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The Association Between Time-Use Behaviors and Physical and Mental Well-Being in Adults: A Compositional Isotemporal Substitution Analysis

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Background: Substantial evidence links activity domains with health and well-being; however, research has typically examined time-use behaviors independently, rather than considering daily activity as a 24-hour time-use composition. This study used compositional data analysis to estimate the difference in physical and mental well-being associated with reallocating time between behaviors. **Methods**: Participants (n = 430; 74% female; 41 [12] y) wore an accelerometer for 7 days and reported their body mass index; health-related quality of life (QoL); and symptoms of depression, anxiety, and stress. Regression models determined whether time-use composition, comprising sleep, sedentary behavior, light physical activity (LPA), and moderate to vigorous physical activity (MVPA), was associated with well-being. Compositional isotemporal substitution models estimated the difference in well-being associated with reallocating time between behaviors. **Results**: Time-use composition was associated with body mass index and physical health-related QoL. Reallocating time to MVPA from sleep, sedentary behavior, and LPA showed favorable associations with body mass index and physical health-related QoL, whereas reallocations from MVPA to other behaviors showed unfavorable associations. Reallocations from LPA to sedentary behavior were associated with better physical health–related QoL and vice versa. **Conclusion**: Results reinforce the importance of MVPA for physical health but do not suggest that replacing sedentary behavior with LPA is beneficial for health and well-being.

Keywords: sedentary behavior, accelerometery, methods, daily activity, sleep, quality of life

There is a substantial body of evidence indicating that activity domains are associated with physical and mental health and well-being. For example, physical activity is positively associated with improved cardiovascular health, reduced risk of metabolic syndrome, type 2 diabetes and cancer, and fewer symptoms of depression and anxiety.[1] In contrast, sedentary behavior is associated with an increased risk of cardiovascular disease, cancer, type 2 diabetes, and depression.[2,3] Both short and long sleep durations are also associated with an increased risk of adverse physical and mental health outcomes.[4–6] However, research tends to examine physical activity, sedentary behavior, and sleep as *independent* predictors of health and well-being, when, in fact, they cannot ever be independent of each other. This is because time use is constrained by the 24-hour day, and only one behavior (eg, physical activity, sitting, or sleep) can be performed at one time. Thus, the behaviors are *codependent*—an increase in time spent in one behavior necessitates an equivalent decrease in time spent in one or more alternative behaviors. The effects of an increase (or decrease) in one behavior on health and well-being may therefore depend on which alternative behavior decreases (or increases) in a compensatory lifestyle "trade-off". It is therefore important for research to measure the whole 24-hour time use, and to use appropriate statistical techniques that can include all time-use behaviors, account for the codependent nature of time-use behaviors, and examine the outcomes associated with reallocating time between these behaviors.[7]

Seminal methods of isotemporal substitution introduced by Mekary et al[8] examined the effects of substituting time in one physical activity behavior for time in another. Traditional methods of analysis preclude the inclusion of all time-use behaviors due to multicollinearity; therefore, Mekary et al included a variable for total time (the sum of all time-use behaviors) in the model to adjust for the necessarily excluded behavior. It has been argued, however, that because time-use data are constrained by 24 hours, they convey relative information and should therefore be analyzed using statistical methods intended for data of a relative nature.[9] One statistical approach for relative data gaining traction in time-use research is compositional data analysis. This approach allows simultaneous examination of all time-use behaviors by representing time use as a set of log ratios that contain relative information about all behaviors in the 24-hour composition (ie, physical activity, sedentary behavior, and sleep) and enables interpretation of behavior as a proportion of total time use (ie, the 24-h d).[10,11] Dumuid et al[12] recently proposed a compositional isotemporal substitution model that uses these log ratios to estimate the associations between reallocations of time between specific pairs of behaviors and health outcomes.

