality[d] (0–21)	4.6 (2.4)		
	%		
Current cigarette smoker (yes/no)	13.7/86.3	65/411	
Physical health	*M* (SD)	N/A	
BMI	24.6 (4.5)		65.3[e]
Waist circumference (cm)	81.8 (11.8)		83.6[f]
Waist-to-hip ratio	.8 (.1)		82.1[f]
Total body fat (mm)	57.5 (25.4)		
Perceived health (1–5)	3.4 (.9)		
Systolic blood pressure (mmHg)	118.2 (10.5)		58.2
Diastolic blood pressure (mmHg)	67.1 (7)		97.1
Triglycerides (mmol/L)	1.1 (.5)		89.5
Total cholesterol (mmol/L): HDL (mmol/L)	3.5 (.9)		58.4
Insulin resistance (HOMA-IR)	1.8 (1.1)		85.5
Mental health		N/A	
Depression[g] (total) (0–21)	6.3 (7.4)		72.9
Anxiety[g] (total) (0–21)	4.1 (4.9)		79.2
Stress[g] (total) (0–21)	8.5 (7.5)		83.6

[a]Percentage engaging in 150 min or more of MVPA per week.
[b]Only participants with a minimum of 10 h waking wear time per day were included in the analysis.
[c]Percentage that meet the fruits and vegetable recommendation guidelines.
[d]Higher scores represent lower sleep quality.
[e]2.9% had low BMI, 23.8% were overweight and 10.9% were obese.
[f]Percentage is the average of males and females.
[g]Higher scores represent greater depression, anxiety and stress.

TABLE 2 Fit statistics of latent profile analyses.

	LL	FP	AIC	BIC	C-AIC	ABIC	LMR *p* Value	BLRT *p* Value	Entropy
1-class	−6257.1	19	12 552.3	12 631.4	12 650.4	12 571.1	-	-	-
2-class	−5888.3	39	11 854.6	12 017.1	12 056.1	11 893.3	<.001	<.001	.79
3-class	−5780.8	59	11 679.7	11 925.4	11 984.4	11 738.2	.05	-	.77
4-class	−5688.6	79	11 535.2	11 864.3	11 943.3	11 613.6	.03	-	.76
5-class	−5630.6	99	11 459.2	11 871.6	11 970.6	11 557.3	.52	-	.76

Note: All profiles were modelled in which the means and variances per profile indicator were allowed to vary across profiles. MLR, BLRT and entropy statistics are unavailable when only 1 profile is calculated. The output (TECH14) did not produce a reliable BLRT *p* value for the 2–5 class profile solutions; hence these have not been reported. According to Muthén, L. (personal communication, 29 July 2020), in such cases, the BIC value should be used instead. Abbreviations: ABIC, sample-size-adjusted BIC; AIC, Akaike information criterion; BIC, Bayesian information criterion; BLRT, bootstrapped loglikelihood ratio test; C-AIC, consistent Akaike information criterion (calculated as the number of free parameters plus the BIC value); FP, free parameters; LL, log-likelihood; LMR, Lo, Mendell and Rubin (2001) adjusted LRT test.

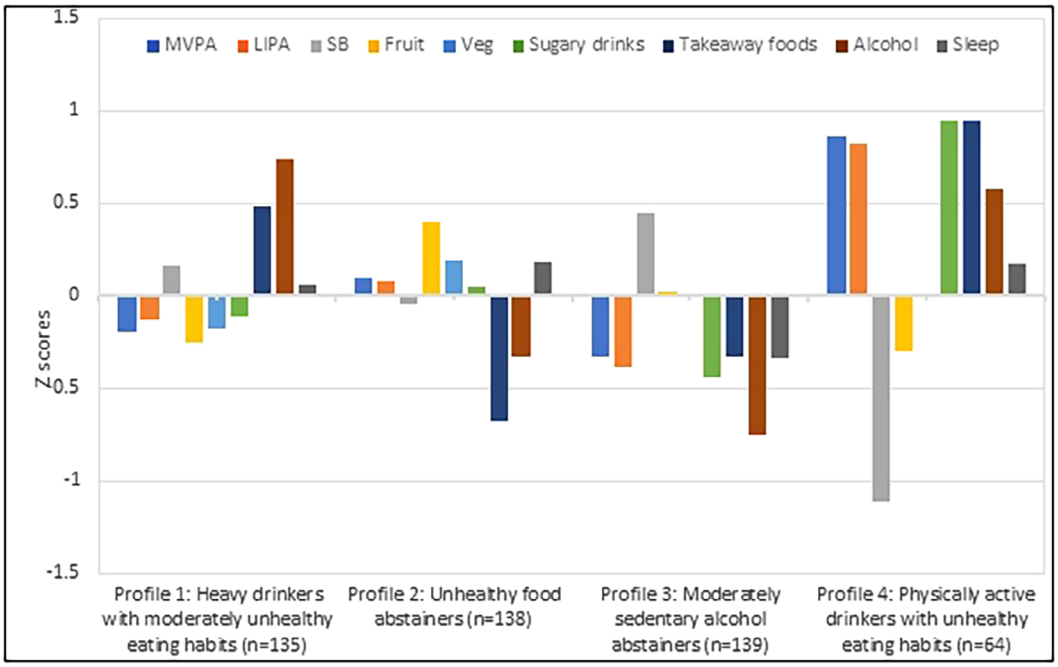

FIGURE 1 Latent profiles of standardised factor scores on health behaviours.

