Accelerometer epoch setting is decisive for associations between physical activity and metabolic health in children

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Accelerometer epoch and metabolic health

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Abstract

When analyzing physical activity (PA) levels using accelerometry, the epoch setting is critical to capture intensity-specific PA correctly. The aim of the present study was to investigate the PA intensity signatures related to metabolic health in children using different epoch settings. A sample of 841 Norwegian children (age 10.2 ± 0.3 years; BMI 18.0 ± 3.0; 50% boys) provided data on accelerometry (ActiGraph GT3X+) and several indices of metabolic health (aerobic fitness, abdominal fatness, insulin sensitivity, lipid metabolism, blood pressure) that were used to create a composite metabolic health score. We created intensity spectra from 0–99 to ≥ 10000 counts per minute (cpm) for files aggregated using 1, 10, and 60-second epoch periods and used multivariate pattern analysis to analyze the data. The association patterns with metabolic health differed substantially between epoch settings. The intensity intervals most strongly associated with metabolic health were 7000–8000 cpm for data analyzed using 1-second epoch, 5500–6500 cpm for data analyzed using 10-second epoch, and 4000–5000 cpm analyzed using 60-second epoch. Aggregation of data over different epoch periods has a clear impact on how PA intensities in the moderate and vigorous range are associated with childhood metabolic health.

Keywords

Multivariate analysis; Risk factors; Child; Accelerometry; Intensity

Introduction

Moderate-to-vigorous physical activity (MVPA) has consistently been associated with metabolic health outcomes in childhood [1-3]. Because clustering of risk factors for cardiovascular disease is evident already in childhood [4], and tracks into adulthood [5], knowledge of how physical activity (PA) and particularly how different intensities of PA relates to metabolic health in children is needed. However, the evidence for the association between intensity-specific PA and metabolic health is limited by several analytic challenges. First, restricting exposure variables to MVPA and sedentary time (SED) [2], probably to avoid collinearity, causes a loss of information, increases susceptibility to residual confounding, and ignores the possible influence of other PA intensities on health outcomes (i.e., light (LPA), moderate (MPA), vigorous (VPA), and very vigorous intensity PA) [2 3 6]. Second, what kind of activities and which intensities are captured as MVPA by accelerometry depends on the data reduction algorithms and scoring protocols applied, which leads to confusion in interpreting results from studies using different methodology [7 8]. Specifically, the choice of epoch durations used to aggregate data and the choice of cut points used to score data have a profound influence on the resulting levels of intensity-specific PA [9 10].

Children's PA is characterized by sporadic and intermittent bursts of PA generally lasting less than 10 seconds [11-14]. Because the vast majority of bouts in the light to vigorous intensity range has a duration of only some few seconds when analyzed at 1-second epoch [13 14], summation of PA over longer epochs leads to loss of time spent in the lower and higher end of the intensity spectrum, as these intensities are averaged over a long period. Thus, SED, VPA, and MVPA are consistently underestimated and LPA overestimated, when epoch duration increases from 1 to 60 seconds [9 10 13-17], suggesting that short epoch settings are recommended to capture PA correctly. Furthermore, MPA is less affected than VPA [9 10 15 17] or show a pattern contrary to VPA [10 13 16], when aggregating data over longer epochs. These effects mask the specific levels, and thus health influence of VPA, when summing these intensities into MVPA. The influence of epoch settings on PA levels also depends on the applied PA intensity cut points, because the specific effect of averaging PA intensities over epochs will differ according to the intensity levels captured [9 10]. Thus, both epoch durations, cut points, and their interaction will determine levels of intensity-specific PA. The chosen accelerometer data reduction and scoring protocols therefore likely impact which PA intensities that are revealed as important to metabolic health.