The compositional isotemporal substitution technique has already been used in a number of studies to examine the relationship between time-use behaviors and health and well-being. For example, reallocation away from moderate to vigorous physical activity (MVPA) to sleep, sedentary behavior, or light physical activity (LPA) has been associated with higher fatness and lower cardiorespiratory fitness in children[13,14] and older adults.[15]

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Reallocation away from sleep, sedentary behavior, or LPA to MVPA has generally been associated with favorable, albeit smaller, differences in health.[13–15] In addition, changes in activity compositions from preretirement to postretirement have been linked with changes in depression, stress, and self-esteem (but not anxiety, well-being, or life satisfaction).[16] Reallocations from work to physical activity or sleep were associated with the most favorable changes in mental health. Despite previous research on children and older adults, to our knowledge, no research has used the compositional isotemporal substitution method to examine the associations of time-use behaviors with physical and mental well-being in young and middle-aged adults. This study therefore aimed to examine the association of time-use compositions with physical and mental well-being in a sample of young and middle-aged adults. Specifically, this study aimed to (1) examine whether time-use composition was associated with body mass index (BMI); physical and mental health–related quality of life (QoL); and symptoms of depression, anxiety, and stress and (2) use the compositional isotemporal substitution model to examine how reallocations between sleep, sedentary behavior, LPA, and MVPA were associated with these physical and mental well-being variables.

Methods

Participants and Design

This study used cross-sectional data from the baseline assessment of a randomized controlled trial, evaluating the effectiveness of an mHealth physical activity intervention, "Active Team" (Portal Australia, Adelaide, Australia). The recruitment and intervention protocol has been described elsewhere.[17] In brief, Active Team is a social and gamified smartphone app designed to encourage inactive adults to engage in at least 150 minutes of MVPA per week. Participants (n = 444) were recruited through Facebook and media recruitment campaigns and were eligible to participate if they were aged 18–65 years, used Facebook at least weekly, were fluent in English, lived in Australia, reported completing less than 150 minutes of MVPA per week on a single self-report screening item, and were able to recruit 2 to 7 of their friends and family members to form a team. Participants completed a baseline survey and accelerometry assessment and were randomly allocated to the waitlist control, basic experimental (pedometer plus a basic version of the app with no social and gamification features), or socially enhanced experimental condition (pedometer plus the app with social and gamification features). The survey and accelerometer assessments were repeated at 3 and 9 months (data collection is ongoing at the time of writing). At baseline, 9 participants did not provide valid accelerometry data and a further 5 participants did not provide valid survey data for the outcome variables. This study therefore included 430 participants. Ethical approval was obtained from the human research ethics committee of the University of South Australia, and participants provided informed consent prior to commencing the study.

Measures

Time-Use Compositions. Time-use behaviors (sleep, sedentary behavior, LPA, and MVPA) were assessed using GENEActiv accelerometers (Activinsights Ltd, Kimbolton, United Kingdom) that participants were asked to wear the accelerometer on their left wrist for 24 hours per day for 7 days, except during water-based activities. Acceleration was measured at 50 Hz, and activity counts were measured in 60-second epochs. When participants wore the accelerometer overnight, sleep and wake times were manually identified on the accelerometer trace (a graph indicating the activity count for each 60-s epoch across a 24-h period). If the accelerometer was not worn overnight, sleep and wake times were taken from participants' sleep diaries. Participants logged the time they went to bed and arose and, if they did not wear the accelerometer overnight, what time they removed and replaced the accelerometer. This enabled the identification of nonwear time between removing the accelerometer and going to bed, and between arising and replacing the accelerometer. Sedentary behavior, LPA, and MVPA were classified using established thresholds (light 188, moderate 403, vigorous 1131 counts per minute[18]; moderate and vigorous activity were summed). Data were considered valid if the accelerometer was worn for at least 10 hours while awake on at least 4 days, including a minimum of 1 weekend day.[17,19] On average, participants wore the accelerometer for 6 (SD = 1) days and 16 (SD = 1) hours per day. Sixty-one percent of participants wore the accelerometer over all nights, 26% wore the accelerometer for some nights, and 13% did not wear the accelerometer for any nights. Periods of 60 minutes of less than 25 counts per minute were considered nonwear time and excluded from the analysis (similar to previous research,[20] although a more conservative threshold was used to reduced misclassification of sedentary time as nonwear time). Once sleep diaries were considered, there was little "nonwear" time remaining, with participants' time-use behaviors summing to 24 hours on average (median 24; interquartile range 23.7–24.0). If behaviors did not sum to 24 hours, small linear adjustments were made to the daily mean durations so that 100% was equivalent to 24 hours for every participant. The GENEActiv has shown excellent reliability (intrainstrument coefficient of variation = 1.4%; interinstrument coefficient of variation = 2.1%) and validity ($r = .98$) using a mechanical shaker and excellent criterion validity when worn on the left wrist, using relative VO_2 as the criterion ($r = .86$).[18]

