Healthier movement behavior profiles are associated with higher psychological wellbeing among emerging adults attending post-secondary education

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For correspondence: denver.brown@utsa.edu

Denver M. Y. Brown,[1] Guy E. J. Faulkner[2] and Matthew Y. W. Kwan[3]

[1]Department of Psychology, University of Texas at San Antonio, 1 UTSA Circle, San Antonio, TX, 78254, USA, [2]School of Kinesiology, University of British Columbia, 6081 University Blvd, Vancouver, BC, V6T 1Z1, Canada, [3]Department of Child and Youth Studies, Brock University, 1812 Sir Isaac Brock Way, St. Catharines, ON, L2S 3A1, Canada

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ABSTRACT

Purpose: Emerging adulthood is a stressful time fraught with new challenges while attending higher education. Identifying protective factors to help reduce the psychological burden that many will experience during this period is therefore important. The objectives of this study were to identify whether emerging adults attending post-secondary education can be classified into distinct profiles based on their 24-hr movement behaviors, evaluate predictors of profile membership, and examine relationships between profile membership and indicators of mental health.

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Authors DB @*TheDenverBrown*, GF @*GuyFaulkner* and MK @*MattKwan_PhD* can be reached on Twitter.

Methods: This cross-sectional study used data from Cycle 1 of the Canadian Campus Wellbeing Survey. Emerging adults (N = 15,080; 67.6% female; Mean age = 20.78 ± 2.00) from 20 post-secondary institutions in Canada self-reported their movement behaviors – moderate-to-vigorous physical activity (MVPA), recreational screen time (ST) and sleep – and completed the Kessler Psychological Distress Scale and Warwick-Edinburgh Mental Well-being Scale. Latent profile analysis was employed.

Results: Five profiles were identified: low ST with very high (12.6%), high (24.4%) and low MVPA (51.2%) as well as high ST with high (2.3%) and low MVPA (9.4%). Profiles had similar sleep patterns and were thus characterized by differences in MVPA and ST. Several socio-demographic variables were associated with profile membership. Profiles characterized by healthier combinations of MVPA, ST and sleep generally reported more favorable scores for indicators of mental health.

Conclusions: Campus-based interventions should focus on getting students to engage in a healthy balance of physical activity and recreational screen use as it has the potential to reduce the mental health burden on emerging adults attending post-secondary education.

INTRODUCTION

Emerging adulthood is a stressful time fraught with new challenges for emerging adults attending post-secondary education. Changing academic and domestic roles and responsibilities represent some of the many shifts in priorities that pose stress on students during this life stage.[1] These changes can displace time spent engaging in health promoting behaviors, and may in turn, elicit an array of negative health consequences. While there has been considerable attention paid to weight gain and other cardiometabolic risk factors observed among post-secondary students,[2] evidence suggests this population faces an even greater risk of experiencing poor mental health.[3] Evidently, it is imperative to identify protective factors that can help prevent or reduce mental health problems so that students can flourish during this critical life stage.

The collective movement behaviors we engage in (or do not) across the course of a day are drawing increased attention for their role in mental health and wellbeing.[4] In particular, the recent release in Canada of the first 24-hour Movement Guidelines for Adults has placed an even greater emphasis on the importance of engaging in a healthy active lifestyle, which consists of accruing adequate amounts of physical activity and sleep as well as limiting engagement in sedentary behaviors – recreational screen time in particular.[5] This integrative approach emphasizes that the whole day matters.[6] A growing body of literature has demonstrated beneficial associations between healthy movement behaviors and several indicators of mental health among adolescents;[7] however, these relationships have received limited attention among emerging adults.

While many post-secondary students relish their newfound independence, attending higher education has been found to disrupt existing habits and enable unhealthy lifestyle-related behaviors to emerge. Specifically, independent investigations have shown major declines in MVPA,[8] poor sleep patterns,[9] and excessive recreational screen use;[10] each of which has been linked with poorer mental health for post-secondary students.[11,12] Considering the high rates of mental health problems reported by emerging adults attending post-secondary education,[3] engaging in a healthy cluster of movement behaviors has the potential to buffer these effects and warrants closer investigation.