Consistent with studies that have recommended inclusion of the whole intensity spectrum when analyzing PA data [3 6], we have recently used multivariate pattern analysis [18 19], which solves the collinearity problem related to accelerometer data [20], to determine the PA signature associated with

metabolic health in childhood [14 21]. In one study we analyzed the intensity spectrum from 0–100 to ≥ 8000 counts per minute (cpm) and found that the variance in metabolic health outcomes were mainly explained by VPA and to a lesser extent MPA [21]. However, a limitation of these findings is that we only analyzed data using a 10-second epoch duration. In another study, however, we evaluated associations for bouts of PA with metabolic health, and observed a strong dependence on epoch setting [14]. Both PA in bouts and total PA levels appears to be misclassified by the use of longer epoch durations compared to shorter, because short bursts of PA are accumulated and averaged over longer periods, leading to an overestimation of time spent in longer bouts and intermediate intensities. Furthermore, our findings suggest associations between MPA and metabolic health are spuriously high when data are analyzed using longer epochs, caused by misclassification of VPA as MPA when averaging PA over longer durations [14]. These findings [14 21] challenge previous studies and recommendations [1-3 22] concluding that children should spend time in MPA to improve their metabolic health, and show that a conscious use of epoch settings is fundamental to our analysis and understanding of how PA is related to health.

Therefore, we aimed to extend our previous analyses [14 21], using the novel analytic technique of multivariate pattern analysis, to determine the impact of different epoch settings (1, 10, and 60-second epoch) on the PA intensity signature associated with metabolic health in children.

Methods and materials

Participants

The present study uses baseline data obtained from fifth-grade children in the Active Smarter Kids (ASK) cluster-randomized controlled trial, conducted in Norway during 2014–2015 [23 24]. Sixty schools, encompassing 1202 fifth-grade children, fulfilled the inclusion criteria, and agreed to participate. This sample represented 86.2% of the population of 10-year-olds in the county, and 95.2% of those eligible for recruitment. Later, three schools encompassing a total of 27 fifth-grade children declined to participate. Thus, 1145 (97.4%) of 1175 available children from 57 schools agreed to participate in the study.

Our procedures and methods conform to ethical guidelines defined by the World Medical Association's Declaration of Helsinki and its subsequent revisions. The South-East Regional Committee for Medical Research Ethics in Norway approved the study protocol. We obtained written informed consent from each child's parents or legal guardian and from the responsible school

authorities prior to all testing. The study is registered in Clinicaltrials.gov with identification number: NCT02132494.

Procedures

We have previously published a detailed description of the study [23], and therefore provide only a brief overview of the relevant procedures herein.

Physical activity

PA was measured using the ActiGraph GT3X+ accelerometer (Pensacola, FL, USA) [25]. Participants were instructed to wear the accelerometer at the waist at all times over seven consecutive days, except during water activities (swimming, showering) or while sleeping. Units were initialized at a sampling rate of 30 Hz. Files were analyzed at 1, 10 and 60-second epochs using the KineSoft analytical software version 3.3.80 (KineSoft, Loughborough, UK). Data were restricted to hours 06:00 to 23:59. In all analyses, consecutive periods of ≥ 60 minutes of zero counts were defined as non-wear time [26]. We applied wear time requirements of ≥ 8 hours/day and ≥ 4 days/week to constitute a valid measurement [27].

We created 23 PA variables of total time (min/day) to capture movement in narrow intensity intervals throughout the spectrum, from 0–99 to ≥ 10000 cpm. For the purpose of reporting descriptive statistics, we used the Evenson cut points of 0–99, 100–2295, 2296–4011, ≥ 4012, and ≥ 2296 cpm for SED, LPA, MPA, VPA, and MVPA [28 29], respectively. We also reported achievement of the guideline PA level (mean of ≥ 60 min MVPA/day).

Metabolic health measures

Aerobic fitness was measured with the Andersen intermittent running test, which has demonstrated acceptable reliability and validity in 10-year-old children [30]. Children ran as long as possible in a to-and-fro movement on a 20-meter track, with 15-second work periods and 15-second breaks, for a total duration of 10 minutes. Body mass was measured using an electronic scale (Seca 899, SECA GmbH, Hamburg, Germany) with children wearing light clothing. Height was measured using a portable Seca 217 (SECA GmbH, Hamburg, Germany). Body mass index (BMI) ($kg \cdot m^{-2}$) was calculated. Waist circumference was measured with a Seca 201 (SECA GmbH, Hamburg, Germany)

ergonomic circumference measuring tape two cm over the level of the umbilicus. Systolic (SBP) and diastolic blood pressures were measured using the Omron HBP-1300 automated blood pressure monitor (Omron Healthcare, Inc, Vernon Hills, IL, US). Children rested quietly for ten minutes in a sitting position with no distractions before blood pressures was measured four times; we used the mean of the last three measurements for analyses. Serum blood samples were collected from the children's antecubital vein between 08:00 and 10:00 in the morning after an overnight fast. All blood samples were analyzed for total cholesterol (TC), triglyceride (TG), high-density lipoprotein cholesterol (HDL), glucose, and insulin at the accredited Endocrine Laboratory of the VU Medical Center (VUmc; Amsterdam, the Netherlands). Low-density lipoprotein cholesterol (LDL) was estimated using the Friedewald formula [31]. We calculated the TC:HDL ratio and homeostasis model assessment (HOMA) (glucose (mmol/L) * insulin (pmol/L) / 22.5) [32].