Outcomes. Body mass index was calculated from self-reported weight and height (in kilograms per meter squared). Health-related QoL was measured using the validated 12-item short-form Health Survey (SF-12).[21] Participants rated their health, the extent to which their health limited their activities, and their emotional experience during the past 4 weeks. Physical and mental health subscales were calculated according to recommendations and standardized to US population norms.[22] The SF-12 has high 2-week test–retest reliability (physical $r = .89$; mental $r = .76$) and is highly correlated with the 36-item version (physical $r = .95$; mental $r = .97$).[21] Emotional states were measured using the validated 21-item short-form Depression Anxiety Stress Scale (DASS-21).[23] Participants rated how much a range of statements (eg, "I felt down-hearted and blue") applied to them during the previous week. Scores for each 7-item subscale were summed and multiplied by 2 to align with the full 42-item version. Three-week test–retest reliability is high (intraclass correlation coefficient: depression .77; anxiety .89; stress .94).[24] Internal consistency (Cronbach alpha) for the current sample at baseline was also high (depression $\alpha = .89$; anxiety $\alpha = .76$; stress $\alpha = .86$).

Demographics. Demographic variables were age, sex, highest education level (high school or less, technical or further education institution, or university degree), and country of birth (open-ended response).

Analysis

Outcome variables (BMI, SF-12, and DASS) were converted to standardized z scores for all analyses. Analyses were controlled for age, sex, and education and were conducted in R (version 3.4.4; R Foundation for Statistical Computing, Vienna, Austria) using the packages "compositions"[25] and "robCompositions."[26] The associations between activity composition (expressed as isometric log ratios) and physical and mental well-being were examined using robust multiple linear regression models (iteratively reweighted least squares using the MM-estimator). The significance of the activity composition was determined using Chi-square type II analysis of deviance tests of the regressions (aim 1). For outcomes that were significantly associated with activity composition (at an $\alpha = .05$), compositional isotemporal substitution models were used to predict the associations between reallocating a period of time spent between 2 behaviors and health outcomes, for all possible combinations of behaviors (aim 2).[12] For each well-being outcome, the regression model first predicted the outcome value based on the mean time-use composition and subsequently predicted the outcome for a composition where 15 minutes of time had been reallocated from one behavior (eg, sleep) to an alternative behavior (eg, MVPA), keeping the 2 other behaviors constant (eg, sedentary and LPA). The difference in well-being outcomes was estimated as the difference between the outcome value predicted from the reallocated composition and the outcome value predicted from the mean composition. This model was repeated for all possible reallocations between sleep, sedentary behavior, LPA, and MVPA for increments of 15, 30, 45, and 60 minutes. Predictions were plotted for reallocations of –60 to 60 minutes to aid interpretation where appropriate.

Results

Participants were predominantly females, born in Australia, overweight, and highly educated and spent an average of 35% of the day in sleep, 42% in sedentary behavior, 16% in LPA, and 7% in MVPA (Table 1). Activity composition was significantly associated with BMI ($P = .02$) and physical health–related QoL ($P = .004$) but was not associated with mental health–related QoL ($P = .15$) or symptoms of depression ($P = .52$), anxiety ($P = .30$), or stress ($P = .44$) (Table 2). Compositional isotemporal substitution models were therefore conducted for BMI and physical health–related QoL.

Table 3 shows the estimated differences in outcomes for reallocations of 15 minutes between time-use behaviors. Figure 1 illustrates the expected difference in BMI z score (y-axis) for reallocations of fixed durations of time between MVPA and other time-use behaviors (x-axis), keeping the remaining behaviors constant, at the mean composition. Reallocations with sleep, sedentary behavior, and LPA are shown as separate lines. Negative values on the x-axis indicate minutes taken away from MVPA and reallocated to another behavior, while positive values on the x-axis indicate time taken from another behavior and reallocated to MVPA. Figure 2 illustrates the expected difference in SF-12 physical health z score for reallocations of fixed durations of time between MVPA and other time-use behaviors. Reallocations from sleep, sedentary behavior, and LPA to MVPA were associated with lower BMI (Figure 1) and better physical health–related QoL (Figure 2), whereas reallocations from MVPA to sleep, sedentary behavior, and LPA were associated with higher BMI (Figure 1) and poorer physical health–related QoL (Figure 2). The estimated differences associated with reallocating MVPA were nonlinear; the negative differences associated with reallocating away from MVPA on BMI and physical health–related QoL were greater than the positive differences associated with reallocating to MVPA. Figure 3 illustrates the expected difference in SF-12 physical health z score for reallocations of fixed durations of time between LPA and other time-use behaviors. In addition, reallocation from sedentary behavior to LPA was associated with poorer physical health–related QoL,

