Oftedal, Stina; Kolt, Gregory S.; Holliday, Elizabeth G.; Stamatakis, Emmanuel; Vandelanotte, Corneel; Brown, Wendy J.; Duncan, Mitch J. “Associations of health-behavior patterns, mental health and self-rated health” Published in *Preventive Medicine*, Vol. 118, Issue January, p. 295-303, (2019).

Available from: https://doi.org/10.1016/j.ypmed.2018.11.017

Title: Associations of health-behavior patterns, mental health and self-rated health.

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Financial disclosures:

Stina Oftedal has no conflicts of interest

Gregory S Kolt has no conflicts of interest

Elizabeth G Holliday has no conflicts of interest

Emmanuel Stamatakis reports relevant grants from the National Health and Medical Research Council (APP1110526), Cancer Council WA, and the British Heart Foundation.

Corneel Vandelanotte reports grants from National Heart Foundation of Australia (ID 100427) and National Health and Medical Research Council (APP1080186)

Wendy J Brown has no conflicts of interest

Mitch J Duncan reports grants from National Heart Foundation of Australia (ID 100029), Diabetes Australia (Y17G-DUNM) and National Health and Medical Research Council (G1700197).

This work was partly supported by a grant from the Diabetes Australia (Y17G-DUNM) and a NSW CVRN Collaborative Project Grant (101584). The study sponsors had no role in deciding the study design; collection, analysis and interpretation of data; writing the report; or the decision to submit the report for publication.

Conflicts of interest:

No financial disclosures were reported by the authors of this paper.

Abstract word count: 237 words

Manuscript word count: 3391 words

Abstract

Diet quality, physical activity, alcohol use, smoking, sleep and sitting-time are behaviors known to influence health. The aims of this study were to identify how these behaviors co-occur to form distinct health-behavior patterns, and to investigate the relationship between these patterns, and mental and self-rated health. Members of the Australian 10,000 Steps project were invited to participate in an online survey in November-December 2011. The participants self-reported demographic and behavioral characteristics (fruit and vegetable intake, fast food, soft drink and alcohol consumption, smoking, physical activity, sitting-time and sleep), frequency of mental distress and self-rated health. Latent Class Analysis was used to identify health-behavior patterns. Latent class regression was used to examine relationships between behavior patterns, mental and self-rated health, and socio-demographic and economic factors. Data were analyzed in October 2017. Complete datasets were obtained from 10,638 participants. Four latent classes were identified, characterized by 'Low-Risk Behavior', 'Poor Sleep, Low-Risk Daytime Behavior', 'Sound Sleep, High-Risk Daytime Behavior' and 'High-Risk Behavior'. The latter two classes, both characterised by high-risk daytime behaviours, were associated with poor self-rated health. Participants in classes with high-risk daytime behaviors were more likely to be younger, non-partnered, non-university educated, from lower income households and work longer hours. Classes characterised by poor sleep quality were associated with higher frequency of mental distress. Findings suggest that experiencing poor sleep is partly independent of daytime behaviors, demographic and socioeconomic factors, but has a strong association with mental health.

Introduction

Poor diet quality, excess alcohol consumption, smoking, low physical activity, prolonged sitting, short or long sleep duration and poor sleep quality are all individually associated with increased risks of morbidity and mortality.[1-5] Mortality risk and risk of poor health-related quality of life also increase in a dose-response manner as the number of poor behaviors increases.[6-15] Combinations of poor lifestyle behaviors have been shown to pose greater morbidity risk than the sum of their individual effects, suggesting a synergistic relationship between risk factors.[9,11] Multiple-behavior change interventions may therefore have a greater potential for positive impact on health outcomes than single-behavior change interventions.[16-18]

Health behaviors are interrelated and not randomly distributed in the population.[19] Simply measuring cumulative risk does not shed light on which lifestyle factors co-occur within individuals, the prevalence of behavior patterns, or relationships with health outcomes, which are critical factors in prioritizing and targeting resource use.[20,21] An increasing number of studies explore the clustering of health behaviors [22] [23], but to our knowledge, few studies have explored the relationships between patterns of multiple behaviors, with mental or self-rated health. In the studies identified, healthier behavior patterns, characterized by better diet quality, more physical activity, lower risk alcohol use, and non-smoking, have been associated with lower levels of psychological distress and improved self-rated health and health-related quality of life.[24,25] [26] [13] However, only one of the studies examining clustering of behaviors included sleep, and only assessed sleep duration, not other measures salient to sleep health such as sleep quality and sleep latency. [13]