Recently, the results from the first deployment of the Canadian Campus Wellbeing Survey (CCWS) dataset found that post-secondary students' adherence to all four components (i.e., physical activity, recreational screen time, sedentary behavior, sleep) of the 24-hour movement guidelines was only 9.9%.[13] Their findings also showed that students who met the guidelines at higher rates were more likely to report better scores on measures of mental health and wellbeing. Such work monitoring guideline adherence and its consequences for students is important from a behavioral surveillance standpoint. However, other statistical techniques can answer different questions that may improve our current understanding of the health of students on campus and identify priorities for intervention. For instance, latent profile analysis can identify groups that stand to benefit the most from intervention, while also providing important information about predictors of group membership (e.g., gender, ethnicity, age) that can be used to tailor interventions towards these groups. Therefore, the purpose of this study is threefold: (1) to identify whether unique movement behavior profiles exist among emerging adults enrolled at post-secondary institutions across Canada; (2) to evaluate predictors of profile membership; and (3) to determine if profile membership is associated with differences in psychological distress and mental wellbeing.

METHOD

Study sample and data collection

Data for the present study is from Cycle 1 (2019/2020 academic year) of the CCWS (www.ccws-becc.ca) collected prior to the COVID-19 pandemic. More detailed information regarding the CCWS study design, methods, survey measures and data access policy can be found elsewhere.[14] In short, the CCWS is an online questionnaire completed by students attending Canadian Post-Secondary Institutions (PSIs). Across the 20 PSIs, 165,997 students were invited to complete the online survey, and 24,760 students responded to the survey (overall response rate = 14.9%).

The current study included only emerging adults (18-25 years of age), resulting in a total sample of 15,080 participants. This sample had a mean age of 20.78 years (SD = 2.00) and included a higher proportion of females (n = 10,118; 67%) from across a fairly diverse ethnic background (e.g., 31.3% White, 28.2% East/Southeast Asian, 20.2% South Asian). Complete details of the sample composition can be found in Table 1. The CCWS was approved by the Behavioral Research Ethics Board at the University of British Columbia as well as at each PSI.

Measures

Demographics.

Participants reported demographic variables assessing their age, gender, race/ethnicity, highest level of parental education, whether they have a chronic health condition and/or disability, the average number of hours they work per week during the school year, the extent to which they experience financial stress, and where they currently live. PSIs provided information about each participant's credential type (e.g., baccalaureate degree, apprenticeship, diploma, etc.), whether they were new to the institution (i.e., first year), if they were a full- or part-time student, and if they were a domestic or international students (as defined by their visa status). For analysis purposes, several demographic covariates were recoded: ethnicity (White/non-White); parental education (high school or less/completed college or university/ graduate or professional degree); place of residence (off campus/on-campus/unstable); and credential type was recoded to reflect the institution type (university/college).

Movement behaviours.

As per the Canadian 24-Hour Movement Guidelines for Adults,[5] movement behaviours were operationalized as consisting of moderate-to-vigorous physical activity (MVPA), recreational screen time (ST), and sleep. Although the 24-hour Movement Guidelines for Adults also include a threshold-based recommended for sedentary time, we elected to focus on only one of the two sedentary behavior recommendations (i.e., recreational ST).

Physical activity.

MVPA was assessed using the International Physical Activity Questionnaire (IPAQ).[15] Participants responded to four items that assessed the frequency (days) and duration (hours and/or minutes on an average day) of their moderate and vigorous physical activity performed in bouts of greater than 10-minutes over the past seven days. Daily MVPA was calculated by multiplying frequency by duration for moderate and vigorous physical activity, respectively, and then summing these products and dividing by seven. As per the scoring rules for IPAQ, daily MVPA times were capped to 180 minutes for any participants who exceeded 3 hours or 180 minutes of MVPA per day.

Screen time.

Participants reported the number of hours and minutes they typically spent engaging in recreational ST on a weekday.

Sleep.

Participants reported the time they went to sleep and wake-up time for weekdays and weekends over the last week. Times were reported to the nearest half hour. The average of total sleep per night was calculated using this formula ([5 x hours of sleep on weekdays + 2 x hours of sleep on weekends]/ 7).

Psychological distress.