Table 1 Participant Characteristics (n = 430)

Characteristic	
Age, mean (SD), y	41.3 (11.7)
Female, n (%)	320 (74)
Country of birth, n (%)	
Australia	343 (80)
United Kingdom	24 (6)
Malaysia	10 (2)
Combined remaining responses (n < 10 for all other countries)	53 (12)
Highest education level, n (%)	
High school or less	67 (16)
Technical or further education institutions	130 (30)
University degree	233 (54)
Time use,[a] n (%), min/d	
Sleep	494 (35)
Sedentary	601 (42)
Light physical activity	238 (16)
Moderate to vigorous physical activity	107 (7)
Body mass index, mean (SD)	30.0 (7.0)
SF-12 physical health QoL, mean (SD)	46.3 (8.3)
SF-12 mental health QoL, mean (SD)	47.7 (8.8)
Depression Anxiety Stress Scale emotional states, mean (SD)	
Depression	7.9 (7.7)
Anxiety	5.8 (5.9)
Stress	12.4 (7.8)

Abbreviations: QoL, quality of life; SF-12, 12-item short-form Health Survey.
[a]Time-use composition is presented as geometric means, adjusted to a sum of 1440 minutes and 100%.

Table 2 Results From Chi-Square Type II Analysis of Deviance Tests Examining the Association Between Activity Composition and Standardized Physical and Mental Well-Being Variables

	χ^2	*P*
Body mass index	**9.8**	**.02**
12-Item short-form Health Survey		
Physical health QoL	**13.2**	**.004**
Mental health QoL	5.3	.15
Depression Anxiety Stress Scale emotional states		
Depression	2.3	.52
Anxiety	3.7	.30
Stress	2.7	.44

Abbreviation: QoL, quality of life. Note: Activity composition expressed as isometric log ratios. Models control for age, sex, and education level. Estimates in boldface are significant at $P < .05$.

Table 3 Estimated Differences (and 95% Confidence Intervals) in zBMI and zSF-12 Physical Health–Related QoL Associated With Reallocation of 15 minutes

Time-use behavior displaced by 15 min	Time-use behavior increased by 15 min			
	↑Sleep	↑Sedentary	↑LPA	↑MVPA
*z*BMI				
↓Sleep	–	0.01 (–0.02 to 0.03)	0.02 (–0.01 to 0.04)	**–0.04 (–0.08 to –0.01)**
↓Sedentary	–0.01 (–0.03 to 0.02)	–	0.01 (–0.01 to 0.03)	**–0.05 (–0.08 to –0.02)**
↓LPA	–0.02 (–0.05 to 0.01)	–0.01 (–0.03 to 0.01)	–	**–0.06 (–0.11 to –0.01)**
↓MVPA	**0.05 (0.01 to 0.09)**	**0.06 (0.02 to 0.09)**	**0.07 (0.02 to 0.12)**	–
*z*SF-12 physical health QoL				
↓Sleep	–	0.01 (–0.01 to 0.04)	–0.02 (–0.05 to 0.01)	**0.07 (0.03 to 0.11)**
↓Sedentary	–0.01 (–0.04 to 0.01)	–	**–0.03 (–0.06 to –0.01)**	**0.05 (0.02 to 0.09)**
↓LPA	0.02 (–0.01 to 0.05)	**0.04 (0.01 to 0.06)**	–	**0.09 (0.04 to 0.14)**
↓MVPA	**–0.08 (–0.12 to –0.04)**	**–0.07 (–0.10 to –0.03)**	**–0.10 (–0.15 to –0.05)**	–

Abbreviations: LPA, light physical activity; MVPA, moderate to vigorous physical activity; QoL, quality of life; *z*BMI, body mass index *z* score; *z*SF-12, 12-item short-form Health Survey *z* score. Note: Estimates control for age, sex, and education level. Estimates in boldface are significant at $P < .05$.