Prolonged sitting and too little sleep or excessive amounts of sleep, increase the risk of morbidity and mortality[1,2,4,5,10,14,27] as well as poor self-rated health. [28,29] But these behaviors have received less research attention than other health behaviors such as smoking and alcohol consumption. Poor sleep and prolonged sitting co-occur with other health behaviors [30] and have been associated with worse health-related quality of life[13]. Poor mental health is also strongly associated with high-risk health behaviors[31] and morbidity[32-34], and furthermore, depression and anxiety disorders have a stronger associations with decreased health-related quality of life than medical risk factors like cardiovascular disease, hypertension, arthritis, or medical injury[35]. It is it therefore paramount to understand the relationship between health-behavior patterns and mental health, as integrating strategies to address both may be more efficacious for improving health status[36].

A better understanding of how sitting and sleep co-occur with diet, physical activity, alcohol consumption and smoking may assist in identifying populations who are at higher risk of poor health outcomes. Further, exploring how identified behavioral patterns vary by sociodemographic and psychological factors may add valuable context for the development and targeting of more efficacious health interventions and public health messaging[23,37-40]. The primary aim of this study was to explore how diet quality, alcohol consumption, smoking status, physical activity, sitting time, and sleep quality, duration, and latency co-occur, and investigate the relationships between the identified behavioral patterns and mental and self-rated health. The conceptual model for this current paper is presented in **Supplemental Figure 1**.

Methods

Study design and participants

Participants were recruited from the member database of a freely available web-based physical activity initiative, the 10,000 Steps project (www.10000steps.org.au), a whole-of-community intervention designed to increase adults' physical activity, which commenced in Rockhampton, Australia, in 2001.[41] In November 2011, all 159,698 members in the 10,000 Steps database were emailed an invitation to participate in an online survey to assess a range of lifestyle behaviors and health outcomes, even if they had stopped using the website prior to this study. A total of 16,515 study participants responded, but as many in the database were likely to have changed their e-mail address, the response rate could not be calculated. An *a priori* decision was made to exclude those with missing data on frequency of mental distress, self-rated health, and sex. (**Supplemental Figure 2**).

The sample for the current analysis included 10,638 (64.4%) participants. The 5778 participants whose data were excluded from analysis due to missing data did not differ from the study sample **(Table 1)** in terms of distribution of sex (males= 27.4%; females= 72.4%), prevalence of poor self-rated health (excellent-to-good= 88%; fair-to-poor=12%) or frequency of poor mental health days (mean ± SD=4.9 ± 7.5 days of the last 30 days). Only 493 (8.5%) of the excluded participants nominated their age. The study design and detailed description of the methods have been reported elsewhere.[12] The Central Queensland

University Human Research Ethics Committee provided approval for the study. All participants provided voluntary and informed consent to participate in the study. Data was analyzed in October, 2017.

Health related behavior measures

Four items assessed diet quality. Daily fruit and vegetable consumption was categorized as meeting recommendations (fruit: ≥2 serves per day and/or vegetables: ≥5 serves per day) or not meeting recommendations (fruit: <2 serves per day and/or vegetables:<5 serves per day), as per Australian Dietary Guidelines.[42] Fast food consumption was classified as low (≤1 time per week) or high (>1 time per week).[43,44] Soft drink consumption was categorized as low (≤5 times per week) or high (>5 times per week).[45,46] These thresholds were based on evidence of being acceptable indicators of diet quality.[43-46]

