Unlocking Academic Success: Exploring Associations Between 24-Hour Movement Compositions and Academic Performance in College Students

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Abstract

Research has established beneficial associations between 24-hour movement behaviors (i.e., sleep, physical activity, sedentary behavior) and academic performance. However, most studies have focused on individual behaviors, overlooking their interdependence. This study examined the relationship between 24-hour movement compositions and academic performance among college students. A total of 150 college students (M_{age} = 19.2 ± 1.42 years; 69.3% female; 42.7% Hispanic) wore an accelerometer to measure 24-hour movement behaviors for 7 full days. Cumulative grade point average (GPA) and standardized test scores (i.e., SAT) were collected from university records. Compositional linear regression models were computed, with adjustment for covariates (gender and SAT). The overall movement composition was significantly associated with GPA. Sedentary behavior and moderate-to-vigorous physical activity (MVPA) were positively associated with GPA, whereas a negative association was observed for light physical activity (LPA). Replacing up to 20 minutes of LPA with sedentary behavior, sleep, or MVPA was associated with higher GPA. Additionally, substituting sleep with MVPA was associated with higher GPA. Findings suggest that college students’ movement compositions may be related to their academic performance. Longitudinal work is needed to pinpoint specific periods within the semester to better understand when each behavior is most important for academic performance.

Keywords: academic achievement, university students, compositional data analysis, sedentary time, physical activity, sleep

Introduction

In recent decades, successful completion of a college education has increasingly become an integral component in obtaining stable employment opportunities (Carnevale et al., 2010), suggesting that academic success is critical to economic success and upward social mobility in America (Adams et al., 2016). Identifying factors that may improve academic performance is especially important for low-income (i.e., young adults whose families fall below the federal poverty line) and/or first-generation college students (i.e., students whose parents have not earned a 4-year college or university degree; Adams et al., 2016; Engle & Tinto, 2008; Gault et al., 2014). Furthermore, higher academic achievement in college can facilitate more job opportunities (French et al., 2015), and plays a significant role in the hiring process, especially in applicants with limited work experience (Rynes et al., 1997). Given the important role academic performance can play in success in adulthood, it is important to identify factors correlated with academic success to inform intervention development.

Previous research has established a link between adopting a healthy lifestyle and experiencing advantageous outcomes in academic performance (Pellerine et al., 2023; Wald et al., 2014). Several behaviors that individuals engage in over the course of a day have received varying amounts of attention for their role in academic performance among college students. The research on the relationship between moderate-to-vigorous physical activity (MVPA) and academic achievement is mixed with some studies finding positive associations (Wald et al., 2014; Wunsch et al., 2021), while other work has observed null associations (Felez-Nobrega et al., 2017, 2018). However, a key limitation is that most of this literature has used self-reported instruments which are prone to bias and recall errors (Sallis & Saelens, 2000). There has also been an emphasis on the influence of sleep. Well-documented evidence has shown better quality, longer duration, and greater consistency of sleep are each positively associated with academic performance among college students (Okano et al., 2019; Taylor et al., 2013; Wald et al., 2014). Finally, there has been much less focus on sedentary behavior in relation to academic performance during college despite significant attention among children and adolescents (Esteban-Cornejo et al., 2015; Syväoja et al., 2013). To our knowledge, the only study to date found sedentary time on weekdays or weekends was not associated with academic achievement among college students (Felez-Nobrega et al., 2018). Taken together, this literature highlights that mixed results have been found in studies examining independent links between movement behaviors and academic performance among college students.

More recently researchers have begun to adopt an integrative approach to examine the interactive influence of sedentary behavior, sleep, and physical activity in relation to a several outcomes (Groves et al., 2024; Rollo et al., 2020). Collectively, these behaviors are commonly referred to as 24-hour movement behaviors or the 24-hour activity cycle (Falck et al., 2021). The emphasis on taking an integrative approach to understand the interactive impact of movement behaviors on health began in 2016 with the release of Canadian 24-hour Movement Guidelines for Children and Youth (Tremblay et al., 2016). The first guidelines for adults were released more recently in 2020 (Ross et al., 2020), and represent threshold-based recommendations for how much physical activity, sedentary behavior (recreational screen time and sitting), and sleep adults should engage in over the course of a whole “healthy” day. The 24-hour movement paradigm acknowledges that movement behaviors are codependent whereby time spent in one behavior (e.g., sleep) takes away from time that can be allocated to others (e.g., physical activity) (Pedišić et al., 2017).

The importance of taking an integrated approach with movement behaviors and academic performance has been well established in literature focused on children and adolescents in that meta-analytic evidence has demonstrated a small effect ($r = .17$) between meeting all three components of the 24-hour movement guidelines and academic performance (Bao et al., 2024). In contrast, only one study has examined these relationships with college students (Pellerine et al., 2023). Findings from a study of 411 Canadian college students revealed that sleep guideline adherence was associated with higher average grades. Conversely, those who adhered to sedentary time guidelines exhibited significantly lower average grades and no substantial distinction in average grades was observed based on adherence to physical activity guidelines (Pellerine et al., 2023). While this study investigated 24-hour movement guideline adherence, associations with academic performance were only examined independently, which fails to consider the collective influence of all movement behaviors engaged in over the course of a whole day. Further, examining adherence to threshold-based guidelines ignores much of the variability in movement behaviors through binary categorization when other approaches that are better suited to analyze the full range of 24-hour movement behavior data are available.

Compositional data analysis (CoDA) is a statistical approach designed for data in which each variable represents parts of a whole, such as percentages or proportions relative to one another. This approach takes into account the constrained nature of the data while also recognizing that each component of the composition is mutually exhaustive and exclusive (Pawlowsky-Glahn & Buccianti, 2011). For these reasons, CoDA is particularly applicable to time-use epidemiology and the 24-hour movement paradigm (Chastin et al., 2015) given that it focuses on the whole day and time spent engaging in one behavior comes at the expense of time that could be spent engaging in other behaviors. Methodological work has shown that adopting a CoDA approach overcomes the potential issue of multicollinearity amongst movement behaviors when absolute time-use values are used in traditional statistical methodologies (Dumuid et al., 2018). CoDA techniques can be used to address this limitation through taking the co-dependent nature of these behaviors into account (Chastin et al., 2015).