The Kessler Psychological Distress Scale (K10) was used to measure symptoms of depression and anxiety.[16] The K10 consists of 10 items with response options ranging on a 5-point scale from (1) "None of the time" to (5) "All the time". Participant's responses were summed to obtain a score ranging from 10 to 50, with higher scores reflecting greater levels of psychological distress.

Mental wellbeing.

The Warwick-Edinburgh Mental Well-being Scale (WEMWBS) was used to assess emotional, social, and psychological well-being over the previous two weeks.[17] The WEMWBS consists of 14 items with response options ranging on a 5-point scale from (1) "None of the time" to (5) "All the time". Participant's responses were summed to obtain a score ranging from 14 to 70, with higher scores reflecting greater levels of mental wellbeing.

Data analysis

First, we subset the larger CCWS dataset to only include participants between the ages of 18 to 25 years (i.e., emerging adults) as per Hochberg and Konner's[18] definition of emerging adulthood. The first part of the primary analysis involved estimating a series of latent models for the sample. Two to six profile solutions were specified using MVPA, ST and sleep as predictors. Latent profile analysis uses a set of predictor variables to fit a model that identifies an optimal number of mutually exclusive subgroups with minimal within-group variance and maximal between-group variance.[19] Four quantitative model fit criteria were used to guide our decision regarding the number of profiles that best represented the data: Bayesian information criterion,[20] adjusted Lo-Mendell-Rubin likelihood ratio test,[21] entropy values and likelihood increment percentage per parameter.[22] Lower Bayesian information criterion values indicate better model fit. A significant *p*-value for the adjusted Lo-Mendell-Rubin likelihood ratio test indicates the *n*-profile model fit the data better than the model with *n*-1 profiles.[21] Entropy values range from 0 to 1 with higher values indicating greater precision of latent profile membership assignment. While there are no threshold values for entropy statistics, values greater than 0.6 have been shown to be acceptable.[23] Likelihood increment percentage per parameter provides an effect size measure for model comparison that takes into account the complexity of the model based on the number of parameters specified.[22] Likelihood increment percentage per parameter values between 0.02 to 0.10 are considered to represent small improvements in model fit, 0.10 to 0.30 are considered medium improvements, and greater than 0.30 are considered larger improvements. When likelihood increment percentage per parameter values drop off or plateau (akin to a scree plot) with an increasing number of classes, the model with the greater number of classes is not warranted.

Once the final latent profile model was determined, we used the manual BCH three-step approach for distal outcomes to examine differences in psychological distress and mental wellbeing between the movement behaviour profiles.[24,25] Age, gender, socioeconomic status, race/ethnicity, financial stress, disability status, weekly hours worked, place of residence, first-year student status, full-time student status, and international student status were included within the distal outcomes model as covariates. These covariates were selected based on previously established[26–29] and hypothesized relationships with movement behaviors and mental health. The three-step approach also allowed us to evaluate predictors of profile membership. Odds ratios with 95% confidence intervals were computed using latent multinomial logistic regression to examine differences in the likelihood of profile membership based on each of the covariates. The "healthiest" movement behaviour profile was pre-determined to serve as the reference group. Mplus Version 8.5 was used to conduct our analyses.[30] All models were specified so that the nested structure of the data was taken into account (i.e., participants attending 20 PSIs). The Mplus code for these analyses is available at https://osf.io/ucbvp/.

Results

Data inspection

Missingness ranged from 0.8% for race/ethnicity to 37.5% for first-year student status (see Table 1). Missingness for movement behaviors and indicators of mental health was predicted by other observed variables (e.g., more missingness among younger participants, international students, and those attending colleges), which led us to consider data missing at random and use appropriate procedures to preserve our sample size. Specifically, full information maximum likelihood was employed for missing data estimation when identifying the best latent profile solution. Although full information maximum likelihood was employed to handle missingness in the first step of our analysis, this procedure uses listwise deletion to handle cases with missing covariate values in the distal outcomes analysis, and therefore, multiple imputation was used to retain the full sample. A total of 40 multiply imputed datasets were created as per recommendations to set m > 100 times the highest fraction of missing information (0.38 for first-year student status).[31]

Descriptive statistics

Descriptive statistics for the sample demographic characteristics, movement behaviors and indicators of mental health are presented in Table 1.