Physical activity during the previous 7 days was measured using the International Physical Activity Questionnaire Long Form (IPAQ-LF),[47] and categorized as high, moderate or low. The ‘high’ category equates to meeting the recommendation of 150 minutes of moderate-to-vigorous physical activity per week.[47] Responses were classified as ‘sufficient activity’ (high IPAQ category) or ‘insufficient activity’ (moderate or low IPAQ categories). The IPAQ-LF has adequate reliability and validity in comparison to other self-report measurement tools.[47] Daily average sitting time was measured using the Workforce Sitting Questionnaire (WSQ)[48] which assesses sitting during travel activities, at work, watching TV, using a computer at home and during other leisure activities on work and non-work days, daily average sitting time was classified as low (<8hrs/day) or high (≥8 hours/ day).[12] The WSQ has acceptable measurement properties for measuring sitting time on work and non-work days.[48]

Alcohol consumption was assessed by usual number of drinks consumed per drinking occasion. Participants were classified as: non-drinkers; low risk drinkers (1-2 standard drinks per occasion); or high risk drinkers (≥3 standard drinks per occasion), in line with the Australian alcohol consumption guidelines[49]. Smoking status was assessed using a single question about the number of cigarettes smoked last month and was categorized as ‘current smoker’ (at least one cigarette per day for the last month) or ‘non-smoker’.

Sleep behaviors were measured using 3 items from the Pittsburgh Sleep Quality Index (PSQI):[50] self-reported average hours of sleep each night; overall sleep quality in the last month (very good, fairly good, fairly bad, very bad); and sleep latency (minutes to go from awake to sleep). Sleep duration was classified as: 'short sleep' (<7hrs); 'meeting recommendation' (7 to ≤9 hours for those aged 18 to <65 years and 7 to ≤8 hours those aged ≥65 years); or 'long sleep' (>9 hours for those aged 18 to <65 years and >8 hours those aged ≥65 years). Sleep quality was re-categorized as: 'very good'; 'fairly good'; or 'fairly-to-very bad' as described elsewhere.[12] Sleep latency was classified as normal (≤30 minutes) or long (>30 minutes), as per suggestions that a sleep latency in excess of 30 minutes is an indicator of having a sleep disorder.[51] The PSQI has strong reliability and validity, and moderate structural validity in a variety of samples.[52]

Mental and self-rated health

Frequency of mental distress was assessed using an item from the BRFSS Healthy Days Module, with a single item reported as a continuous variable (days): "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the last 30 days was your mental health not good?"[53] A difference of one day is meaningful from the perspective of an individual respondent, and any statistically significant difference in population Healthy Days Measures can be interpreted as meaningful.[54] Self-rated health was assessed with the question "in general, would you say your health is 'excellent', 'very good', 'good', 'fair' or 'poor'?". Responses were grouped into 2 categories, 'poor' (poor, fair) or 'good' (good, very good or excellent).[53] Self-rated health status serves as a proxy measure for the perceived symptom burden of both acute and chronic health conditions. It has been demonstrated to be a more powerful predictor of mortality and morbidity than many objective measures of health.[55]

Socio-demographic characteristics

Participants reported their age in years, marital status, household income, highest level of education completed, and work hours. Age was included as a continuous variable. Marital status was categorized as 'partnered' (married or de-facto) or 'non-partnered' (single, widowed, divorced or separated). Household income was reported in seven categories and collapsed into three categories of: 'above AUD$70,000 per annum'; 'AUD$70,000 or less per annum'; or 'unsure/ prefer not to state'. The selected threshold of $70,000 was the median Australian household income in 2011.[56] Highest education level completed was reported as: 'primary school'; 'secondary school'; 'TAFE' ('Technical and Further Education', similar to a diploma); or 'university degree', and collapsed to 2 categories,

’university educated’ or ‘non-university educated’ (primary or secondary education or TAFE). Daily work hours were reported as a continuous variable.[57] Participants not in the workforce were classified as working 0 hours.