While CoDA techniques are commonly used in the field of behavior medicine to examine 24-hour movement compositions in relation to health indicators (Groves et al., 2024; Janssen et al., 2020), associations with academic performance have seen limited attention. In the only study to our knowledge, Ng and colleagues (2021) observed positive and negative associations for sedentary time and LPA in relation to academic performance, respectively, among a sample of 931 Australian adolescent students. They also found that reallocating time from LPA to other behaviors and increasing sedentary time from other behaviors was beneficial for academic performance. Collectively, these findings demonstrate which behaviors may hold promise for improving academic performance, however, future work is needed to examine the replicability of these results and generalizability to other samples (e.g., college students).

Another key limitation in the literature examining the relationship between 24-hour movement behaviors and academic performance – regardless of the analytic approach – is the omission of general intelligence as a covariate within these models. Extensive research in the field of cognitive psychology has demonstrated that general intelligence (*g*) is positively correlated with academic performance (e.g., rho = .21; Richardson et al., 2012). Standardized tests such as the SAT and ACT are highly *g*-loaded and positively predict college grade point averages (GPAs) before and after removing variance shared with *g* (Coyle & Pillow, 2008). Therefore, models examining 24-hour movement behaviors in relation to academic performance should be adjusted for *g* or a *g*-loaded factor (i.e., SAT or ACT) to estimate the magnitude and direction of the associations more precisely for each movement behavior.

In light of the aforementioned knowledge gaps, the purpose of this study was to (1) examine the relationship between device-assessed 24-hour movement compositions and academic performance among college students using CoDA, and (2) determine the influence of reallocating time between movement behaviors (i.e., MVPA, light physical activity [LPA], sedentary behavior, and sleep) on academic performance. Based on previous literature (Felez-Nobrega et al., 2018; Ng et al., 2021; Okano et al., 2019; Pellerine et al., 2023), it was hypothesized that sedentary behavior and sleep would be positively associated with academic performance, whereas a negative and null associations would be observed for LPA and MVPA, respectively. Additionally, it was hypothesized that replacing MVPA or LPA with sleep or sedentary behavior would be associated with favorable benefits for academic performance.

Method

Participants and procedure

A convenience sample of 150 participants (Mean age = 19.2 ± 1.42 years) was recruited from an introductory psychology participant pool at a large Hispanic-serving institution in the Southwestern United States. The student body of this institution consists of 45% first-generation post-secondary education attendees and over 40% of students who are Pell Grant eligible (awarded only to students who display exceptional financial need). The sample was primarily female (69.3%; 28.0% male; 2.7% other/missing), with the majority of the sample identifying as Hispanic (42.7%), followed by White (18.0%), Multi-ethnic (17.3%), Asian (10.0%), Black (8.0%), and other/missing (4.0%).

This cross-sectional study was part of a larger project designed to examine correlates of physical activity behavior among college students. Data collection occurred during the Spring 2023 semester. In total, 376 students participated in the larger project, however, only 150 participants consented to have their university records accessed and had a valid accelerometry sample, which represents the analytic sample in the present study. All participants completed an online survey in which they first provided consent, which also included consenting for the research team to obtain their SAT, ACT, and GPAs from university records, followed by a series of questionnaires (see Porter et al., 2024 for more details about the larger project). Following their completion of the survey, participants attended a research lab on campus to receive an accelerometer that was placed their non-dominant wrist to be worn for a total of nine days, after which they returned the device to the lab. Participants were compensated with course credit for study completion. The Institutional Review Board at the University of Texas at San Antonio (FY21-22-334) approved the study procedures.

Measures

Device-assessed Movement Behaviors

Movement behaviors were assessed using ActiGraph GT3X+ triaxial accelerometers (ActiGraph Corp., Pensacola, FL, USA). The wear time period consisted of nine days during which participants were asked to wear the accelerometer on their non-dominant wrist for seven full consecutive days (second to eighth day) and to only take the device off for prolonged water immersion. The first (device pick-up) and last day (device return) of the wear period were only partial wear days and were therefore removed from our analyses. Accelerometer placement on the wrist was selected based on prior research demonstrating greater compliance in comparison to placement on the waist (Ellis et al., 2016). The accelerometers were initialized to sample at 30 Hz with idle sleep mode enabled and the subsequent data were downloaded using ActiLife (Version 6.13.5) in GT3X+ file format. Raw accelerometry data files were processed in R and R Studio using the free open-source *GGIR* package (Version 2.9.0; Van Hees et al., 2024). Signal processing using the *GGIR* package was performed according to the default GGIR settings for autocalibration using local gravity as a reference (van Hees et al., 2014), detection of implausible values, and identification of non-wear time. Periods of non-wear time are imputed by default in *GGIR* whereby missing data is imputed by the average at similar time points on other days of the week for that participant (van Hees et al., 2013). Average daily time spent in MVPA, LPA, and sedentary behavior was computed using the Hildebrand et al. (2017) cut points for segmenting levels of intensity among adults wearing an ActiGraph device on their non-dominant wrist: sedentary behavior (<44.8 milligravitational [m*g*] units), LPA (44.8 to 100.59 m*g*), MVPA (≥ 100.6 m*g*). A polysomnography-validated accelerometer algorithm was used to calculate average daily sleep duration (van Hees et al., 2018). Time-based estimates were averaged across all valid days for the 24-hour movement composition. The measurement day was determined from each measurement day's wake time to the next measurement day's wake time (i.e., wake-to-wake) as opposed to midnight-to-midnight, which captures two separate periods of sleep. Two inclusion criteria were specified to be considered valid accelerometry data in the present study: 1) a valid day was defined as at least 16 hours of accelerometer wear; and 2) a valid sample was defined as having ≥ 1 valid day. One day of data has been determined to be sufficient for generating stable group-level estimates of physical activity in population-level research (Belcher et al., 2021). No specific restrictions were made regarding sleep duration.

Academic Performance

Institutional cumulative GPAs were collected from university records at the end of the semester (Spring 2023) during which the study was conducted and used as an estimate of academic performance. Institutional cumulative GPAs are calculated across all courses taken at that time and do include any transfer course credit. College GPA ranged from 0 to 4.0, with higher scores indicating higher levels of academic performance.

Covariates

Covariates included gender, and a measure of general intelligence (SAT/ACT test scores). Gender was self-reported by participants and was included based on previously established associations with 24-hour movement behaviors among college students (Brown et al., 2022). SAT and ACT scores were collected from university records. ACT scores were converted to SAT scores as recommended by the College Board as ACT scores correlate strongly with SAT scores (r=.89; College Board, 2018). SAT scores were included as covariates as they have been shown to positively predict college GPAs (Coyle & Pillow, 2008).