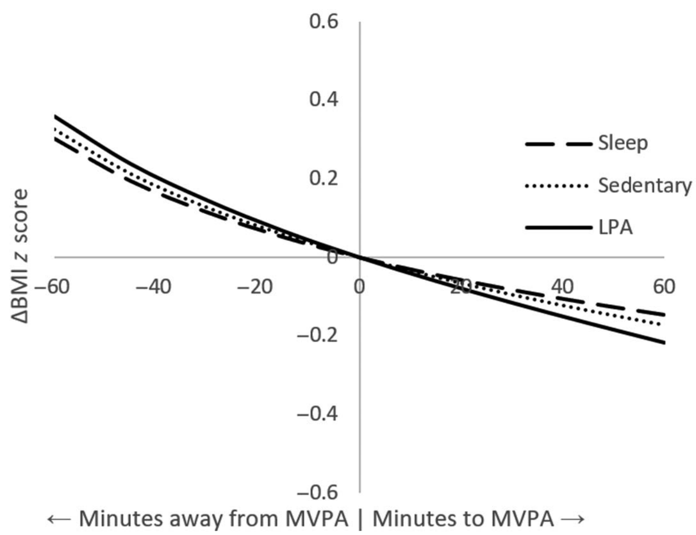

Figure 1 — Estimated differences in BMI *z* score associated with reallocation of minutes spent in MVPA. *Note*. Analyses controlled for age, sex, and education. BMI indicates body mass index; LPA, light physical activity; MVPA, moderate to vigorous physical activity.

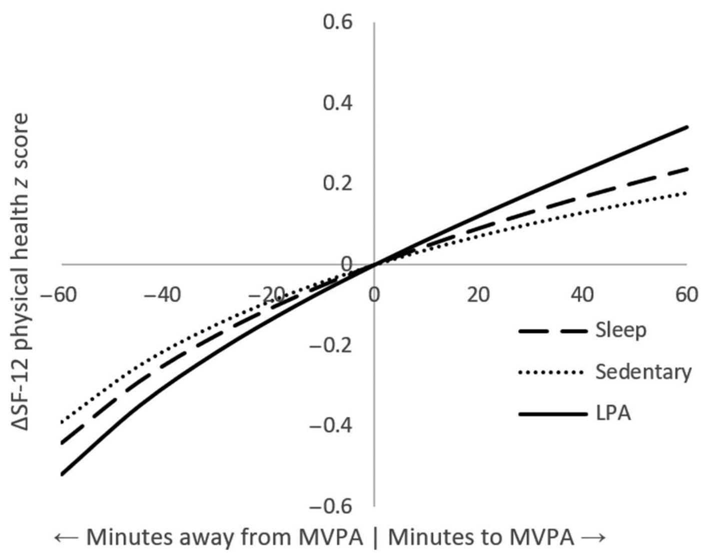

Figure 2 — Estimated differences in SF-12 physical health *z* score associated with reallocation of minutes spent in MVPA. *Note*. Analyses controlled for age, sex, and education. LPA indicates light physical activity; MVPA, moderate to vigorous physical activity; SF-12, 12-item short-form Health Survey.

whereas reallocation from LPA to sedentary behavior was associated with better health-related QoL (Figure 3).

Discussion

This study examined how time-use compositions were related to physical and mental well-being in young and middle aged-adults. Not unexpectedly, MVPA had the largest associations with physical health (BMI and physical health–related QoL) relative to other behaviors. This is consistent with previous research using traditional analysis that demonstrates positive associations between MVPA and health in adults.[1] In line with previous compositional data analyses with children[13,14] and older adults,[15] the associations were asymmetrical; the deficits associated with reallocating a period of time from MVPA to another behavior were greater than the benefits associated with reallocating the same period of time from a behavior to MVPA. Although no causal conclusions can be made from the cross-sectional data, this study highlights the potential importance of at least maintaining (and not reducing) one's current level of MVPA. The associations were, however, relatively small. Converting to raw scores shows that, at the mean BMI, reallocating 15 minutes to MVPA was associated with a lower BMI of 0.3 to 0.4 kg/m^2, while reallocating 15 minutes away from MVPA was associated with a higher BMI of 0.4 to 0.5 kg/m^2. As an example, a difference of 0.4 kg/m^2 for someone 170 cm tall equates to 1.2 kg. Notably, reallocating 15 minutes of LPA to MVPA was associated with a smaller difference in BMI in this study (–0.4 kg/m^2) than the previous study with older adults (–0.7 kg/m^2).[15] Additionally, reallocating time to or from MVPA was associated with small differences in SF-12 physical health scores, suggesting that fairly large reallocations may be required for clinically significant differences. Effects in this study may be