Statistical analysis

Latent Class Analysis (LCA) was used to identify mutually exclusive classes within the heterogeneous study population, based on responses to 11 indicators of the 6 health behaviors outlined above. To examine the underlying structure of the data and identify the fewest number of classes best representing all possible combinations of the behaviors, a series of LCA specifying 2 to 6 classes was examined. Each LCA was conducted using randomly generated seed values, 100 iterations of each model (i.e. from two to six classes) were performed and compared using G^2 criterion values. The Bayesian and Akaike Information Criterions (BIC and AIC) were generated for each LCA (with lower BIC and AIC suggesting better goodness of fit) and used in combination with the interpretability of the solution to select the appropriate number of classes and maximize model fit (**Supplemental Table 1**). [58]

The 4-class solution was chosen because although the BIC and AIC continued to decrease with greater number of classes, there was a leveling off in the decrease after 4 solutions. The 5- and 6-class solutions were also less interpretable and resulted in classes representing <5% of the sample, and classes which were only minimally different on a single variable resulting in poor latent class separation. The number of seeds associated with the 4-class solution (100%) also indicated it was well identified as a maximum likelihood solution, in contrast to the solutions with a greater number of classes. As evidence suggests differences in the prevalence and patterning of risk behaviors between men and women,[23] separate models were examined by estimating and comparing the G^2 criterion of models constrained and unconstrained by sex, using the selected 4-class solution. The G^2 criterion values indicated that models estimated separately for men and women provided a better fit to the data. A latent class regression approach was used to examine the associations between class membership, and mental and self-rated health, and sociodemographic variables. A latent class regression is an ordinary logistic regression built in to the PROC LCA procedure for SAS, the only difference is that the outcome (i.e. class membership) is latent rather than directly observed. [58] The continuous covariates of age, work hours and frequency of mental distress were transformed to z-scores prior to inclusion in analysis, so a 1 unit change in the covariate is equivalent to a change of one standard deviation in the covariate (age: 1 SD=11.3 years, work hours: 1 SD=2.4 hours, frequent mental distress: 1 SD=7.2 days). All health behaviors and other covariates were entered as categorical variables. The PROC LCA command procedure in SAS version 9.4 (Release 9.4. Cary, NC: SAS Institute Inc.) was used to estimate model parameters [59]. Stata (version 12.0, College Station, TX: StataCorp) was used for data management and descriptive analysis.

Results

Descriptive characteristics of the sample

The final study sample consisted of more women (71%; n=7,555) than men (29%; n=3,083), with a mean age of 46.2 years (SD=11.3 years; range 18-100 years), and 11.9% (n=1,259) reported their health as "poor". Participant characteristics are outlined in **Table 1**.

Latent class descriptions

The 4 classes in the chosen solution were named to best represent their health-behavior characteristics based on the response probabilities for each indicator (**Table 2**). While the individual response probabilities within the four classes were different for men and women, the overarching characteristics of the classes were similar, and the same names were used to describe the classes for men and women (**Figure 1a/b**).

- Class 1 accounted for 35.6% of men and 37.4% of women, and was characterized by a 'Low-Risk Behavior' profile. Class 1 had the highest probability of low-risk dietary behaviors, low-risk drinking, sufficient physical activity and short daily sitting time, very good sleep quality, recommended sleep duration, and short sleep latency.

- Class 2 accounted for 8.7% of men and 10.2% of women, and was characterized by a 'High-Risk Behavior' profile. This class had the highest probability of high-risk dietary behaviors, insufficient physical activity, long daily sitting time, long sleep latency, and high-risk alcohol use, as well as fairly-to-very bad sleep quality and short sleep duration.

- Class 3 accounted for 31.3% of men and 25.6% of women, and was characterized by a 'Poor Sleep, Low-Risk Daytime Behaviors' profile. The class had a similar probability of high-risk dietary behaviors, low-risk drinking, sufficient physical activity, and low daily sitting time to Class 1, but had the second highest probability of fairly-to-very bad sleep quality and short sleep duration of all classes.

- Class 4 accounted for 24.4% of men and 28.8% of women, and was characterized by a 'Sound Sleep, High-Risk Daytime Behaviors' profile. This class had a similar probability of high-risk dietary behaviors, long daily sitting time, high-risk drinking, and insufficient physical activity to Class 2, but had the second highest probability of at least fairly good sleep quality, recommended sleep duration, and short sleep latency.