Data Analysis

All analyses were performed in R (Version 4.3.2) and R Studio (Version 2022.12.0+353). Descriptive statistics and frequencies were computed for each variable. Missing data on covariates were imputed using multiple imputation using the *mice* and *miceadds* packages (Buuren & Groothuis-Oudshoorn, 2011; Robitzsch & Grund, 2023). A total of 38 multiply imputed datasets were created as per recommendations to set m > 100 times the highest fraction of missing information (38% for SAT scores; White et al., 2011). One of the 38 dataset generated was selected at random and used for analyses given that the subsequent package used for transforming data to perform compositional data analysis cannot handle multiply imputed datasets. When multiple imputation and full information maximum likelihood cannot be implemented to handle missing data, single stochastic regression imputation (i.e., using only one of N multiply imputed datasets) is considered the next best alternative over other procedures such as listwise deletion and mean imputation because it models in random error to obtain more realistic values (Allison, 2001).

Next, CoDA was conducted using the *compositions* package (Boogaart et al., 2023). Average minutes of LPA, MVPA, sedentary behavior, and sleep across all valid days were calculated, and then linearly adjusted to sum to 1440 min (24hrs). Next, the compositional variation matrix was calculated. The variation matrix describes the dispersion of the components within the composition and was derived by calculating the variation of the logarithms of all possible pair-wise ratios. Smaller values (closer to zero) indicate that the time spent between the two movement behaviors are highly co-dependent (Chastin et al., 2015), whereas larger values represent less co-dependency.

The next step involved transforming the absolute movement behavior data into relative values to reflect that the behaviors exist within a finite period (i.e., 24-hour), which was done by creating a set of isometric log-ratio (ilr) coordinates (Aitchison, 1982). Given that ilrs cannot be computed if there are zeros in the data, the first step involved checking each behavioral component of the four-part composition (i.e., sleep, sedentary behavior, LPA, MVPA) for zero values. Once we confirmed none were present, we created ilr coordinates using a sequential binary partition process (Egozcue & Pawlowsky-Glahn, 2005). The sequential binary partition was set up with the following ilr coordinates: (1) sleep vs sedentary behavior + LPA + MVPA, (2) sedentary behavior vs LPA + MVPA, (3) LPA vs MVPA. To address Aim 1, a compositional multivariate analysis of covariance model was computed to examine if the daily composition was associated with academic performance. Next, three additional sets of ilrs were constructed, with each set treating a different movement behavior as the primary variable of interest. Using the four sets of ilrs, a series of multiple linear regression models (one for each set of ilrs) were computed to examine the associations between each movement behavior (relative to the remaining behaviors) and academic performance. The regression coefficients and standard errors for the first ilr coordinate for sleep, sedentary behavior, LPA, and MVPA are presented. All analyses were adjusted for gender and standardized test scores. Assumptions for linearity, homogeneity and normality were examined using the performance package (Lüdecke et al., 2021). All assumptions were satisfied for each model.

For Aim 2, the *deltacomp* package (Stanford & Dumuid, 2022) was used to compute a series of 1-to-1 compositional isotemporal substitution models to assess the hypothetical influence on academic performance of reallocating 5 to 20 minutes of time across each pair of movement behaviors (e.g., sleep to MVPA, sedentary behavior to LPA, LPA to MVPA), adjusted for gender and standardized test scores. Compositional isotemporal substitution modeling estimates the relative effect of replacing time spent in one behavior with an equivalent amount of time in another behavior

(Dumuid et al., 2019). Beta coefficients and 95% confidence intervals are presented. Statistical significance was set at $p < .05$.

Results

Missing data ranged from 2.0% for age/gender to 32% for SAT scores. Of the 150 participants who met inclusion criteria for a valid accelerometry sample ($n = 9$ did not meet the inclusion criteria), an average of 5.55 + 1.83 SD total valid days were recorded with an average wear time of 1430 ± 64.4 SD minutes and an average non-wear time percentage of 6.90% ± 11.4 SD. Participants' average GPA was 3.21 ± 0.7 SD, and their average SAT score was 1120 ± 138 SD. On average, participants' 24-hour movement composition was comprised of 10.6 hours sleeping (44.2% of the 24-hour period), 10.2 hours of sedentary behavior (42.5%), 2.2 hours of LPA (9.2%), and 1.0 hours of MVPA (4.2%) (Figure 1). The variation matrix for the movement composition is presented in Table 1.

Aim 1

The daily time-use composition, adjusted for gender and standardized test scores, was significantly associated with academic performance; $F(3,143) = 5.67$, $p = .001$, explaining 11.8% of the variance (Adjusted $R^2 = 0.118$). When examining each behavior relative to the other behaviors, positive associations were observed between sedentary behavior (B = 0.68 ± 0.30 *SE*, $p = .03$) and MVPA (B = 0.27 ± 0.12 *SE*, $p = .03$) with academic performance, whereas a negative association was observed for LPA (B =

-0.56 ± 0.16 *SE*, $p < .001$) and a null association was observed for sleep (B = -0.39 ± 0.34 *SE*, $p = .25$).

Aim 2

Compositional isotemporal substitution modeling revealed that reallocating up to 20 minutes of LPA to sedentary behavior, sleep, or MVPA (B = 0.02 to 0.15, *p*s < .05) was associated with significantly higher academic performance. Moreover, substituting up to 20 minutes of sleep with MVPA was also associated with significantly higher academic performance (B = 0.02 to 0.77, *p*s < .05). Other reallocations across behaviors were non-significant ($p > .05$). Results are presented visually in Figure 2.

Discussion

The purpose of this study was to examine the relationship between device-assessed 24-hour movement compositions and academic performance among college students and determine the hypothetical influence of reallocating time between movement behaviors. Students' daily time-use composition was significantly associated with academic performance in college. Notably, positive associations were observed between sedentary behavior and MVPA with academic performance, whereas a negative association was found for LPA and a null association for sleep. Replacing up to 20 minutes of LPA with sedentary behavior, sleep, or MVPA was associated with higher academic performance. Moreover, reallocating up to 20 minutes of sleep with MVPA was also associated with higher academic performance. Findings from the current study suggest daily time use behaviors may be an intervention target for improving academic performance among college students, but more work is needed to test the causal nature of these relationships.