Table 1. *Descriptive statistics for demographic characteristics, movement behaviors and indicators of mental health.*

	Sample (N = 15,080) *n* (%)	Missing *n* (%)
Gender		312 (2.1)
Females	10,118 (67.1)	
Males	4,650 (30.8)	
Age *M (SD)*	20.78 (2.00)	
Ethnicity		118 (0.8)
White	4,719 (31.3)	
Middle Eastern	448 (3.0)	
Black	303 (2.0)	
East/Southeast Asian	4,256 (28.2)	
South Asian	3,041 (20.2)	
Indigenous	127 (0.8)	
Latino	325 (2.2)	
Mixed/Other	1,744 (11.6)	
Parental Education		1,231 (8.2)
High school or less	3,092 (20.5)	
Completed college/university	7,457 (49.4)	
Graduate or professional degree	3,300 (21.9)	
Disability status (yes)	3,935 (26.1)	2,208 (14.6)
New to institution (yes)	2,857 (18.9)	5,658 (37.5)
International student (yes)	3,682 (24.4)	
Institution type		
University	9,918 (65.8)	
College	5,162 (34.2)	
Housing		283 (1.9)
Off-campus	13,054 (86.6)	
On-campus	1,656 (11.0)	
Unstable	87 (0.6)	
Work hours *M (SD)*	9.20 (10.26)	820 (5.4)
Financial stress		183 (1.2)
No stress at all	1,773 (11.8)	
Very little stress	3,096 (20.5)	
Some financial stress	4,381 (29.0)	
Quite a bit of financial stress	2,975 (19.7)	
A great deal of financial stress	2,672 (17.7)	
MVPA *M (SD)*	0.71 (0.63)	1,664 (11.0)
Screen time *M (SD)*	4.77 (2.69)	593 (3.9)
Sleep duration *M (SD)*	7.93 (1.35)	505 (3.3)
Psychological distress *M (SD)*	26.26 (8.25)	211 (1.4)
Mental wellbeing *M (SD)*	44.51 (10.12)	345 (2.3)

Estimating the number of latent profiles

Model fit indices are presented in Table 2. The results found that the solution consisting of a five-class model resulted in the most appropriate fit for the data. Although the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test values were non-significant beyond the two-profile solution, the Bayesian information criteria values suggested increasing model fit up to the five-profile model, which appeared to be a moderate improvement over the four-profile solution when examining the likelihood increment percentage per parameter value. Moreover, the entropy value for the five-profile solution was equivalent or greater than values observed for each of the preceding solutions. The best loglikelihood for the six-profile solution was unable to be replicated and was therefore not considered trustworthy for interpretation.

Table 2. *Model fit criteria.*

	2-Profile	3-Profile	4- Profile	5- Profile	6- Profile#
Estimated Parameters	10	14	18	22	26
BIC	142976.65	141653.50	140869.65	140303.78	139729.50
Entropy	0.73	0.74	0.72	0.74	0.73
LMR	2753.23*	1327.16	801.50	589.05	563.89
LIPpp	0.48	0.24	0.15	0.11	0.11

Note: BIC = Bayesian Information Criteria; LMR = Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; LIPpp = Likelihood Increment Percentage per parameter; * = $p < .05$ (for LMR only). #The 6-profile solution did not converge and is therefore not interpretable.

Latent profiles

The mean values for each movement behavior used in the latent profile analysis are presented by profile in Table 3. Sleep patterns were relatively homogenous across the profiles, resulting in five profiles characterized by differences observed for MVPA and ST. Approximately 12.6% of the sample were considered among the healthiest profile, with very high reported MVPA and low ST, with an additional 24.4% reporting high levels of MVPA along with low ST. The majority of the sample (51.2%) reported both low MVPA and ST. Finally, there were two profiles that reported high ST alongside low and high levels of MVPA, representing 9.4% and 2.3% of the sample, respectively.