The results of the LCA regression analysis are displayed in **Table 3**, using the 'Low-Risk Behavior' class (Class 1) as the reference group. Both men and women in Class 2 ('High-Risk Behavior') had higher odds of frequent mental distress and poor self-rated health, being non-partnered and not having a university education. Class 2 members were also likely to be younger than Class 1 members. Men in Class 2 also had higher odds of having a household income of ≤$70,000 than men in Class 1, while women in Class 2 worked longer hours than women in Class 1. Men in Class 3 ('Poor Sleep, Low-Risk Daytime Behaviors') had higher odds of frequent mental distress and poor self-rated health than men in Class 1. Women in Class 3 had higher odds of frequent mental distress and poor self-rated health, and not being university educated than women in Class 1. Both men and women in Class 4 ('Sound Sleep High-Risk Daytime Behaviors') had higher odds of frequent mental distress and poor self-rated health than Class 1, and had higher odds of being non-partnered, working longer hours and not having a university education. Class 4 members were also likely to be younger than Class 1 members.

Discussion

Consistent with previous research, the findings of this study confirmed that health behaviors cluster together at both ends of the risk spectrum.[19,23,30] Four latent health-behavior classes were identified, two which were characterized by overall 'Low Risk Behavior' and 'High Risk Behavior, and two mixed-risk behaviors classes characterized by 'Poor Sleep Low-Risk Daytime Behavior' and 'Sound Sleep High-Risk Daytime Behavior'. In agreement with previous research, classes with overall low-risk (Class 1) and high-risk (Class 2) behaviors had the lowest and highest odds of frequent mental distress and poor self-rated health respectively.[13,24] Furthermore, both classes with high-risk daytime behaviors were characterized by participants who were younger, non-university educated, did not have a partner, worked longer hours and had a lower annual household income than those in the low-risk classes.[60 61,62]

The mixed-behavior class characterized by low-risk daytime behaviors but a high-risk sleep pattern described almost one third of the male and one quarter of the female participants. The identification of this prevalent class may indicate that sleep differs from other health behaviors, in that sleep behavior may be less volitional in nature than daytime behaviors like diet and activity. Achieving good sleep quality can be influenced by circadian rhythms, daytime behaviors (e.g. sleep hygiene, daytime sleeping) and also cognitive aspects (e.g. worry about sleep).[63,64] Individuals who are more anxiety-prone and experience more chronic daily stress are also more likely to be vulnerable to disturbed sleep,[63] and in agreement with this, the current study found that the ‘Poor Sleep Low-Risk Daytime Behavior’ class had higher frequency of mental distress than the overall ‘Low-Risk Behavior’ class. This was particularly true for men in the ‘Poor Sleep Low-Risk Daytime Behavior’ class, for whom the odds of mental distress were five times higher than in the “Low Risk Behavior” class. The relationship between sleep and mental health is thought to be bidirectional, in that sleep disturbance is a risk factor for poor mental health, and poor mental health is a risk factor for developing sleep disturbances.[65,66] While the understanding of the causal pathways between sleep and mental health is still in its infancy, emerging evidence suggests interventions to improve sleep can produce significant improvements in mental health.[67]

The prevalence of non-drinkers in the male ‘Poor Sleep Low Risk Daytime’ class was quite distinct compared to the other classes (10% vs. 1-2%), whereas for women the prevalence of non-drinkers was overall higher and more equally dispersed between the classes (9-13%). This is in agreement with previous research which shows alcohol use being more prevalent in men.[68] The non-drinker category is likely to include those who have always consumed no alcohol as a lifestyle choice as well as former drinkers who abstain from alcohol due to a health scare related to their drinking habits or alcohol use dependency. [68] It is of interest to note that complaints of insomnia are common in alcohol recovery, and furthermore, alcohol is a frequently reported means of self-medicating for sleep problems and chronic insomnia also increases the risk of developing alcohol dependency.[69] To better understand the effect of alcohol use on health and its complex association with other health behaviors, using lifetime alcohol use in combination with current alcohol use would be beneficial. [69]