While prior studies have established independent links between movement behaviors and academic performance, this study considers their co-dependence through the implementation of CoDA. As hypothesized, there was a significant association between the movement composition and academic performance. The present findings build on previous research of Pellerine and colleagues (2023) through moving beyond examining threshold-based guideline adherence – which fails to consider much of the variability in behaviors – and the use of device-based estimates of physical activity, sedentary behavior, and sleep. Important differences emerged upon closer inspection of the individual behaviors. Specifically, a positive association was observed between sedentary behavior and academic performance, which aligns with previous research by Pellerine and colleagues (2023). This finding aligns with expectations, as sedentary activities like studying and attending lectures are often performed in stationary postures (Felez-Nobrega et al., 2018). In contrast to our hypothesis of a null association, MVPA was also positively associated with academic performance. This finding does, however, support accumulating evidence demonstrating favorable associations between MVPA and academic achievement among college students (Wald et al., 2014; Wunsch et al., 2021). Previous work has shown MVPA is positively linked to cognition, which is understood to drive learning, memory, and ultimately, academic performance (Gomez-Pinilla & Hillman, 2013). In contrast to the beneficial associations observed for MVPA, an inverse relationship was found for LPA and academic performance. This finding is consistent with previously observed CoDA results among adolescents (Ng et al., 2021). LPA may include time spent socializing or working, detracting from activities that are more beneficial to academic success.

Sleep is believed to play a crucial role in memory consolidation (Diekelmann & Born, 2010; Lewis & Durrant, 2011), thus potentially enhancing academic performance among college students. However, this notion was not supported in the present study. Contrary to our expectations and previous research (Okano et al., 2019; Taylor et al., 2013; Wald et al., 2014), we did not find a significant association between sleep duration and academic performance relative to other behaviors. One potential explanation for this null effect is the methodological differences in sleep assessment via accelerometry versus polysomnography (PSG), which is a gold standard for assessing sleep (Van Hees et al., 2015). The American Academy of Sleep Medicine recognizes accelerometry – which measures sleep based on immobility (i.e., low frequency of changes in arm angle; Van Hees et al., 2015) – as a valid method (Littner et al., 2003), although it introduces more noise compared to PSG, which uses brain electrical activity to determine sleep periods. Sleep measured via accelerometry is more of a reflection of time in bed and commonly overestimates sleep periods as sleep will often occur well after a period of wrist immobility (Marino et al., 2013). This may mean that sleep was overestimated in the present study at the expense of sedentary behavior. Research has also shown that accelerometry has reduced validity for assessing sleep-wake patterns in individuals with poor sleep quality, which is a common issue among college students (Owens et al., 2017). Together, these limitations may partly explain why students' sleep durations exceeded recommendations. It is possible students were on their phone or watching TV while lying in bed, which could have been captured as sleep rather than sedentary behavior. Using alternative sleep assessment methods that use electroencephalographic sensors such as at-home research-grade sleep devices (e.g., DREEM, Zmachine) are becoming more readily available and can be used to improve measurement precision in future studies.

While significant associations with academic performance were observed for several individual movement behaviors (relative to others), it is important to recognize which behaviors time should be reallocated to (or away from) to optimize students’ grades. Findings from our isotemporal substitution models suggest that students should look to replace time spent engaging in LPA with MVPA, sedentary behavior, or sleep to improve their academic performance. These substitutions align with previous research that suggests MVPA and sleep support memory consolidation and time spent studying (sedentary behavior) can aid in memory formation and improve academic performance (Erickson et al., 2011; Felez-Nobrega et al., 2017; Okano et al., 2019). Despite sedentary behavior often being associated with negative health outcomes, it can play a beneficial role in academic settings. Further, prioritizing MVPA at the expense of sleep also appears to be beneficial for grades among this sample, which may be a reasonable approach considering sleep duration exceeded the recommendation for this age group (i.e., 7 to 9 hours). Collectively, our isotemporal substitution findings provide insight into the trade-offs between time spent engaging in different behaviors over the course of the day as it relates to students' grades. This information can be utilized by campus-based health promotion campaigns to tailor their efforts towards promoting certain behaviors at the expense of others to support their academic success.

Behavioral interventions on campuses have traditionally focused on addressing individual behaviors in isolation, such as campaigns designed to increase physical activity or improve sleep quality (Haverkamp et al., 2020; Saruhanjan et al., 2021). However, focusing strictly on one behavior may be insufficient as movement behaviors (physical activity, sleep, and sedentary behavior) are co-dependent over the course of a day and thus have an interactive influence on academic achievement (Chastin et al., 2015). From this perspective, promoting a single behavior neglects the fact that increasing time in one behavior inevitably results in less time available for other behaviors. Adopting an integrative "whole day" intervention approach is therefore worth considering and our isotemporal substitution findings highlight certain behavioral trade-offs that can be targeted. For example, our estimates suggest an intervention aiming to replace LPA with MVPA may be most promising for improving academic performance. Moving forward, collaboration between campus health services and academic researchers can help develop a more comprehensive understanding of the relationship between movement behaviors and academic performance via longitudinal designs, which is becoming more feasible with the increased use of commercial wearable devices (e.g., Fitbit, Garmin, Apple Watch) that can provide data over longer periods.

While this study has many strengths such as the use of device-based movement behavior assessment and consideration of the co-dependent nature of movement behavior data within a compositional framework, it is not without limitations. First, relying solely on accelerometer-measured sedentary behavior fails to provide any contextual information which would provide insight into time spent studying versus time spent engaging in recreational activities such as watching TV or playing video games (i.e., active versus passive sedentary pursuits). Future research should gather contextual information about movement behaviors by using sensor-based triggering of ecological momentary assessment prompts in combination with accelerometers. Second, convenience sampling was employed, and data from this study was part of a larger study focused on correlates of physical activity behavior. Therefore, the findings may not be generalizable as it is possible that only individuals interested in participating in a study focused on physical activity signed up, which may explain the above guideline levels of physical activity behavior observed. Third, the study's design, consisting of a baseline assessment of behavior and evaluation of cumulative academic performance, limits the insight provided on movement compositions and academic performance. Further longitudinal work is needed to pinpoint specific periods within the semester, such as midterms or finals, to better understand when each behavior is most important for academic performance. Fourth, this study only assessed sleep duration in relation to academic performance. Other sleep metrics such as sleep quality and consistency have been shown to be stronger predictors of academic achievement than sleep duration and deserve attention in future studies (Okano et al., 2019; Phillips et al., 2017). Finally, it should be acknowledged that idle sleep mode, a function of ActiGraph devices, was left enabled on the accelerometers. Idle sleep mode can impact accurate assessment of low-intensity behaviors such as sleep and sedentary behavior and imposes a proprietary pre-processing of the data (Van Hees et al., 2024).