We calculated a composite score as the mean of six variables (SBP, TG, TC:HDL ratio, HOMA, waist circumference:height ratio, and aerobic fitness) by averaging standardized scores after adjustment for sex and age. A similar approach have been used previously [33].

Statistical analyses

Children's characteristics were reported as frequencies, means, and standard deviations (SD). We tested for differences in characteristics between boys and girls, as well as between included and excluded children, using a linear mixed model to account for the clustering among schools. Models for PA were adjusted for wear time.

Associations between PA intensities and metabolic risk were determined using Pearson's correlation coefficient (r) and multivariate pattern analysis, as previously described [21]. Partial least squares (PLS) regression analyses [20] were used to determine the multivariate PA association pattern with the composite metabolic health score, including all standardized PA variables as explanatory variables. Through decomposing the explanatory variables into orthogonal linear combinations (PLS components), while simultaneously maximizing the covariance with the outcome variable, PLS regression can handle collinear variables [20]. Monte Carlo resampling [34] with 100 repetitions was used to select the number of PLS components optimizing the predictive performance of the models by randomly keeping 50% of the subjects as an external validation set. For each cross-validated PLS regression model, a single predictive component was calculated by means of target projection, expressing all the predictive variance in the PA variables related to the metabolic response variable in a single vector [18 35]. Selectivity ratios (SRs) were obtained as the ratio of this explained predictive

variance to the residual variance for each PA variable [36 37]. The results are shown in an SR plot, which quantitatively display the PA variables' importance for metabolic health. We compared the association patterns related to metabolic health between boys and girls, by correlating the variable loadings from the separate multivariate models using Pearson's r. Adjustment for wear time in these models did not change any findings [21], thus, unadjusted models are reported.

Multivariate pattern analyses were performed using the commercial software Sirius version 11.0 (Pattern Recognition Systems AS, Bergen, Norway).

Results

Children's characteristics

We included 841 children (50% boys) who provided valid data on all relevant variables (Table 1 and Table 2). Total time spent in SED, LPA, and VPA differed greatly between the epoch settings, while the influence of epoch setting was minor for overall PA and moderate for MPA and MVPA. In the total sample, SED and VPA increased substantially, whereas LPA decreased substantially, when data were analyzed using shorter epochs. Moreover, the number of children achieving the guideline amount of MVPA differed substantially between epoch settings. Time spent in the 23 PA intensity intervals (0–99 to ≥ 10000 cpm) across epoch setting is shown in Supplemental Table 1.

The children included in the present analyses did not differ from the excluded children (n = 288, 57% boys) with respect to age ($p \geq .689$) or anthropometry ($p \geq .166$). Yet, the included children performed better on the Andersen test ($p < .001$), had lower fasting insulin concentrations ($p = .001$) and HOMA scores ($p = .002$), exhibited less SED time ($p = .002$), and spent more time in PA ($p \leq .031$) than the excluded children.

Associations between physical activity intensity and metabolic health

The explained variance in models of metabolic health improved when epoch durations decreased (1-second epoch: $R^2 = 17.0\%$; 10-second epoch: $R^2 = 13.4\%$; 60-second epoch: $R^2 = 10.8\%$). Furthermore, the multivariate association patterns with metabolic health differed between the epoch settings (Figure 1) (bivariate correlations are shown in Table 3): The intensities most strongly associated with metabolic health were 7000–8000 cpm for data analyzed using 1-second epoch, 5500–6500 cpm for data analyzed using 10-second epoch, and 4000–5000 cpm analyzed using 60-second epoch. Thus,

the association patterns were skewed towards lower intensities when using longer compared to shorter epoch durations. Consistent with this finding, associations with metabolic health for moderate intensities (2000–4000 cpm) were evident for data analyzed using 60-second epoch, whereas these associations weakened substantially when using shorter epoch durations. The lowest intensity range associated with metabolic health was 2000-2499, 2499-2999, and 3000-3499 cpm for 60-, 10-, and 1-second epochs, respectively. SED was weakly positively associated with metabolic health using all epoch settings in the bivariate analyses. However, SED and LPA were not associated with metabolic health using any epoch setting in the multivariate pattern analysis.