Strengths and limitations

Significant strengths include the sample size, the inclusion of measures which have strong associations with chronic disease risk and mortality, and good psychometric properties, as well as the range of health behaviors included, and the inclusion of mental distress. The findings must however be viewed in light of several potential limitations. The study population included a high proportion of middle-aged women with a partner, who were in full-time work and university educated, reflecting the membership profile of the 10,000 steps program.[41] The smallest identified class was the 'High Risk Behavior' class which was more likely to report low SES indicators (less education, lower income) than the 'Low Risk Behavior' class. This may be because this sub-population is less likely to continue engaging in the study over a longer period of time and therefore not respond to the email questionnaire. There was also a relatively larger proportion of the female sample (10.2%) compared to the male sample (8.7%) in the 'High Risk Behavior' class. Confirming findings in a more representative sample both in terms of SES indicators and sex would therefore be useful to gain more accurate population estimates of prevalence of behavior patterns and their characteristics to guide interventions. Further limitations include the use of self-report measures, the cross-sectional design, a modest response rate (estimated to be around 10%),[70] and 35.6% missing data.

Conclusion

This study demonstrated that health behaviors co-occur, and that classes with behavior patterns characterized by high-risk daytime behaviors were more likely to include younger, non-partnered, non-university educated participants who worked longer hours, and had higher odds of frequent mental distress and poor self-rated health. A novel finding was that poor sleep appeared to be partly independent of daytime behaviors, demographic, and socioeconomic factors, but had a strong association with mental health. This study provided further support for the rationale that interventions that address multiple health behaviors, and take into account mental health and social determinants of health, may have potential to facilitate behavior change and improve health outcomes.

Acknowledgments

This work was partly supported by a grant from the Diabetes Australia (Y17G-DUNM) and a NSW CVRN Collaborative Project Grant (101584). ES is supported by a grant from National Health and Medical Research Council (NHMRC, APP1110526), Cancer Council WA, and the British Heart Foundation; CV by grants from the Heart Foundation of Australia (ID 100427) and NHMRC (APP1080186); and MJD by grants from the National Heart Foundation of Australia (ID 100029), Diabetes Australia (Y17G-DUNM) and NHMRC (G1700197). The study sponsors had no role in deciding the study design; collection, analysis and interpretation of data; writing the report; or the decision to submit the report for publication. No financial disclosures were reported by the authors of this paper.

SO performed the data analysis and drafted the paper. SO, GSK, WGH, ES, CV, WJB and MJD were involved in the conception and design of the paper and interpretation of the data. GSK, WGH, ES, CV, WJB and MJD were involved in the acquisition of funding, and critically revising the paper for intellectual content. CV and MJD were involved with the acquisition of the data. EGH provided statistical expertise.

Supplemental table 1: Criteria to assess model fit, 10,000 Steps study, Australia, Nov-Dec 2011

Number of latent classes	G^2	df	AIC	BIC	Log likelihood	Seeds associated with the best model (out of 100 iterations)
2	5104	6882	5162	5373	-66944	100%
3	3956	6867	4044	4364	-66374	100%
4	3519	6852	3637	4066	-66225	100%
5	3360	6837	3508	4046	-66145	25%
6	3205	6822	3205	4031	-66068	47%

Table 1: Characteristics of the study population (10,000 Steps study, Australia, Nov-Dec 2011)

