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Estimating treatment effects of physical activity on subcategories of mental health: A propensity score analysis among a global sample of 341,956 adults

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Abstract:	<p>Background</p> <p>Evidence indicates that physical activity (PA) can be a clinically useful and low-cost option for preventing and managing many mental health problems. Further investigation into which specific aspects of mental health are most influenced by PA can help to elucidate the differential effects that PA may confer.</p> <p>Purpose</p> <p>This study used cross-sectional data from the Global Mind Project to investigate the influence of regular PA on overall mental well-being and specific subcategories of mental health across different adult age groups.</p> <p>Methods</p> <p>Participants completed the 47-item Mental Health Quotient (MHQ) and reported how frequently they engaged in daily bouts of PA for 30 min or more. Weighted propensity score models were used to estimate the Average Treatment effect on the Control (ATC) of PA engagement on overall mental well-being as well as six subcategories of mental health.</p> <p>Results</p> <p>An estimated ATC of 17.8 was found for overall MHQ, corresponding to a standardized mean difference (SMD) of 0.25. Among the mental health subcategories, PA engagement was estimated to have the largest treatment effect for Mind-Body Connection (ATC=19.25; SMD=0.31), followed by Adaptability and Resilience (ATC=17.57; SMD=0.26), Core Cognition (ATC=16.33; SMD=0.25), Drive and Motivation (ATC=15.86; SMD=0.24), Mood and Outlook (ATC=15.27; SMD=0.22), and Social Self (ATC=13.02; SMD=0.17).</p>

	<p>Conclusion</p> <p>Our findings support the existing literature demonstrating an exposure effect of regular PA engagement on overall mental well-being, and builds on this work by revealing consistent effects that exist across specific subcategories and the adult lifespan.</p>
Suggested Reviewers:	

May 25, 2023

Dr. Tracey Revenson,
Editor-in-Chief, *Annals of Behavioral Medicine*

Dear Dr. Revenson,

On behalf of my co-authors, we submit an *Original Research Article* titled, “Estimating treatment effects of physical activity on subdomains of mental health: A propensity score analysis among a global sample of 341,956 adults” for consideration by *Annals of Behavioral Medicine*. Engaging in an inadequate amount of physical activity is known to have downstream effects on mental health. However, there is a dearth of literature that has considered which aspects of mental health may be impacted most, let alone during different periods of the adult lifespan. At the same time, advanced analytical approaches that can strengthen inferences made from cross-sectional data have received limited attention in the literature investigating physical activity and mental health.

To address these knowledge gaps, we estimated the treatment effects of physical activity engagement on a comprehensive indicator of mental health and its subcategories using propensity score weighted regression methods, and whether these effects may differ across age cohorts among a global sample of 341,956 adults living in 229 countries. This cross-sectional study used data from the Mental Health Million project, which included the novel Mental Health Quotient (MHQ) instrument. Advanced covariate balancing techniques were employed to reduce bias in our estimates. Our results showed that for adults who are inactive, becoming physically active could provide significant small beneficial effects for overall mental health and each of the six subdomains of the MHQ, although differences in the magnitude of these effects were observed across the subdomains. Furthermore, evidence indicated the strongest associations between physical activity and mental health appear to occur during the early and middle-aged adult life stages, with effects becoming weaker into old age. Collectively, our findings further buttress the growing body of evidence in support of promoting physical activity to improve various aspects of mental health and well-being among the population.

All authors have participated in the work and have reviewed and agreed with the content of the article. The material in this manuscript is original research, and none of the article contents are under consideration for publication elsewhere. All individuals listed as authors meet the appropriate authorship criteria, nobody who qualifies for authorship has been omitted from the authorship list and contributors and their funding sources have been properly acknowledged.

Thank you in advance for considering our article,



Christopher Huong, BA



Denver Brown, PhD

**Estimating treatment effects of physical activity on subcategories of mental health: A
propensity score analysis among a global sample of 341,956 adults**

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USA. E-mail: christopher.huong@utsa.edu. We have no conflicts of interest to disclose.

CRedit Author Statement: **Christopher Huong**: formal analysis, writing – original draft,
methodology (equal). **Denver Brown**: conceptualization, methodology (equal), writing – review
and editing

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Transparency Statement

1. Study registration.

- This study was not formally registered.

2. Analytic plan pre-registration.

- The analysis plan was not formally pre-registered.

3. Data availability:

- Data from the Global Mind Database can be requested directly from Sapien Labs:

<https://sapienlabs.org/global-mind-project/researcher-hub/>

4. Analytic code availability.

- Analytic code used to conduct the analyses presented in this study are not currently available in a public archive. They may be available by emailing the corresponding author. Once the authors are completed with organizing and annotating the analytic code, it will be made publicly available on a GitHub repository.

5. Materials availability.

- Materials concerning the development of the Mental Health Quotient instrument used from the Global Mind Project can be found in the references of the methods section of the main paper and on their website: <https://sapienlabs.org/global-mind-project/>

Abstract

Background: Evidence indicates that physical activity (PA) can be a clinically useful and low-cost option for preventing and managing many mental health problems. Further investigation into which specific aspects of mental health are most influenced by PA can help to elucidate the differential effects that PA may confer.