The association patterns were similar for boys (R^2 = 16.2%) and girls (R^2 = 17.3%) (r for pattern of variable loading for boys and girls = 0.80, $p < .001$).

Discussion

Current evidence and PA guidelines recommend that children engage in MVPA to improve metabolic health [1-3 22]. However, whereas the association with health for accelerometer-derived MPA is clearly evident when using a 60-second epoch setting, our findings suggest that MPA is only weakly associated with health when using a 1-second epoch setting, that is, an epoch setting with a sufficient resolution to capture VPA accurately. These results challenge researchers' understanding of how PA is accrued, how accelerometer data should be handled optimally, as well as the prevailing PA guidelines.

To handle a high number of strongly correlated intensity variables from accelerometry, we investigated the multivariate PA signature associated with metabolic health in children by means of multivariate pattern analyses. Extending on our previous findings [14 21], we show herein the PA intensity signature associated with metabolic health using 3 different epoch settings. Consistent with previous studies [9 10 13 15-17], we found that a short epoch setting is needed to capture VPA correctly in children. Using a longer epoch setting will cause averaging of VPA over longer periods, thus, VPA will be partially captured as MPA. The consequence of this misclassification is a spuriously strong association between MPA and metabolic health. When using a 60-second vs. a 1-second epoch setting, the PA intensity signature associated with metabolic health is substantially left-skewed; the strongest associations with metabolic health was found for 7000-8000 cpm vs. 4000-5000 cpm, respectively. Nevertheless, consistent with current evidence [3], our findings, irrespective of epoch setting, provide further support for encouraging PA of vigorous effort to improve childhood metabolic health.

The implication of our findings may be straight-forward: when researchers analyze their accelerometer data, the PA intensities of interest (if not analyzing the full intensity specter) must reflect the chosen epoch setting. Because the dataset underlying the current analyses are identical for the different epoch settings, the activities performed and their intensity, duration, and frequency is obviously similar across the analyses. The single difference is therefore how these activities are captured by the different aggregation methods. Highly intermittent team sports like football, handball, and basketball will probably be captured very differently across epoch settings. For example basketball, having a mean cpm of approximately 2400-2500 in lab-based calibration trials [28] [29], might be captured solely as MPA using a 60-second epoch setting, but be captured partly as SED, LPA, MPA, and VPA using a 1-second epoch setting. Considering the sporadic nature of children's PA, a similar effect might be expected for activities like running, although running could be regarded as a continuous activity in adults. This epoch effect might further complicate the choice and interpretation of intensity cut points. To the best of our knowledge, however, no calibration studies have directly compared equations and cut points between epoch settings. Of major importance, though, average activity counts of activities used for the purpose of calibration will probably not capture differences in intensity-specific PA, because such trials average cpm over a period of several minutes. Nevertheless, the PA intensity signatures presented herein partly circumvent the cut point challenge by showing how intensity profiles associates with metabolic health. Still, knowledge of the underlying activities and their metabolic demand are needed to translate our findings into PA guidelines.

As argued above, it might seem like the choice of epoch setting for analysis is a matter of taste, as far as the interpretation of the findings is adjusted accordingly. However, the explained variance of 17.0, 13.4, and 10.8% for the 1, 10, and 60-second epoch setting clearly illustrates that aggregation of PA over shorter periods are superior to longer periods, as association patterns become stronger. Thus, shorter epochs are able to capture relevant information about the children's PA, in relation to health, that longer epochs are not. This finding is consistent with previous findings that show strong associations with metabolic health for very short (2-10 seconds) and short (10-40 seconds) bouts of VPA when data is analyzed at 1 and 10-second epoch, respectively [14]. These findings collectively indicate that every second of VPA counts.