		Men	Women	Whole sample
Sample size	n	3083	7555	10638
Socio-demographics and health status		*Percentage (%) or mean±SD*		
Age	Years	48.4±10.8	45.3±11.4	46.2±11.3
Marital status	Married/ de-facto	81.0	71.7	74.4
	Single	19.0	28.3	25.6
Education	Less than university[1]	39.7	37.9	38.4
	University	60.3	62.1	61.6
Employment status	Full time	91.1	71.4	77.1
	Part time	3.7	20.1	15.3
	Not in workforce	5.2	8.5	7.6
Work hours	Mean hours per day	8.2±2.3	7.5±2.4	7.7±2.4
Household income	>70k per annum	71.3	60.7	63.7
	≤70k per annum	13.1	20.7	18.5
	Private/ unsure	15.6	18.6	17.8
Mental distress	Days/30 past days	3.8±6.7	5.0±7.3	4.7±7.2
Self-rated health	Poor	12.1	11.7	11.8
	Good	87.9	88.3	88.2
Diet Quality		*Percentage (%)*		
Fruit intake	≥2 serves per day	52.8	61.0	58.7
	0-1 serves per day	47.2	39.0	41.3
Vegetable intake	≥5 serves per day	6.5	14.5	12.1
	0-4 serves per day	93.5	85.6	87.9
Soft drink	≥5times per week	18.8	14.9	84.0
	0-4 times per week	81.2	85.1	16.0
Fast food	>1 time per week	16.5	90.0	11.9
	0-1 time per week	83.5	10.0	88.1
Alcohol and smoking		*Percentage (%)*		
Alcohol consumption	Low risk	51.5	64.3	60.6
	Non-drinker	9.0	11.1	10.5
	High-risk	39.5	24.7	28.9
Smoking	Non-smoker	93.2	92.9	92.9
	Current smoker	6.8	7.2	7.1
Activity and sitting		*Percentage (%)*		
Physical activity	Sufficient	55.9	45.4	51.6
	Insufficient	44.1	54.6	48.4
Sitting	<8 hours per day (low)	34.5	42.6	40.3
	≥8 hours per day (high)	65.5	57.4	59.7
Sleep		*Percentage (%)*		
Sleep duration	Excess sleep	0.3	0.7	0.6
	Adequate sleep	57.9	63.1	61.6
	Inadequate sleep	41.8	36.2	37.8
Sleep latency	Long (≥30 min)	10.6	17.8	84.3
	Normal (<30 min)	89.4	82.2	15.7
Sleep quality	Very good	17.8	17.6	17.7
	Fairly good	59.9	58.4	58.8
	Fairly poor/ Poor	22.3	24.0	23.5

[1]Primary/ Secondary or TAFE (trade college)

Table 2: Latent class analysis: probability of class membership and item-response probabilities within each of the four classes, 10,000 Steps study, Australia, Nov-Dec 2011

	Class 1: Low Risk Behaviors	Class 2: High Risk Behaviors	Class 3: Poor Sleep Low Risk Daytime behaviors	Class 4: Sound Sleep High Risk Daytime Behaviors	Class 1: Low Risk Behaviors	Class 2: High Risk Behaviors	Class 3: Poor Sleep Low Risk Daytime behaviors	Class 4: Sound Sleep High Risk Daytime Behaviors
	Men (*n*=3083)				*Women* (*n*=7555)			
Percentage of sample in class	35.6%	8.7%	31.3%	24.4%	37.4%	10.2%	25.6%	28.8%
Diet quality[1]								
Fruit ≥2 serves	0.70	0.26	0.61	0.26	0.78	0.30	0.73	0.40
Vegetables ≥5 serves	0.10	0.02	0.08	0.02	0.21	0.05	0.18	0.06
Fast food ≤1/week	0.97	0.57	0.94	0.60	0.99	0.81	0.97	0.68
Soft drink ≤4/week	0.91	0.57	0.90	0.60	0.92	0.65	0.92	0.78
Alcohol and smoking[1]								
Alcohol consumption								
Non-drinker	0.01	0.02	0.10	0.01	0.12	0.12	0.13	0.09
Low risk	0.59	0.33	0.55	0.42	0.73	0.48	0.70	0.54
High risk	0.32	0.61	0.35	0.49	0.15	0.40	0.18	0.37
Non-smoking	0.96	0.82	0.96	0.89	0.97	0.81	0.96	0.89
Activity and sitting[1]								
Sufficient physical activity	0.63	0.37	0.60	0.46	0.56	0.32	0.50	0.33
Sitting <8 hours/day (low)	0.46	0.18	0.37	0.20	0.56	0.20	0.46	0.30
Sleep[1]								
Sleep quality								
Very good	0.38	<0.001	0.03	0.13	0.34	<0.001	<0.001	0.17
Fairly good	0.62	0.13	0.53	0.82	0.65	0.21	0.39	0.79
Fairly-to-very bad	<0.001	0.86	0.44	0.05	0.01	0.79	0.61	0.04
Sleep duration								
Recommended	0.82	0.18	0.31	0.71	0.85	0.19	0.23	0.83
Short sleep	0.18	0.81	0.68	0.29	0.15	0.80	0.77	0.16
Long sleep	0.002	0.004	0.004	0.002	0.007	0.008	0.002	0.01
Sleep latency ≤30 min	1.00	0.52	0.85	0.93	0.98	0.44	0.65	0.90