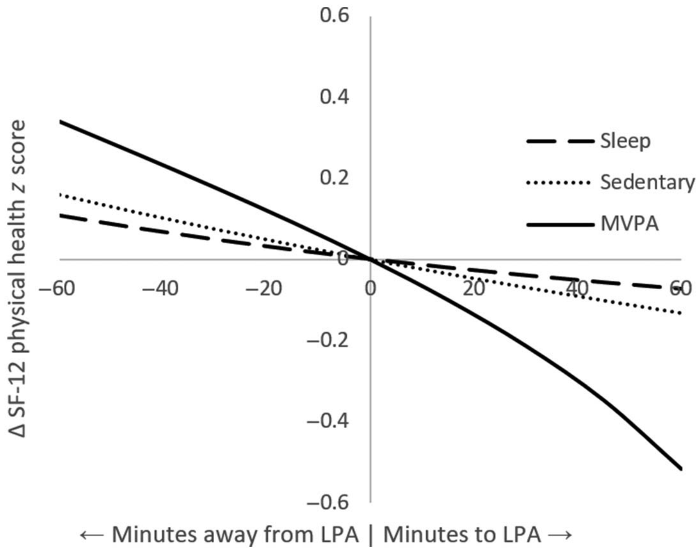

Figure 3 — Estimated differences in SF-12 physical health *z* score associated with reallocation of minutes spent in LPA. *Note*. Analyses controlled for age, sex, and education. LPA indicates light physical activity; MVPA, moderate to vigorous physical activity; SF-12, 12-item short-form Health Survey.

small because participants in the present study recorded high levels of daily MVPA (107 min/d). Differences in health associated with increases in physical activity tend to be greater at lower levels of physical activity.[1,27]

Reallocating time spent in LPA to sedentary behavior was associated with better physical health–related QoL, while reallocating time spent in sedentary behavior to LPA was associated with poorer physical health–related QoL. This suggests there may be benefits to engaging in periods of rest or restorative sedentary activity. Alternatively, the association could be attributable to a third factor such as socioeconomic status, which could be linked to both better health-related QoL and occupation (though the present study controlled for educational attainment). For example, those with higher socioeconomic status might have better health despite also having relatively sedentary (ie, office) professions. Similarly, those with occupations that require high levels of LPA, such as nursing, may be more likely to report on the SF-12 that their physical health or pain interfered with their work than those with more sedentary occupations whose work might be relatively less affected by illness or pain. Similar to differences in SF-12 physical health scores associated with reallocations between MVPA and other behaviors, the differences associated with the reallocation between LPA and sedentary behavior were small. This suggests that large reallocations between LPA and sedentary behavior would be needed to show meaningful differences.

Reallocations between LPA and sedentary behavior were not associated with BMI or mental well-being. Previous compositional research has also failed to demonstrate that reallocation of time spent in sedentary behavior to LPA is associated with positive outcomes in children or older adults.[13,15] These studies, in conjunction with the present study, challenge the previous noncompositional literature and public health messages, which suggest that the negative effects of sedentary behavior are independent of MVPA.[3,28] We note that our analysis included total minutes of sedentary behavior, regardless of the duration of the sedentary bouts. Previous research has shown that the negative health effects of sedentary behavior are greatest for longer, unbroken bouts.[29] Results from our study might have differed if our analysis framework differentiated between short and long bouts of sedentary behavior, with reallocation to or from longer bouts showing greater associations with health.

Reallocating time between sleep and sedentary behavior or LPA was not associated with physical health. This is congruent with the previous study of older adults that found that reallocations between sleep and MVPA, but not between sleep and sedentary behavior or LPA, were associated with physical health.[15] On average, participants slept for 35% of the 24-hour day, or 8 hours per night, meeting current recommendations that adults should obtain 7 to 9 hours of sleep per night.[30] Future research could examine whether these results would differ for participants whose activity compositions indicate insufficient sleep.