Table 3. *Mean scores for each movement behavior subdomain by profile and sample.*

	Profile 1 Low MVPA/ High ST (*n* = 1419)	Profile 2 High MVPA/ High ST (*n* = 350)	Profile 3 Low MVPA/ Low ST (*n* = 7717)	Profile 4 High MVPA/ Low ST (*n* = 3687)	Profile 5 Very High MVPA/ Low ST (*n* = 1907)
MVPA (hours/day)	0.19	1.22	0.26	0.99	1.83
ST (hours/day)	9.31	9.56	4.15	3.86	4.20
Sleep (hours/day)	8.08	7.97	7.91	7.93	7.87

Values in the table represent the mean and standard deviation. Variance between the profiles was fixed at 0.07 for MVPA, 3.99 for ST, and 1.83 for sleep.

Variables predicting latent profile membership

Odds ratios demonstrating the likelihood of profile membership based on covariates compared to the very high MVPA/low ST (referent) profile are presented in Table 4. Relative to the healthiest group, those classified as high MVPA/low ST were more likely to be female, work less hours each week and live on campus. Participants in the low MVPA/low ST group were more likely to be female, non-White, international students, have parents with lower educational attainment, older, work less hours each week and live on campus. Participants classified as high MVPA/high ST were less likely to be White. Finally, those in the least healthy group (i.e., low MVPA/high ST) were more than half as likely to be White, while also being more likely to be older, have parents with lower educational attainment, have been diagnosed with a disability and/or chronic health condition, work less hours each week and live on campus.

Table 4. *Associations between demographic variables and latent profile membership*

Variable	Latent Profile							
	Low MVPA/Low ST		High MVPA/Low ST		Low MVPA/High ST		High MVPA/High ST	
	Odds Ratio	95% CI	Odds Ratio	95% CI	Odds Ratio	95% CI	Odds Ratio	95% CI
Male (yes)	**0.63**	**0.56-0.71**	**0.85**	**0.74-0.96**	1.05	0.85-1.30	1.31	0.98-1.75
Age	**1.08**	**1.03-1.13**	1.02	0.97-1.08	**1.08**	**1.03-1.13**	1.05	0.97-1.15
Socioeconomic status	**0.91**	**0.86-0.97**	1.02	0.93-1.10	**0.81**	**0.72-0.91**	0.97	0.73-1.31
Ethnicity (White)	**0.69**	**0.61-0.79**	1.06	0.96-1.16	**0.45**	**0.40-0.51**	**0.67**	**0.49-0.91**
Institution type (University)	1.02	0.94-1.11	1.17	0.99-1.37	1.30	0.98-1.73	0.94	0.66-1.35
International student (no)	**0.75**	**0.64-0.86**	1.07	0.86-1.34	1.10	0.77-1.57	1.09	0.79-1.52
First year (yes)	1.08	0.92-1.28	0.99	0.83-1.18	1.04	0.79-1.35	0.81	0.55-1.18
Disability status (yes)	1.05	0.89-1.24	0.97	0.83-1.14	**1.43**	**1.12-1.83**	1.34	0.99-1.81
Work hours	**0.98**	**0.98- 0.99**	**0.98**	**0.98-0.99**	**0.96**	**0.95-0.97**	0.98	0.96-1.00
Financial stress	1.00	0.95-1.05	0.98	0.92-1.05	1.08	0.96-1.21	1.01	0.90-1.13
Housing Off campus (referent)	-	-	-	-	-	-	-	-
On-campus	**1.27**	**1.03-1.56**	**1.31**	**1.15-1.48**	**1.58**	**1.30-1.92**	0.96	0.72-1.28
Unstable	1.11	0.54-2.29	0.75	0.29-1.93	1.11	0.36-3.45	0.69	0.19-2.49
Full-time (yes)	1.09	0.95-1.24	1.00	0.82-1.23	**0.77**	**0.62-0.96**	0.81	0.58-1.13

Reference class = Very High MVPA/Low ST. CI = Confidence interval. Bolded values represent significance.

Comparison of distal outcomes by latent profile

Table 5 presents the adjusted model-based means for mental wellbeing and psychological distress by profile and the mean differences between profiles. Our findings revealed significantly higher mental wellbeing among the healthiest groups (i.e., high and very high MVPA with low ST) compared to each of the other profiles. Scores for mental wellbeing scores were similar across the two profiles characterized by consistently high or low MVPA and ST, although the low MVPA/low ST profile had significantly higher mental wellbeing than the least healthy profile (i.e., low MVPA/high ST), whereas the high MVPA/high ST profile did not.