[1] Item response probabilities within each class (all item-response probabilities included if >2 possible response categories, total sum of item categories = 1.00)

Table 3: Odds of class membership by sociodemographic and health measures, 10,000 Steps study, Australia, Nov-Dec 2011

	Class 1: 'Low-Risk Behaviors'	Class 2: 'High-Risk Behaviors'	Class 3: 'Poor Sleep Low-Risk Daytime Behaviors'	Class 4: 'Sound Sleep High-Risk Daytime Behaviors'
		OR (95%C.I.)[1]	OR (95%C.I.)[1]	OR (95%C.I.)[1]
			Men	
Frequency of mental health distress (z-score)[2]	Ref	6.02 (2.91-12.20)	5.10 (2.49-10.48)	3.02 (1.49-6.14)
Poor self-rated health[3]	Ref	38.56 (13.9-107.08)	5.33 (1.91-14.88)	12.81 (4.77-34.41)
Age (standardized)[4]	Ref	0.94 (0.91-0.96)	1.01 (0.99-1.02)	0.95 (0.93-0.96)
Non-partnered[5]	Ref	2.25 (1.34-3.78)	1.04 (0.70-1.56)	1.60 (1.06-2.41)
Work hours[6]	Ref	1.23 (0.91-1.67)	1.16 (1.0-1.35)	1.37 (1.13-1.66)
Non-university educated[7]	Ref	2.58 (1.61-4.14)	1.06 (0.78 – 1.44)	1.61 (1.12-2.31)
Household income: ≤$AUD 70k per annum[8]	Ref	2.65 (1.21-5.78)	1.11 (0.40-1.75)	1.10 (0.66-1.82)
Household income: 'Prefer not to state/ unsure'[8]	Ref	2.06 (0.85-4.98)	1.04 (0.62-1.76)	0.67 (0.36-1.27)
			Women	
Frequency of mental health distress (z-score)[2]	Ref	3.50 (2.73-4.50)	2.75 (2.20-3.44)	2.14 (1.64-2.78)
Poor self-rated health[3]	Ref	26.00 (14.89-45.32)	4.43 (2.61-7.52)	9.19 (5.35-15.80)
Age (standardized)[4]	Ref	0.92 (0.90-0.93)	1.01 (1.00-1.02)	0.92 (0.91-0.93)
Non-partnered[5]	Ref	2.08 (1.51-2.87)	1.10 (0.88-1.38)	1.45 (1.12-1.88)
Work hours[6]	Ref	1.58 (1.32-1.89)	1.07 (0.99-1.18)	1.33 (1.18-1.49)
Non-university educated[7]	Ref	4.00 (2.93-5.36)	1.25 (1.02-1.53)	2.37 (1.87-3.00)
Household income: ≤$AUD 70k per annum[8]	Ref	1.20 (0.82-1.75)	0.98 (0.77-1.24)	1.20 (0.88-1.62)
Household income: 'Prefer not to state/ unsure'[8]	Ref	1.23 (0.79-1.91)	1.18 (0.90-1.56)	1.05 (0.73-1.50)

[1] Multinomial logistic regression; [2]Mean±SD poor mental health days: 4.7±7.2 days; [3]Compared to good self-rated health; [4]Mean±SD age: 46.2±11.3 years; [5]Compared to partnered; [6]Mean±SD work hours: 7.7±2.4 hours; [7]Compared to university educated; [8]Compared to >AUD$70k per annum

Figure legends

Supplemental Figure 1: Conceptual framework for relationship between variables, 10,000 Steps study, Australian, Nov-Dec 2011

Supplemental Figure 2: Flowchart for inclusion of data, 10,000 Steps study, Australia, Nov-Dec 2011

Figure 1a: Item-response probabilities for health behavior indicator by latent class for men, 10,000 Steps study, Australia, Nov-Dec 2011.

(1) ‘Fairly good’ and ‘very good’ sleep quality collapsed for illustrative purposes.

Figure 1b: Item-response probabilities for health behavior indicator by latent class for women, 10,000 Steps study, Australia, Nov-Dec 2011.

(1) ‘Fairly good’ and ‘very good’ sleep quality collapsed for illustrative purposes.

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