labelled these individuals 'heavy drinkers with moderately unhealthy eating habits'. They were 99.2% likely to report as non-smokers. The smallest profile (Profile 4; $n = 64$) was characterised by participants who reported high levels of both moderate and light intensity physical activity, low sedentary behaviour, and high consumption of sugary drinks, alcohol, and take-away food; we labelled these individuals 'physically active drinkers with unhealthy eating habits'. They were 62.5% likely to report as non-smokers.

3.1 | Profile differences on health outcomes

An overview of differences between the profiles on health outcomes is presented in Table 3. The 'physically active drinkers with unhealthy eating habits' had the greatest number of unhealthy outcomes. Specifically, their scores on most adiposity-related outcomes, perceived health, systolic blood pressure, depression, and anxiety were less desirable than the other profiles. However, participants in this profile exhibited the lowest levels of insulin resistance. 'Heavy drinkers with moderately unhealthy eating habits' and 'moderately sedentary alcohol abstainers' had more mixed profiles. 'Heavy drinkers with moderately unhealthy eating habits' had higher waist circumference and waist-hip ratios than 'unhealthy food abstainers', and higher depression than 'moderately sedentary alcohol abstainers', yet also had lower diastolic blood pressure than the 'moderately sedentary alcohol abstainers', and lower BMI than 'physically active drinkers with unhealthy eating habits'. 'Moderately sedentary alcohol abstainers' had higher waist-hip ratio than 'unhealthy food

TABLE 3 Latent profile differences in all outcomes.

	Total body fat					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	55.82	2.62	na			
P2: Unhealthy food abstainers	56.84	2.51	.79	na		
P3: Moderately sedentary alcohol abstainers	61.02	2.54	.17	.28	na	
P4: Physically active drinkers with unhealthy eating habits	55.40	3.24	.93	.73	.17	na
	Body mass index					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	24.05	.40	na			
P2: Unhealthy food abstainers	24.34	.41	.63	na		
P3: Moderately sedentary alcohol abstainers	24.61	.47	.38	.68	Na	
P4: Physically active drinkers with unhealthy eating habits	25.84	.59	.02	.04	.10	na
	Waist circumference					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	82.46	1.11	na			
P2: Unhealthy food abstainers	78.64	1.01	.02	na		
P3: Moderately sedentary alcohol abstainers	81.06	1.13	.39	.14	na	
P4: Physically active drinkers with unhealthy eating habits	85.63	1.65	.134	<.001	.02	na
	Waist: hip ratio					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	.83	.01	na			
P2: Unhealthy food abstainers	.80	.01	<.01	na		
P3: Moderately sedentary alcohol abstainers	.83	.01	.48	.03	na	
P4: Physically active drinkers with unhealthy eating habits	.85	.01	.24	<.001	.07	na
	Perceived health					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	3.29	.09	na			
P2: Unhealthy food abstainers	3.49	.09	.12	na		
P3: Moderately sedentary alcohol abstainers	3.42	.09	.30	.59	na	
P4: Physically active drinkers with unhealthy eating habits	3.15	.14	.46	.05	.11	na
	Systolic blood pressure					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	118.50	1.12	na			
P2: Unhealthy food abstainers	115.93	1.02	.11	na		
P3: Moderately sedentary alcohol abstainers	118.35	.95	.92	.11	na	
P4: Physically active drinkers with unhealthy eating habits	121.51	1.43	.12	<.01	.06	na
	Diastolic blood pressure					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	66.40	.68	na			
P2: Unhealthy food abstainers	66.04	.69	.73	na		
P3: Moderately sedentary alcohol abstainers	68.73	.66	.02	.01	na	
P4: Physically active drinkers with unhealthy eating habits	67.15	1.06	.57	.39	.20	na

TABLE 3 (Continued)