Overall, the findings from the present study suggest that college students’ movement compositions may be related to their academic performance when adopting an integrative 24-hour approach. Sedentary behavior and MVPA were linked with better academic performance, whereas time spent engaging in LPA may detract from student performance. Reallocating time from LPA to sedentary behavior, sleep, or

MVPA appears to have potential for optimizing academic performance. Although more longitudinal work is needed to better understand these relationships, these findings suggest campus-based campaigns seeking to improve academic performance should consider recognizing the importance of all movement behaviors students engage in over the course of a whole day as opposed to isolated approaches focused on individual components of a 24-hour period.

References

Adams, D. R., Meyers, S. A., & Beidas, R. S. (2016). The relationship between financial strain, perceived stress, psychological symptoms, and academic and social integration in undergraduate students. *Journal of American College Health*, *64*(5), 362–370. http://dx.doi.org/10.1080/07448481.2016.1154559

Aitchison, J. (1982). The statistical analysis of compositional data. *Journal of the Royal Statistical Society: Series B (Methodological)*, *44*(2), 139–160. https://doi.org/10.1111/j.2517-6161.1982.tb01195.x

Allison, P. D. (2001). *Missing Data*. SAGE Publications. https://books.google.com/books?id=ZtYArHXjpB8C

Bao, R., Qin, H., Memon, A. R., Chen, S., López-Gil, J. F., Liu, S., Zou, L., & Cai, Y. (2024). Is adherence to the 24-h movement guidelines associated with greater academic-related outcomes in children and adolescents? A systematic review and meta-analysis. *European Journal of Pediatrics*. https://doi.org/10.1007/s00431-024-05461-2

Belcher, B. R., Wolff-Hughes, D. L., Dooley, E. E., Staudenmayer, J., Berrigan, D., Eberhardt, M. S., & Troiano, R. P. (2021). US population-referenced percentiles for wrist-worn accelerometer-derived activity. *Medicine and Science in Sports and Exercise*, *53*(11), 2455–2464. https://doi.org/10.1249/MSS.0000000000002726

Boogaart, K. G. van den, Tolosana-Delgado, R., & Bren, M. (2023). *compositions: Compositional Data Analysis*. https://CRAN.R-project.org/package=compositions

Brown, D. M. Y., Faulkner, G. E. J., & Kwan, M. Y. W. (2022). Healthier movement behavior profiles are associated with higher psychological wellbeing among emerging adults attending post-secondary education. *Journal of Affective Disorders*, Online Ahead of Print. https://doi.org/10.1016/j.jad.2022.09.111

Buuren, S. van, & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Carnevale, A. P., Smith, N., & Strohl, J. (2010). Help Wanted: Projections of Jobs and Education Requirements through 2018. Executive Summary. In *Georgetown University Center on Education and the Workforce*. Georgetown University Center on Education and the Workforce. https://eric.ed.gov/?id=ED524311

Chastin, S. F., Palarea-Albaladejo, J., Dontje, M. L., & Skelton, D. A. (2015). Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: A novel compositional data analysis approach. *PloS One*, *10*(10), e0139984. https://doi.org/10.1371/journal.pone.0139984

Coyle, T. R., & Pillow, D. R. (2008). SAT and ACT predict college GPA after removing g. *Intelligence*, *36*(6), 719–729.

Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature Reviews Neuroscience*, *11*(2), 114–126. https://doi.org/10.1038/nrn2762

Dumuid, D., Pedišić, Ž., Stanford, T. E., Martín-Fernández, J.-A., Hron, K., Maher, C. A., Lewis, L. K., & Olds, T. (2019). The compositional isotemporal substitution model: A method for estimating changes in a health outcome for reallocation of time between sleep, physical activity and sedentary behaviour. *Statistical Methods in Medical Research*, *28*(3), 846–857. https://doi.org/10.1177/0962280217737805

Dumuid, D., Stanford, T. E., Martin-Fernández, J.-A., Pedišić, Ž., Maher, C. A., Lewis, L. K., Hron, K., Katzmarzyk, P. T., Chaput, J.-P., & Fogelholm, M. (2018). Compositional data analysis for physical activity, sedentary time and sleep research. *Statistical Methods in Medical Research*, *27*(12), 3726–3738. https://doi.org/10.1177/0962280217710835

Egozcue, J. J., & Pawlowsky-Glahn, V. (2005). Groups of parts and their balances in compositional data analysis. *Mathematical Geology*, *37*(7), 795–828. https://doi.org/10.1007/s11004-005-7381-9

Ellis, K., Kerr, J., Godbole, S., Staudenmayer, J., & Lanckriet, G. (2016). Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification. *Medicine and Science in Sports and Exercise*, *48*(5), 933–940. https://doi.org/10.1249/MSS.0000000000000840

Engle, J., & Tinto, V. (2008). Moving beyond access: College success for low-income, first-generation students. *Pell Institute for the Study of Opportunity in Higher Education*.

Erickson, K. I., Voss, M. W., Prakash, R. S., Basak, C., Szabo, A., Chaddock, L., Kim, J. S., Heo, S., Alves, H., White, S. M., & others. (2011). Exercise training increases size of hippocampus and improves memory. *Proceedings of the National Academy of Sciences*, *108*(7), 3017–3022. https://doi.org/10.1073/pnas.1015950108

Esteban-Cornejo, I., Martinez-Gomez, D., Sallis, J. F., Cabanas-Sánchez, V., Fernández-Santos, J., Castro-Piñero, J., Veiga, O. L., & UP & DOWN Study Group. (2015). Objectively measured and self-reported leisure-time sedentary behavior and academic performance in youth: The UP&DOWN Study. *Preventive Medicine*, *77*, 106–111. https://doi.org/10.1016/j.ypmed.2015.05.013

Falck, R. S., Davis, J. C., Li, L., Stamatakis, E., & Liu-Ambrose, T. (2021). Preventing the '24-hour Babel': The need for a consensus on a consistent terminology scheme for physical activity, sedentary behaviour and sleep. *British Journal of Sports Medicine*. https://doi.org/10.1136/bjsports-2021-104487

Felez-Nobrega, M., Hillman, C. H., Cirera, E., & Puig-Ribera, A. (2017). The association of context-specific sitting time and physical activity intensity to working memory capacity and academic achievement in young adults. *The European Journal of Public Health*, *27*(4), 741–746. https://doi.org/10.1093/eurpub/ckx021

Felez-Nobrega, M., Hillman, C. H., Dowd, K. P., Cirera, E., & Puig-Ribera, A. (2018). ActivPAL™ determined sedentary behaviour, physical activity and academic achievement in college students. *Journal of Sports Sciences*, *36*(20), 2311–2316. https://doi.org/10.1080/02640414.2018.1451212

French, M. T., Homer, J. F., Popovici, I., & Robins, P. K. (2015). What you do in high school matters: High school GPA, educational attainment, and labor market earnings as a young adult. *Eastern Economic Journal*, *41*, 370–386. https://doi-org.libweb.lib.utsa.edu/10.1057/eej.2014.22

Gault, B., Reichlin, L., & Román, S. (2014). *College affordability for low-income adults: Improving returns on investment for families and society*.