For psychological distress, the high MVPA/low ST profile reported significantly lower scores than each of the other profiles. Interestingly, the low MVPA/low ST profile reported similar levels of psychological distress as the very high MVPA/low ST profile; which for both profiles, were significantly greater than the two profiles characterized by high ST. Finally, there was no difference in psychological distress scores between the two high ST profiles.

Table 4. *Mental health scores by profile and differences between profiles.*

	Mental Wellbeing				
Profile	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1. Low MVPA/High ST (41.74 ± 0.53)	-	-1.42 (0.80)	-2.37 (0.42)***	-4.01 (0.28)***	-3.96 (0.29)***
2. High MVPA/High ST (43.16 ± 0.67)		-	-0.95 (0.63)	-2.60 (0.65)***	-2.54 (0.72)***
3. Low MVPA/Low ST (44.11 ± 0.32)			-	-1.65 (0.27)***	-1.59 (0.26)***
4. High MVPA/Low ST (45.76 ± 0.35)				-	0.06 (0.28)
5. Very High MVPA/Low ST (45.70 ± 0.47)					
	Psychological Distress				
Profile	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1. Low MVPA/High ST (28.26 ± 0.25)	-	-0.48 (0.89)	1.96 (0.28)***	3.05 (0.31)***	2.22 (0.31)***
2. High MVPA/High ST (28.74 ± 0.83)		-	2.44 (0.77)**	3.53 (0.75)***	2.70 (0.78)**
3. Low MVPA/Low ST (26.30 ± 0.15)			-	1.09 (0.22)***	0.26 (0.26)
4. High MVPA/Low ST (25.21 ± 0.29)				-	-0.83 (0.20)***
5. Very High MVPA/Low ST (26.04 ± 0.31)					-

Note: * = $p < .05$; ** = $p < .01$; *** = $p < .001$. Values in parentheses in the first column represent the mean and standard error for each respective profile. Values within the matrix represent the mean of the Profile in each column minus the mean of the Profile in each row. Higher values represent greater levels of mental wellbeing and psychological distress.

Discussion

Results of our analyses identified five distinct movement behavior profiles that were characterized by differences in MVPA and ST patterns. Sleep duration was relatively consistent across the profiles, while descriptively indicating that most students were engaging in sufficient sleep time consistent with 24-hour movement guidelines. Profile membership was associated with several socio-demographic factors, with results suggesting that non-White, older or international students may be most susceptible to poorer lifestyle behaviors. Finally, scores for psychological distress and mental wellbeing were more favorable among students classified into profiles characterized by healthier patterns of movement behaviors (i.e., more MVPA, less ST, adequate sleep). Collectively, these results demonstrate the importance of engaging in a healthy balance of MVPA, ST and sleep as it relates to mental health for emerging adults attending post-secondary institutions, while also highlighting several sociodemographic factors that campus-based interventions should consider targeting to optimize impact.

Previous research has typically found four movement behavior profiles consistently observed during the adolescent period.[32,33] The present study was to our knowledge the first to extend this research by examining movement behavior profiles during emerging adulthood. Overall, the evidence suggests that movement profiles are similar to studies of adolescents, though a fifth profile characterized by very high amounts of MVPA and low ST appears during the emerging adulthood period. Importantly, our findings are compatible with results from studies investigating adolescents in that the majority of emerging adults were classified into a low MVPA/low ST profile (51.2%), followed by profiles characterized by low ST and either high (24.4%) or very high MVPA (12.6%). While it is promising that a small proportion of emerging adults were classified into profiles characterized by high ST (9.4% with low MVPA, 2.3% with high MVPA), overall screen usage among these individuals is over three times the guideline recommendations. Critically, daily reported ST engagement across all five profiles were above the guideline recommendations, suggesting that post-secondary strategies to reduce recreational ST may warrant the most attention among this population.