	Triglycerides					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	1.09	.04	na			
P2: Unhealthy food abstainers	1.02	.05	.26	na		
P3: Moderately sedentary alcohol abstainers	1.08	.05	.96	.35	na	
P4: Physically active drinkers with unhealthy eating habits	1.05	.05	.56	.68	.61	na
	Total cholesterol: HDL					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	3.46	.08	na			
P2: Unhealthy food abstainers	3.44	.09	.90	na		
P3: Moderately sedentary alcohol abstainers	3.57	.09	.36	.33	na	
P4: Physically active drinkers with unhealthy eating habits	3.62	.16	.38	.32	.79	na
	Insulin resistance					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	1.76	.10	na			
P2: Unhealthy food abstainers	1.69	.08	.60	na		
P3: Moderately sedentary alcohol abstainers	2.02	.11	.08	.02	na	
P4: Physically active drinkers with unhealthy eating habits	1.59	.10	.27	.44	<.01	na
	Depression					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	7.12	.78	na			
P2: Unhealthy food abstainers	6.64	.74	.67	na		
P3: Moderately sedentary alcohol abstainers	4.54	.58	.01	.04	na	
P4: Physically active drinkers with unhealthy eating habits	7.35	1.26	.89	.64	.04	na
	Anxiety					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	4.40	.46	na			
P2: Unhealthy food abstainers	4.00	.51	.57	na		
P3: Moderately sedentary alcohol abstainers	3.29	.38	.07	.30	Na	
P4: Physically active drinkers with unhealthy eating habits	5.35	.96	.41	.22	.05	na
	Stress					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	8.39	.66	na			
P2: Unhealthy food abstainers	9.44	.83	.34	na		
P3: Moderately sedentary alcohol abstainers	7.36	.65	.28	.07	na	
P4: Physically active drinkers with unhealthy eating habits	8.75	1.25	.81	.65	.32	na
	Wear time					
	M	SE	P1	P2	P3	P4
P1: Heavy drinkers with moderately unhealthy eating habits	893.10	9.19	na			
P2: Unhealthy food abstainers	906.95	9.13	.31	na		
P3: Moderately sedentary alcohol abstainers	902.35	8.05	.46	.73	na	
P4: Physically active drinkers with unhealthy eating habits	905.41	13.66	.48	.93	.85	na

TABLE 4 Multinomial logistic regression analysis examining associations between profile membership and socio-demographic characteristics.

	B	*p*	ORs
P2: Unhealthy food abstainers			
Female	1.72	<.001	5.94
In a relationship but not co-habiting	.03	.93	1.03
In a relationship and co-habiting	−.62	.18	.54
Secondary school	−.76	.55	.47
TAFE	−.28	.83	.75
University	.02	.99	1.02
P3: Moderately sedentary alcohol abstainers			
Female	1.28	<.001	3.59
In a relationship but not co-habiting	−.09	.79	.91
In a relationship and co-habiting	−.12	.76	.88
Secondary school	−.42	.73	.66
TAFE	−.55	.66	.58
University	.06	.96	1.06
P4: Physically active drinkers with unhealthy eating habits			
Female	−.09	.82	.91
In a relationship but not co-habiting	−.31	.45	.73
In a relationship and co-habiting	−.63	.22	.53
Secondary school	.00	1.00	1.00
TAFE	−.05	.97	.95
University	−.25	.87	.78

Note: Profile 1 ('heavy drinkers with moderately unhealthy eating habits') is the reference category and is therefore not presented in the table. The sex variable is dummy coded with 0 for males and 1 for females. The two relationship status variables are dummy coded with 0 for single and in a relationship but not co-habiting/in a relationship and co-habiting codes as 1. The three education variables are dummy coded with 0 for primary school and 1 for secondary school/TAFE/University.

abstainers', higher diastolic blood pressure than the 'moderately sedentary alcohol abstainers' and 'unhealthy food abstainers', and the highest level of insulin resistance. Yet, their level of depression was lower compared to all other profiles. 'Unhealthy food abstainers' had the greatest number of healthy characteristics with more favourable adiposity-related outcomes (except for total body fat) than the other profiles. They also perceived their health as better and had lower systolic blood pressure than 'physically active drinkers with unhealthy eating habits', lower diastolic blood pressure compared to 'moderately sedentary alcohol abstainers', and lower insulin resistance than 'moderately sedentary alcohol abstainers'. No significant differences between profiles were observed for total body fat, triglycerides or total cholesterol: HDL, stress, or wear time.

Socio-demographic characteristics were equally distributed across profiles, except that females, compared to males, were more likely to be 'unhealthy food abstainers' (P2) and 'moderately sedentary alcohol abstainers' (P3) than 'heavy drinkers with moderately unhealthy eating habits' (see Table 4).