Gomez-Pinilla, F., & Hillman, C. (2013). The influence of exercise on cognitive abilities. *Comprehensive Physiology*, *3*(1), 403. https://doi.org/10.1002%2Fcphy.c110063

Groves, C. I., Huong, C., Porter, C. D., Summerville, B., Swafford, I., Witham, B., Hayward, M., Kwan, M. Y. W., & Brown, D. M. Y. (2024). Associations between 24-h movement behaviors and indicators of mental health and well-being across the lifespan: A systematic review. *Journal of Activity, Sedentary and Sleep Behaviors*, *3*(1), 9. https://doi.org/10.1186/s44167-024-00048-6

Haverkamp, B. F., Wiersma, R., Vertessen, K., van Ewijk, H., Oosterlaan, J., & Hartman, E. (2020). Effects of physical activity interventions on cognitive outcomes and academic performance in adolescents and young adults: A meta-analysis. *Journal of Sports Sciences*, *38*(23), 2637–2660. https://doi.org/10.1080/02640414.2020.1794763

Hildebrand, M., Hansen, B. H., van Hees, V. T., & Ekelund, U. (2017). Evaluation of raw acceleration sedentary thresholds in children and adults. *Scandinavian Journal of Medicine & Science in Sports*, *27*(12), 1814–1823. https://doi.org/10.1111/sms.12795

Janssen, I., Clarke, A. E., Carson, V., Chaput, J.-P., Giangregorio, L. M., Kho, M. E., Poitras, V. J., Ross, R., Saunders, T. J., Ross-White, A., & Chastin, S. F. M. (2020). A systematic review of compositional data analysis studies examining associations between sleep, sedentary behaviour, and physical activity with health outcomes in adults. *Applied Physiology, Nutrition, and Metabolism = Physiologie Appliquee, Nutrition Et Metabolisme*, *45*(10 (Suppl. 2)), S248–S257. https://doi.org/10.1139/apnm-2020-0160

Lewis, P. A., & Durrant, S. J. (2011). Overlapping memory replay during sleep builds cognitive schemata. *Trends in Cognitive Sciences*, *15*(8), 343–351.

Littner, M., Kushida, C. A., Anderson, W. M., Bailey, D., Berry, R. B., Davila, D. G., Hirshkowitz, M., Kapen, S., Kramer, M., & Loube, D. (2003). Practice parameters for the role of actigraphy in the study of sleep and circadian rhythms: An update for 2002. *Sleep*, *26*(3), 337–341.

Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). performance: An R Package for Assessment, Comparison and Testing of Statistical Models. *Journal of Open Source Software*, *6*(60), 3139. https://doi.org/10.21105/joss.03139

Marino, M., Li, Y., Rueschman, M. N., Winkelman, J. W., Ellenbogen, J. M., Solet, J. M., Dulin, H., Berkman, L. F., & Buxton, O. M. (2013). Measuring sleep: Accuracy, sensitivity, and specificity of wrist actigraphy compared to polysomnography. *Sleep*, *36*(11), 1747–1755.

Ng, E., Wake, M., Olds, T., Lycett, K., Edwards, B., Le, H., & Dumuid, D. (2021). Equivalence curves for healthy lifestyle choices. *Pediatrics*, *147*(4).

Okano, K., Kaczmarzyk, J. R., Dave, N., Gabrieli, J. D., & Grossman, J. C. (2019). Sleep quality, duration, and consistency are associated with better academic performance in college students. *NPJ Science of Learning*, *4*(1), 16. https://doi.org/10.1038/s41539-019-0055-z

Owens, H., Christian, B., & Polivka, B. (2017). Sleep behaviors in traditional-age college students: A state of the science review with implications for practice. *Journal of the American Association of Nurse Practitioners*, *29*(11), 695–703. https://doi.org/10.1002/2327-6924.12520

Pawlowsky-Glahn, V., & Buccianti, A. (2011). *Compositional data analysis*. Wiley Online Library.

Pedišić, Ž., Dumuid, D., & S Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology*, *49*(2), 252–269.

Pellerine, L. P., Bray, N. W., Fowles, J. R., Furlano, J. A., Morava, A., Nagpal, T. S., & O'Brien, M. W. (2023). Increased recreational screen time and time to fall asleep are associated with worse academic performance in Canadian undergraduates. *International Journal of Health Promotion and Education*, 1–11. https://doi.org/10.1080/14635240.2023.2248091

Phillips, A. J. K., Clerx, W. M., O'Brien, C. S., Sano, A., Barger, L. K., Picard, R. W., Lockley, S. W., Klerman, E. B., & Czeisler, C. A. (2017). Irregular sleep/wake patterns are associated with poorer academic performance and delayed circadian and sleep/wake timing. *Scientific Reports*, *7*(1), 3216. https://doi.org/10.1038/s41598-017-03171-4

Porter, C., Groves, C., Huong, C., & Brown, D. (2024). *Predicting Physical Activity Behavior among University Students using the Multi-Process Action Control Framework*. PsyArXiv. https://doi.org/10.31234/osf.io/q4zjw

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353–387. https://psycnet.apa.org/doi/10.1037/a0026838

Robitzsch, A., & Grund, S. (2023). *miceadds: Some Additional Multiple Imputation Functions, Especially for "mice."* https://CRAN.R-project.org/package=miceadds

Rollo, S., Antsygina, O., & Tremblay, M. S. (2020). The whole day matters: Understanding 24-hour movement guideline adherence and relationships with health indicators across the lifespan. *Journal of Sport and Health Science*, *9*(6), 493–510. https://doi.org/10.1016/j.jshs.2020.07.004

Ross, R., Chaput, J.-P., Giangregorio, L. M., Janssen, I., Saunders, T. J., Kho, M. E., Poitras, V. J., Tomasone, J. R., El-Kotob, R., McLaughlin, E. C., Duggan, M., Carrier, J., Carson, V., Chastin, S. F., Latimer-Cheung, A. E., Chulak-Bozzer, T., Faulkner, G., Flood, S. M., Gazendam, M. K., … Tremblay, M. S. (2020). Canadian 24-Hour Movement Guidelines for Adults aged 18–64 years and Adults aged 65 years or older: An integration of physical activity, sedentary behaviour, and sleep. *Applied Physiology, Nutrition, and Metabolism*, *45*(10), S57–S102. https://doi.org/10.1139/apnm-2020-0467