Findings from the present study also contribute to the growing body of literature that has demonstrated beneficial associations between engaging in healthy movement behavior patterns and indicators of mental health among post-secondary students.[13,34,35] Our results are consistent with previous person-centered analyses among adolescent cohorts,[32,33] in that the unhealthiest profile (i.e., low MVPA/high ST) reported the lowest scores for mental wellbeing and the highest for psychological distress. Moreover, the healthiest profiles – characterized by high or very high MVPA and low ST – reported the most favorable mental health scores. The similarities in mental health scores observed for the healthiest profiles suggests there may be an optimal level of MVPA participation, wherein increasing amounts (i.e., above ~1 hr per day on average) may not provide further benefits and could even be associated with detrimental effects. Closer inspection of the profiles with a combination of consistently low or high levels of both MVPA and ST provides important insight into the influence of each movement behavior on different aspects of mental health. For example, these profiles reported similar scores for mental wellbeing, which suggests that healthier amounts of participation in one movement behavior may partially offset the negative influence of unhealthy amounts of another movement behavior. Different effects were, however, observed for psychological distress. Specifically, engaging in low levels of MVPA and ST was associated with significantly lower psychological distress than high levels of MVPA and ST, thus indicating that ST may have a stronger relationship with psychological distress than MVPA. A systematic review has demonstrated the beneficial effects on mental health of replacing ST with MVPA.[36] Considering sleep duration was adequate across all profiles and only two profiles were characterized by insufficient amounts of weekly MVPA, health promotion strategies that emphasize the importance of reallocating ST to sleep or physical activity may be an optimal approach for improving campus wellbeing.

Having identified predictors of profile membership, our findings provide useful information for the development of interventions that promote campus wellbeing. Although interventions implemented at the population level can have excellent reach, adopting a one-size-fits-all approach may only have a modest impact as it may fail to appeal specifically to those who stand to benefit the most.[37] Taking a socio-culturally targeted approach to intervention design and delivery has been proposed to have a strong potential for reaching sub-groups at greatest risk for poor health outcomes.[38] Considered for our sample, individuals classified into the profile characterized by the least healthy combination of movement behaviors (i.e., low MVPA/high ST) should be targeted given that they reported the poorest scores for both indicators of mental health. Going beyond simply targeting this subgroup by tailoring intervention components based on their sociodemographic attributes may have the largest effects. For instance, our findings would suggest that to help facilitate greater MVPA and reduce ST use, PSI officials should focus on a combination of sociodemographic variables including, but not limited to age, gender, international student status, and race/ethnicity. Despite representing only ~1 in 10 students, allocating resources to facilitate behavior change among the low MVPA/high ST subgroup stands to benefit those experiencing the poorest mental health.

Although the present study provides novel findings that address current knowledge gaps, it is not without limitations. First, the CCWS is a cross-sectional study of students assessed at one single time, and therefore causality cannot be inferred between movement behavior profile membership and mental health outcomes. Second, movement behavior data was self-reported and therefore are prone to recall errors and/or social desirability biases.[39] Third, although the current study had a fairly large overall sample, it should be noted that the response rates were fairly modest across the different PSIs, and that these data are susceptible to response biases. Finally, Cycle 1 was the pilot deployment of the CCWS and was primarily administered among PSIs located in British Columbia and Ontario; and despite most institutions electing to use a stratified random sample, some elected to use alternative methods. As a result, generalizability to all emerging adults attending higher education in Canada may be limited.

In sum, the present study identified subgroups of emerging adults attending higher education based on their movement behaviors and found that profiles characterized by healthier combinations of MVPA, ST and sleep generally report better mental health. Our findings also outlined key sociodemographic characteristics that health promotion materials should be targeted and tailored towards to help those who need it most. Given the disparities in mental health observed in the present study, interventions promoting healthy movement behavior patterns may be a cost-effective means to improve campus health.

Contributions

Conceptualization (DB, MK), Methodology (DB), Formal Analysis (DB), Data Curation (DB), Writing – Original Draft (DB, MK), Writing - Review & Editing (GF), Funding Acquisition (DB, MK)

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Data and Supplementary Material Accessibility

The CCWS dataset is available through protected access (https://www.ccws-becc.ca/). All Mplus code for the analyses is available at https://osf.io/ucbvp/ (DOI 10.17605/OSF.IO/UCBVP).

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