Purpose: This study used cross-sectional data from the Global Mind Project to investigate the influence of regular PA on overall mental well-being and specific subcategories of mental health across different adult age groups.

Methods: Participants completed the 47-item Mental Health Quotient (MHQ) and reported how frequently they engaged in daily bouts of PA for 30 min or more. Weighted propensity score models were used to estimate the Average Treatment effect on the Control (ATC) of PA engagement on overall mental well-being as well as six subcategories of mental health.

Results: An estimated ATC of 17.8 was found for overall MHQ, corresponding to a standardized mean difference (SMD) of 0.25. Among the mental health subcategories, PA engagement was estimated to have the largest treatment effect for Mind-Body Connection (ATC=19.25; SMD=0.31), followed by Adaptability and Resilience (ATC=17.57; SMD=0.26), Core Cognition (ATC=16.33; SMD=0.25), Drive and Motivation (ATC=15.86; SMD=0.24), Mood and Outlook (ATC=15.27; SMD=0.22), and Social Self (ATC=13.02; SMD=0.17).

Conclusion: Our findings support the existing literature demonstrating an exposure effect of regular PA engagement on overall mental well-being, and builds on this work by revealing consistent effects that exist across specific subcategories and the adult lifespan.

Estimating treatment effects of physical activity on subcategories of mental health: A propensity score analysis among a global sample of 341,956 adults

Introduction

Suboptimal mental well-being and mental health problems have proven to be a significant burden on the global population. Approximately 29% of individuals have experienced a common mental disorder during their lifetime, with a 9.6%, 12.9%, and 10.7% lifetime prevalence for mood, anxiety, and substance-use disorders, respectively [1]. The global burden of mental disorders was estimated at 125.3 million disability-adjusted life-years (DALY) in 2019 – an increase from 80.8 million DALYs in 1990 [2]. Moreover, lost productivity due to poor mental health is estimated to cost the global economy \$2.5T annually and is projected to more than double over the next decade, reaching \$6T by 2030 [3]. The COVID-19 pandemic may also have conferred a toll on population mental health and well-being worldwide. Evidence from reviews is somewhat mixed, but findings suggest there has been an increase in depressive and anxiety symptoms most consistently in younger cohorts [4–8]. Collectively, it is clear that mental health problems and poor mental well-being are a growing issue in society today, but certain subpopulations may experience an even greater toll.

Emerging evidence in addition to recent findings from the COVID-19 pandemic suggests younger age cohorts of adults may be at the greatest risk for poor mental health and well-being [9,10]. For example, a recent study showed that younger adults living in the US consistently report the lowest scores on all domains of mental well-being, including happiness, health, meaning and purpose, character, social relationships, and financial stability, with a linear pattern of improvements in well-being observed with increased age [11]. These findings are in contrast to previous work that had demonstrated an inverted-U relationship between age and mental well-

being in which mental well-being was lowest in middle adulthood [12]. Further, the onset of an estimated half of first mental disorders occurs by age 18, which speaks to the pervasiveness of mental health challenges experienced when transitioning into early adulthood [13]. Evidently, more research is needed to better understand these age-related trends from a global perspective, including a focus on protective factors that may moderate the relationship between age and mental well-being.

Physical activity is one aspect of our lifestyle that has received increasing attention for its potential to promote mental well-being as well as assist in the prevention and management of mental health disorders. Observational and experimental evidence has consistently shown a relationship between higher levels of physical activity and benefits across various mental health outcomes, including, but not limited to depression [14–16], anxiety [17,18], and general mental health and well-being [19]. For example, in a large cross-sectional dataset of over 1.2M adults living in the United States, Chekroud et al [20] showed that engaging in physical activity in the past month was associated with 43.2% lower self-reported days with poor mental health over that period. Despite these robust findings, particularly for depression and anxiety, physical activity remains an underutilized treatment tool among clinical practitioners [21]. The inclusion of physical activity – albeit as an alternative and/or complementary treatment – in several recent national guidelines for the treatment of depression holds promise for promoting greater uptake in primary care services [22–24].

While evidence supports the importance of physical activity for preventing and/or reducing a range of mental health problems and improving overall well-being, for some other psychiatric symptoms and disorders (e.g., bipolar disorder, schizophrenia), the evidence is less suggestive of benefits, or remains unclear [25–27]. More recently, however, researchers have

demonstrated that there is considerable overlap in symptomatology across the most commonly classified mental health disorders, which illustrates the complexity and heterogeneous nature of mental health as a construct [28,29]. Such knowledge has sparked the development of novel measures – the Mental Health Quotient (MHQ) for example – to address these considerations. Yet, due to their recency, these instruments have seldom been utilized.

One promising avenue in which comprehensive measures of mental health can be applied is in studies examining the specific aspects of mental health that physical activity may especially favor. Findings stemming from such studies have the potential to improve precision in the treatment of mental health problems and therefore may have important implications for clinical outcomes [30,31]. Determining whether physical activity is associated with differential effects for certain aspects of mental health across the lifespan is but one fruitful area of inquiry to pursue for the purpose of improving population-level mental health and well-being.