Rynes, S. L., Orlitzky, M. O., & Bretz Jr., R. D. (1997). Experienced Hiring Versus College Recruiting: Practices and Emerging Trends. *Personnel Psychology*, *50*(2), 309–339. https://doi.org/10.1111/j.1744-6570.1997.tb00910.x

Sallis, J. F., & Saelens, B. E. (2000). Assessment of physical activity by self-report: Status, limitations, and future directions. *Research Quarterly for Exercise and Sport*, *71*(sup2), 1–14. https://doi.org/10.1080/02701367.2000.11082780

Saruhanjan, K., Zarski, A.-C., Bauer, T., Baumeister, H., Cuijpers, P., Spiegelhalder, K., Auerbach, R. P., Kessler, R. C., Bruffaerts, R., Karyotaki, E., & others. (2021). Psychological interventions to improve sleep in college students: A meta-analysis of randomized controlled trials. *Journal of Sleep Research*, *30*(1), e13097. https://doi.org/10.1111/jsr.13097

Stanford, T., & Dumuid, D. (2022). *deltacomp: Functions to Analyse Compositional Data and Produce Confidence Intervals for Relative Increases and Decreases in the Compositional Components*.

Syväoja, H., Kantomaa, M. T., Ahonen, T., Hakonen, H., Kankaanpää, A., & Tammelin, T. H. (2013). Physical activity, sedentary behavior, and academic performance in Finnish children. *Medicine and Science in Sports and Exercise*, *45*(11).

Taylor, D. J., Vatthauer, K. E., Bramoweth, A. D., Ruggero, C., & Roane, B. (2013). The role of sleep in predicting college academic performance: Is it a unique predictor? *Behavioral Sleep Medicine*, *11*(3), 159–172. https://doi.org/10.1080/15402002.2011.602776

Tremblay, M. S., Carson, V., Chaput, J.-P., Connor Gorber, S., Dinh, T., Duggan, M., Faulkner, G., Gray, C. E., Gruber, R., Janson, K., Janssen, I., Katzmarzyk, P. T., Kho, M. E., Latimer-Cheung, A. E., LeBlanc, C., Okely, A. D., Olds, T., Pate, R. R., Phillips, A., … Zehr, L. (2016). Canadian 24-hour movement guidelines for children and youth: An integration of physical activity, sedentary behaviour, and sleep. *Applied Physiology, Nutrition, and Metabolism*, *41*(6 (Suppl. 3)), S311–S327. https://doi.org/10.1139/apnm-2016-0151

van Hees, V. T., Fang, Z., Langford, J., Assah, F., Mohammad, A., da Silva, I. C. M., Trenell, M. I., White, T., Wareham, N. J., & Brage, S. (2014). Autocalibration of accelerometer data for free-living physical activity assessment using local gravity and temperature: An evaluation on four continents. *Journal of*

Applied Physiology (Bethesda, Md.: 1985), *117*(7), 738–744. https://doi.org/10.1152/japplphysiol.00421.2014

van Hees, V. T., Gorzelniak, L., Dean León, E. C., Eder, M., Pias, M., Taherian, S., Ekelund, U., Renström, F., Franks, P. W., Horsch, A., & Brage, S. (2013). Separating movement and gravity components in an acceleration signal and implications for the assessment of human daily physical activity. *PloS One*, *8*(4), e61691. https://doi.org/10.1371/journal.pone.0061691

Van Hees, V. T., Migueles, J. H., Fang, Z., Zhao, J. H., Heywood, J., Mirkes, E., & Sabia, S. (2024). *GGIR: Raw Accelerometer Data Analysis*. https://doi.org/10.5281/zenodo.1051064

Van Hees, V. T., Sabia, S., Anderson, K. N., Denton, S. J., Oliver, J., Catt, M., Abell, J. G., Kivimäki, M., Trenell, M. I., & Singh-Manoux, A. (2015). A novel, open access method to assess sleep duration using a wrist-worn accelerometer. *PloS One*, *10*(11), e0142533. https://doi.org/10.1371/journal.pone.0142533

van Hees, V. T., Sabia, S., Jones, S. E., Wood, A. R., Anderson, K. N., Kivimäki, M., Frayling, T. M., Pack, A. I., Bucan, M., Trenell, M. I., Mazzotti, D. R., Gehrman, P. R., Singh-Manoux, B. A., & Weedon, M. N. (2018). Estimating sleep parameters using an accelerometer without sleep diary. *Scientific Reports*, *8*(1), Article 1. https://doi.org/10.1038/s41598-018-31266-z

Wald, A., Muennig, P. A., O'Connell, K. A., & Garber, C. E. (2014). Associations between healthy lifestyle behaviors and academic performance in US undergraduates: A secondary analysis of the American College Health Association's National College Health Assessment II. *American Journal of Health Promotion*, *28*(5), 298–305.

White, I. R., Royston, P., & Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine*, *30*(4), 377–399. https://doi.org/10/cmwhtz

Wunsch, K., Fiedler, J., Bachert, P., & Woll, A. (2021). The tridirectional relationship among physical activity, stress, and academic performance in university students: A systematic review and meta-analysis. *International Journal of Environmental Research and Public Health*, *18*(2), 739. https://doi.org/10.3390/ijerph18020739