As discussed above, a misclassification of VPA as MPA when using longer versus shorter epochs leads to a skew in the association pattern for different intensities with metabolic health. In addition, the misclassification of MVPA versus lower intensities leads to different proportions of children achieving the guideline amount of PA. Herein, we show that while 74% achieved the recommended PA level of 60 min/day of MVPA using 1-second epochs, only 52% reached this level using 60-second epochs

(mean MVPA 76 vs. 65 min/day, respectively). However, this effect will depend on the intensity cut points [9 10], because time spent in intermediate intensities (LPA and MPA) will depend on misclassification of both lower and higher intensities, as opposed to the extreme categories (SED and VPA). As shown herein, while VPA was 86% higher (39 vs. 21 min/day) for a 1-second epoch setting, MPA was 22% lower. Still, in sum, MVPA was 17% higher using a 1-second compared to a 60-second epoch setting. Hence, these findings clearly illustrate that the epoch setting is decisive for determining both PA levels and associations with other outcomes, and adds to the existing complexity of data reduction of accelerometry [7 8]. A practical implication is that levels of MVPA, if accepting that a 1-second epoch setting is the favorable choice, has been underestimated in most previous studies as the majority of studies in children and adolescents have used 10- to 60-second epochs [7 8]. This underestimation also apply to the International Children's Accelerometry Database (ICAD), which synthesize existing evidence that mainly have applied long epochs because of former memory limitations of accelerometry [38]. However, PA levels in children and youth is still insufficient for optimal health and development, which calls for global actions of PA promotion. Such efforts may particularly benefit girls, who are consistently found to exhibit lower PA levels than boys [38]. Importantly, we found that the association patterns were similar for boys and girls, which suggests the health-enhancing effects of PA are independent of sex.

Strengths and limitations

The main strength of the present study is the use of multivariate pattern analysis, a novel statistical approach, which allows simultaneously modeling the whole intensity spectra of PA. The use of these intensity spectra circumvent the challenge of choosing the right accelerometer intensity cut points that vary considerably between studies [7], and which hamper the interpretation of results regarding the different PA intensities' importance for health. We argue that our findings is a breakthrough relating to the call for solving the collinearity problem accompanying the analysis of PA data. Thus, it has important implications for understanding and methodology in the field. Also, we included a moderate to large population-based sample, lending credit to the generalizability of the findings, despite our analysis indicated selective attrition. Despite recognizing this selection, we believe our differing findings using different epoch settings would apply to population samples of children participating in various physical and everyday activities.

Because our analyses were restricted to cross-sectional associations, as discussed previously [21], a limitation is that we could not infer causality from our findings. Further limitations of the present study is the narrow age range of the children. Future studies should attempt to replicate our findings

using a similar analytic approach applied to data sets including children that are more heterogeneous in age.

Conclusion

This study breaks new ground by using multivariate pattern analysis to investigate the PA signature of childhood metabolic health including the whole spectrum of PA intensities using 3 different epoch settings. We conclude that the association pattern associated with health differed substantially between epoch settings. The use of longer epoch settings caused a skew in association patterns towards lower intensities and lead to poorer models of childhood metabolic health compared to shorter epoch settings. Researchers need to be aware of these effects to make the best possible choice of epoch setting for analysis and make the appropriate interpretation of their findings. We recommend future studies use short epochs when analyzing accelerometry data in children in order to mirror their activity patterns and capture VPA correctly. We further recommend that studies adapt the present multivariate analytic approach to develop the field of PA epidemiology.

Competing interests

The authors declare that they have no competing interests.

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Figure Legend

Figure 1. The multivariate PA signature associated with a composite metabolic health score in children using different epoch settings displayed as a selectivity ratio plot. Explained variance for **t**he partial least squares regression was 17.0, 13.4, and 10.8% for data analyzed at 1, 10, and 60-seconf epoch periods adjusted for age and sex. The selectivity ratio for each variable is calculated as the ratio of explained to residual variance on the predictive (target projected) component. A negative bar implies that increased PA are associated with better metabolic health.

448 **Table 1.** Children's characteristics for demography, anthropometry and metabolic health.