In contrast to the findings for physical health, there was no association between time-use composition and depression, anxiety, or stress symptoms or mental health–related QoL. Participants tended to report average mental well-being, with DASS scores in the normal range and SF-12 scores similar to the US scaling norms.[22] Future research could examine whether these results would differ in a sample with poorer mental health. The lack of association with mental well-being is in contrast to one previous study, which indicated that changes in activity compositions from preretirement to postretirement were linked with changes in depression, stress, and self-esteem.[16] Notably, the previous study measured within-person change in activity composition, rather than between-person differences as in the present study. Additionally, while activities in the present study were classified based on accelerometer-recorded intensity, the previous study used the Multimedia Activity Recall for Children and Adults to define a different set of activities based on alternative characteristics.

Strengths and Limitations

To our knowledge, this is the first study to use compositional isotemporal substitution to examine associations between time-use compositions and physical and mental well-being in young and middle-aged adults. The data were cross-sectional; therefore, causal conclusions about the associations between activity composition and physical and mental well-being cannot be made. Causation could be in the reverse direction; for example, individuals with lower BMI and better physical health–related QoL may choose to engage in more MVPA than those with higher BMI and poorer physical health–related QoL. Such associations could also be influenced by a third factor, including socioeconomic status. Nonetheless, this study provides important insights by using a novel analysis technique to examine all time-use behaviors simultaneously, as well as reallocations between specific pairs of behaviors. Such analysis overcomes the issues inherent in using traditional statistical approaches and provides more robust results.[7,11] Future longitudinal studies using this technique will allow examination of how activity compositions and well-being are associated across time. Other strengths of this study include a large sample and that the accelerometry assessment measured multiple days (average 6 d) and included both weekdays and weekend days. This study also utilized widely used and validated measures of physical and mental well-being.

There are also some limitations to this study. Predictions obtained from compositional isotemporal substitution are calculated based on the mean time-use composition. Predictions may differ for alternative compositions. For example, reallocation of MVPA may show greater associations with health and well-being outcomes for a mean composition showing relatively less MVPA. Similarly, reallocations of sleep might be associated with health and well-being for a mean composition indicating insufficient sleep. In addition, participants were from the baseline assessment of a randomized controlled trial where eligibility criteria included self-reporting as physically inactive, resulting in a selective sample of primarily well-educated, overweight women who were born in Australia. Despite self-reporting as physically inactive during screening, the accelerometry assessment suggests participants were quite active. Participants were also required to recruit 2 to 7 additional participants to be eligible for the study. Therefore, participants were likely to have good social networks, which is associated with better mental health and lower rates of psychological distress (eg, symptom of stress and depression).[31] The findings of this study may therefore not generalize well to other populations. Future research should examine the associations between time-use compositions and health and well-being in more diverse samples with different activity patterns.

An additional limitation is that accelerometry provides information about the intensity of activity, but it does not provide further contextual information about the types of activity performed. Time-use estimates using accelerometry can be affected by measurement error. Different models of accelerometer can produce different estimates of time use. Different placement of the accelerometer on the body (ie, wrist vs hip) can also produce different results.[19,32] For example, a wrist-worn accelerometer may not accurately capture activities that occur while the arms are in a stable position, such as cycling, thereby underestimating participants' MVPA. Additionally, while this study used previously validated thresholds for classifying activity,[18] we note that the choice of thresholds for classifying activities can differ between studies, making them difficult to compare. Additional research using alternative measures of activity is needed to validate our results.

Conclusion

In summary, this study used compositional data analysis to examine how activity composition was associated with physical and mental well-being in young and middle-aged adults. MVPA demonstrated the strongest associations, with reallocations of time to MVPA having favorable associations with BMI and physical health–related QoL. Differences were nonlinear with reallocations of time away from MVPA, showing stronger unfavorable associations with BMI and physical health–related QoL. Reallocations from sedentary behavior to LPA were also associated with poorer physical health–related QoL, while reallocations from LPA to sedentary behavior were associated with better physical health–related QoL. Activity composition was not associated with mental health–related QoL or symptoms of depression, anxiety, or stress. Further research using compositional data analysis is required. In particular, research should examine the association between time-use compositions and health and well-being longitudinally in more diverse samples with different activity patterns.

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