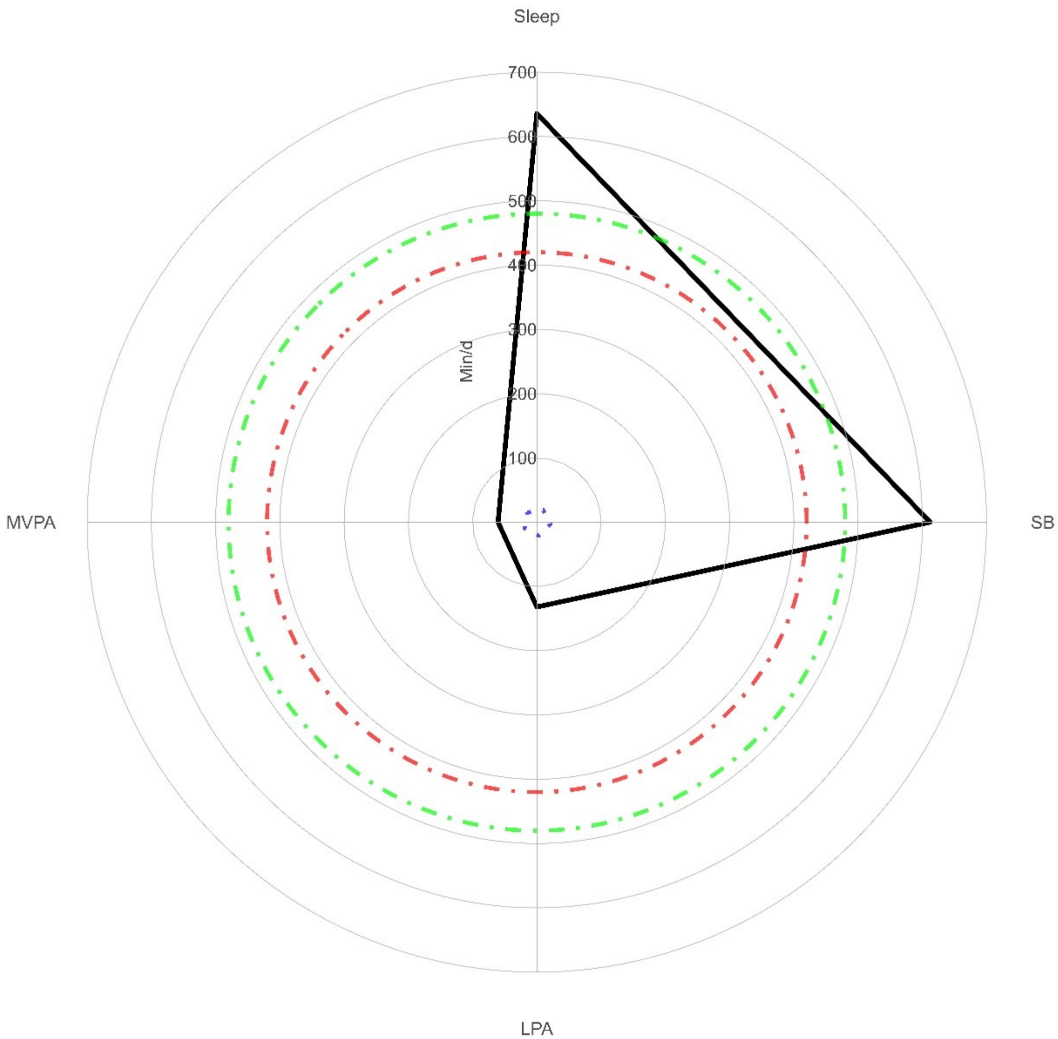

Figure 1. Radar plot of the sample’s movement composition of time spent in sedentary behavior (SB), light physical activity (LPA), moderate-to-vigorous physical activity (MVPA), and sleep over the course of a 24-hour period. *Note.* Blue circle indicates adult MVPA guideline of 21 minutes per day or 150 minutes per week; red circle indicates lower bound of sleep guideline (7 hours or 420 minutes); green circle indicates sedentary behavior guideline level (8 hours or 480 minutes)

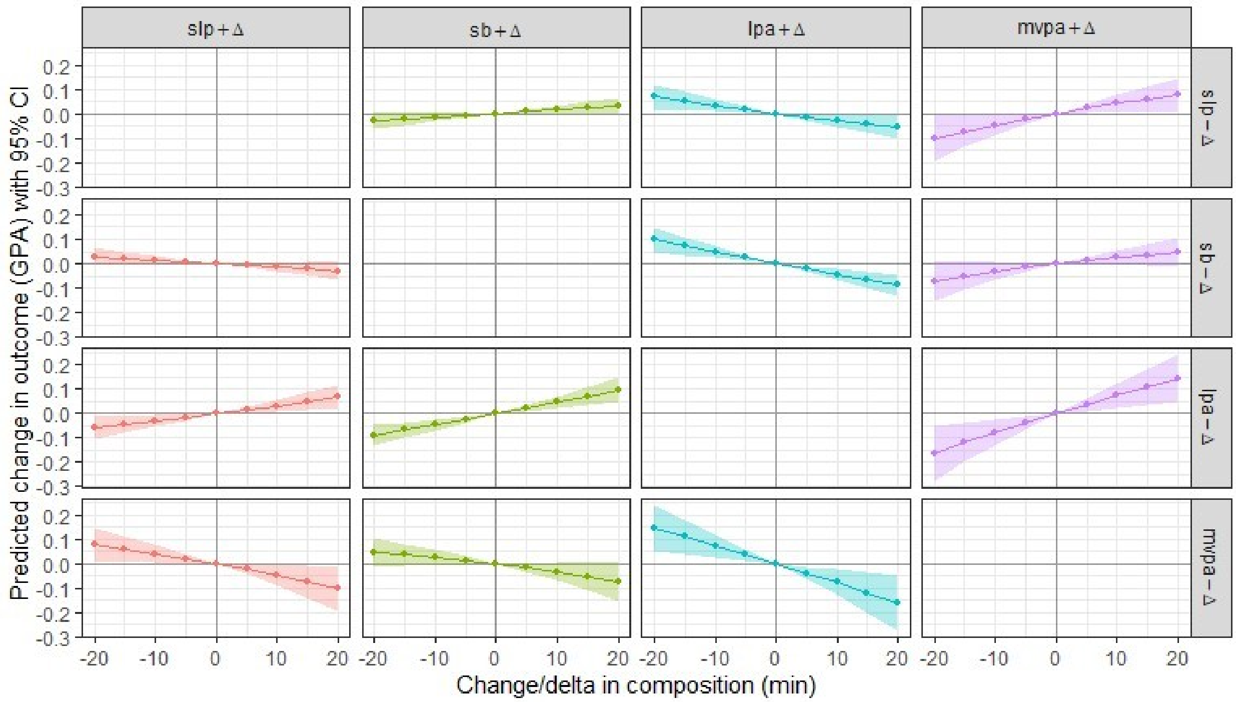

Figure 2. The impact of reallocating time (5 to 20 min) between movement behaviors (e.g., replacing 20 min of sedentary behavior with 20 min of light physical activity, while holding moderate-to-vigorous physical activity and sleep constant) on academic performance. SLP = sleep; SB = sedentary behaviors; LPA = light physical activity; MVPA = moderate-to-vigorous physical activity.

Table 1. Compositional variation Matrix

	Sleep	SB	LPA	MVPA
Sleep	-			
SB	.041	-		
LPA	.283	.342	-	
MVPA	.461	.574	.273	-

Note. SB = sedentary behaviors; LPA = light physical activity; MVPA = moderate-to-vigorous physical activity. Values closer to zero indicate higher codependence.