4 | DISCUSSION

We identified four latent health behaviour profiles; members across each profile engaged in a mix of healthy and unhealthy behaviours. The health behaviours that primarily distinguished the profiles in this young adult sample included alcohol consumption, take-away food consumption, physical activity (MVPA and LIPA), sedentary behaviour, and sugary drinks. Regarding alcohol consumption and eating behaviours, these findings align with previous research with young adults.[1,9] In contrast to previous research with young adults,[1] physical activity and sedentary behaviour were well differentiated between our profiles. This may be explained by our use of device-based assessment that offers a much more fine-grained analysis of MVPA, LIPA and sedentary behaviour than methods that rely on self-reports.

Our result pertaining to 'physically active drinkers with unhealthy eating habits' is similar to results of previous research showing that heavy drinking clusters with high levels of physical activity in young adults.[8,9] We add to these findings by showing that drinking behaviours extend to consumption of sugar sweetened beverages and unhealthy take-away food, thus identifying additional behaviour risk indicators for this group. Additionally, individuals in this profile had the highest probability of cigarette smoking, a finding consistent with prior research with general adult populations showing that alcohol consumers are also more likely to smoke.[4,6] Our 'mixed' profiles may reflect the presence of compensatory health beliefs in young adults, which are beliefs that any negative effects of an unhealthy behaviour can be compensated for by engaging in healthy behaviours.[39] The presence of such compensatory beliefs has been identified in other research with young adults.[40]

Sleep quality was not well differentiated between our profiles. This finding diverges from results in a general population of adults.[7] We decided to use the overall score due to the number of health behaviours we examined, but the use of an aggregated PSQI score may have diluted any differences that could exist between our profiles. It may be worthwhile in future research to examine profiles across different components of sleep in young adults (e.g., duration, quality, latency etc.) in combination with some of the other health behaviours to obtain a more nuanced picture. Further, intra-individual sleep variability may be an important metric to examine in future studies, as research has shown that consistent sleep duration (i.e., low variability) is associated with lower levels of stress in young adults.[41]

Our findings showed that 'unhealthy food abstainers' had the greatest number of favourable health outcomes. It may therefore be important that public health messages for young adults focus on the avoidance of fast food. In addition, 'moderately sedentary alcohol abstainers' had lower levels of depression than members of the other profiles, which is consistent with evidence showing that alcohol consumption often co-occurs with depression.[42] Thus, it may be important to promote alcohol abstinence to young people who are at risk of depression. Finally, profile differences between 'heavy drinkers with moderately unhealthy eating habits' and 'physically active drinkers with unhealthy eating habits' speak to the possible protective nature of high physical activity with low sedentary behaviour for

cardiometabolic risk factors (i.e., insulin resistance), even when people consume high amounts of alcohol, sugary drinks and takeaway food and have unfavourable adiposity outcomes.

Our results also showed that males were more likely than females to be 'heavy drinkers with moderately unhealthy eating habits', which is consistent with prior research.[3,6] These results suggest that future intervention approaches may need to target young males. In contrast, we could not differentiate the profiles on relationship status or educational attainment, possibly due to these not yet having stabilised in this young group.

The cross-sectional design does not allow for inference regarding causal effects of the profiles on the outcomes. Further, our design did not allow for the examination of the stability of profile membership. The use of longitudinal designs in future studies could provide important insight on profile membership through the employment of Latent Transition Analysis. Additionally, the accelerometers used in the present study primarily assess ambulatory activity, so the assessment of strength training is most likely less accurate. Finally, although we examined how profile membership was characterised by sex, our sample was likely insufficient to allow for measurement invariance tests to be conducted for males and females.[43] Strengths of our study include a relatively representative Australian cohort of young adults, and the use of a range of device-based, clinical and biomarker assessments. Additionally, we examined a larger range and more diverse set of physical and mental health outcomes than previous studies. Finally, in contrast to previous studies in this area,[3,7] we used LPA, which has the advantage of using continuous model indicators, rather than the dichotomous variables used in Latent Class Analysis.

5 | CONCLUSIONS

The present study is among the first to examine health behaviour profiles in young adults. Four distinct latent profiles were identified: 'Heavy drinkers with moderately unhealthy eating habits', 'unhealthy food abstainers', 'moderately sedentary alcohol abstainers', and 'physically active drinkers with unhealthy eating habits'. These profiles differ somewhat from those conducted with general populations of adults. Overall, 'unhealthy food abstainers' had the greatest number of positive health outcomes, possibly suggesting that public health messages should focus on the avoidance of fast food in young adults. A novel finding was that 'physically active drinkers with unhealthy eating habits' had low insulin resistance. Sex, but not relationship nor educational status, differed between profiles, suggesting future interventions may need to be sex specific.

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CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Raine Study. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://rainestudy.org.au/information-for-researchers/available-data/ with the permission of Raine Study.

ETHICS STATEMENT

Ethics approval for the 22-year follow up was obtained from the University of Western Australia's Human Research Ethics Committee.

CONSENT FOR PUBLICATION

Written consent was obtained from all participants.

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