	Overall (n = 841)	Boys (n = 424)	Girls (n = 417)	p between groups
Demography				
Age (years)	10.2 (0.3)	10.2 (0.3)	10.2 (0.3)	.803
Anthropometry				
Body mass (kg)	37.0 (8.1)	36.8 (7.8)	37.2 (8.3)	.641
Height (cm)	142.9 (6.7)	143.1 (6.7)	142.6 (6.8)	.197
BMI (kg/m^2)	18.0 (3.0)	17.9 (2.9)	18.1 (3.1)	.218
Overweight and obese (%)	20.8	20.0	21.5	.583
Waist circumference (cm)	61.9 (7.5)	62.2 (7.3)	61.6 (7.7)	.169
Waist:height (ratio)	0.43 (0.05)	0.43 (0.05)	0.43 (0.05)	.322
Indices of metabolic health				
Andersen test (m)	898 (103)	925 (112)	871 (85)	< .001
Systolic blood pressure (mmHg)	105.2 (8.4)	105.3 (8.2)	105.2 (8.6)	.612
Diastolic blood pressure (mmHg)	57.7 (6.2)	57.4 (6.0)	58.1 (6.3)	.180
Total cholesterol (mmol/l)	4.46 (0.69)	4.46 (0.70)	4.46 (0.68)	.976
LDL-cholesterol (mmol/l)	2.51 (0.64)	2.50 (0.65)	2.53 (0.62)	.570
HDL-cholesterol (mmol/l)	1.59 (0.35)	1.63 (0.34)	1.55 (0.35)	.001
Total:HDL-cholesterol (ratio)	2.91 (0.71)	2.82 (0.66)	2.99 (0.74)	.001
Triglyceride (mmol/l)	0.78 (0.38)	0.72 (0.31)	0.84 (0.42)	< .001
Glucose (mmol/l)	4.98 (0.32)	5.02 (0.31)	4.94 (0.33)	.001
Insulin (pmol/l)	7.91 (4.29)	7.05 (3.48)	8.33 (4.83)	< .001
HOMA (index)	1.71 (0.98)	1.54 (0.83)	1.89 (1.09)	< .001
Composite score (1SD)*	0.00 (1.00)	0.00 (0.93)	0.00 (1.07)	-

449 BMI = body mass index; LDL = low density lipoprotein; HDL = high density lipoprotein; HOMA = homeostasis
450 model assessment; *The composite score includes waist circumference, systolic blood pressure, total:HDL
451 ratio, triglycerides, HOMA, and the Andersen test.

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Table 2. Physical activity levels (mean (SD)) by epoch setting.

	1-second epoch	10-second epoch	60-second epoch
Wear time (min/day)	795 (56)	795 (56)	796 (57)
Overall PA (cpm)	708 (272)	707 (271)	705 (269)
SED (min/day)	597 (56)	490 (60)	390 (64)
LPA (min/day)	122 (22)	231 (38)	340 (54)
MPA (min/day)	37 (10)	44 (13)	45 (17)
VPA (min/day)	39 (15)	31 (16)	21 (16)
MVPA (min/day)	76 (23)	74 (25)	65 (28)
Guideline amount (%)	74	69	52

PA = physical activity; SED = sedentary time; LPA = light physical activity, MPA = moderate physical activity; VPA = vigorous physical activity; MVPA = moderate-to-vigorous physical activity. Intensity-specific PA is calculated using the Evenson cut points [28]; The guideline PA levels is defined as a mean of ≥ 60 min of MVPA per day.

Table 3. Correlations (Pearson's r) for PA intensity intervals with metabolic health, adjusted for age and sex.

Physical activity intensity (cpm)	1-second epoch	10-second epoch	60-second epoch
0–99	0.07	0.09	0.10
100–249	-0.03	0.01	0.01
250–499	-0.01	0.03	0.08
500–999	0.02	0.03	0.04
1000–1499	0.04	0.00	-0.01
1500–1999	0.03	-0.02	-0.06
2000–2499	0.00	-0.05	-0.15
2500–2999	-0.04	-0.11	-0.21
3000–3499	-0.10	-0.17	-0.27
3500–3999	-0.15	-0.23	-0.29
4000–4499	-0.19	-0.26	-0.31
4500–4999	-0.22	-0.30	-0.30
5000–5499	-0.26	-0.33	-0.27
5500–5999	-0.29	-0.33	-0.24
6000–6499	-0.32	-0.35	-0.19
6500–6999	-0.33	-0.33	-0.18
7000–7499	-0.33	-0.30	-0.10
7500–7999	-0.34	-0.27	-0.09
8000–8499	-0.33	-0.24	-0.11
8500–8999	-0.31	-0.23	-0.07
9000–9499	-0.31	-0.18	-0.06
9500–9999	-0.29	-0.17	-0.04
≥ 10000	-0.14	-0.08	-0.06

Associations ≤ -.07 and ≥ .07 are significant at $p < .05$ without adjustment for multiple comparisons.