The primary purpose of the present study was to estimate the treatment effect of physical activity engagement on overall mental health in a large global sample, as well as various subcategories of mental health, while statistically accounting for a range of observed covariates using a machine learning technique underutilized in exercise psychology and behavioral medicine. The secondary purpose of this study was to examine whether differential effects of physical activity are observed on indicators of mental health across age cohorts.

Methods

The reporting of the methods and results in this study adhere to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for cross-sectional studies. [32]

Study Sample and Data Collection. This cross-sectional study used data from the Global Mind Project (GMP; formally the Mental Health Million Project), an on-going online

study with the purpose of assessing global mental well-being through administration of the Mental Health Quotient. The sample for our present study included 341,956 participants from 229 countries who completed the GMP survey between December 31st, 2021 and October 14th, 2022. The start of this period coincided with the launch of Version 3 of the MHQ. Additional information concerning the GMP and recruitment strategy may be found elsewhere [33]. This study involved secondary analysis of existing non-identifiable data and therefore Institutional Research Ethics Board approval was not required.

Measures

Mental health. The MHQ is a 47-item instrument designed to assess a comprehensive range of common attributes found across widely used existing mental health assessment tools in a single questionnaire to estimate overall mental well-being and functioning in the population. Items were developed by consolidation of 170 symptoms coded from 126 commonly used assessment tools covering depression, anxiety, bipolar disorder, ADHD, post-traumatic stress disorder, obsessive-compulsive disorder, addiction, schizophrenia, eating disorders and autism spectrum disorder. The MHQ is unique from other psychiatric tools in that the items assess level of functioning and impact on one's life associated with each mental health element, as opposed to frequency, duration, or severity of symptoms. The questionnaire took an average of 14 minutes for participants to complete.

Responses from the 47 items were used to compute the MHQ, which represents an overall score of mental health and well-being. The MHQ originally ranged from -100 to +200, however, the lower limit was recently expanded to -166 to improve the distribution of scores that previously demonstrated a floor effect at the lower bound. Scores on the MHQ can be classified into six levels of functioning, with negative scores indicating clinical risk and positive scores

representing normal range: Clinical (≤ -50), At Risk (-50 to <0), Enduring (0 to <50), Managing (50 to <100), Succeeding (100 to <150) and Thriving (150 to 200). To compute the overall score, individual item responses were weighted to reflect the nonlinearity of risk associated with increases in symptom severity, as well as the differential risk associated with different symptoms (e.g., suicidal thoughts vs irritability).

In addition to the overall MHQ score, scores for six broad subcategories of mental health and well-being were computed: Core Cognition (e.g., executive functioning and other cognitive processes), Adaptability and Resilience (e.g., creativity and flexibility), Mood and Outlook (e.g., emotional regulation, optimism), Drive and Motivation (e.g., sustained interest, persistence), Social Self (e.g., maintaining relationships, self-image), and Mind-Body Connection (e.g., physical functioning, psychosomatic wellbeing). Subcategory scores ranged from -100 to $+200$, and were computed by a weighted average of scores from 10 to 24 relevant symptom items based on a review of cognitive and brain functioning models. Further details on the development, full descriptions, and psychometric properties of the MHQ can be found elsewhere [33,34],

Physical activity. Participants responded to single item that asked: “How regularly do you engage in physical exercise (30 minutes or more)?” Response options included “Rarely/never”; “Less than once a week”; “Once a week”; “Few days a week”; and “Every day”. In line with Chekroud et al. [28], responses to the physical activity frequency item were recoded into binary groups with participants who reported “Rarely/never” coded as the control (inactive; no exposure to physical activity), and all other responses coded as the treated (physically active; exposure to physical activity).

Covariates. To adjust for potential confounders, the following covariates were considered for inclusion in our analysis: age, biological sex, gender identity, ethnicity,

educational attainment, employment status, relationship status, frequency of adequate sleep, frequency of socializing, diagnosis of a medical condition (Y/N), whether they are currently seeking mental health treatment (Y/N), and whether they reported a significant traumatic childhood or adult experience (Y/N). Data inspection revealed considerable missingness for ethnicity (84.2%) and gender identity (98.5%) due to only having been included on surveys for individuals who reported residing in certain countries, and therefore these variables were excluded. All responses in which participants answered “Prefer not to say” were recoded as missing.

Statistical Analysis

All data preprocessing and statistical analyses were done using the statistical software R version 4.1.2 [35] and RStudio (Version 2022.07.2). First, distributions of covariates were balanced between the non-exposure (i.e., Inactive) and exposure (i.e., Physically Active) groups using propensity score weights estimated with generalized boosted modeling (GBM) [36,37], and implemented in the R Package *WeightIt* [38]. The propensity score is defined as “the conditional probability of assignment to a particular treatment given a vector of observed covariates” [39]. Weighting was preferred over matching procedures for the purpose of preserving sample size. Propensity scores weights were computed based on the Average Treatment effect on the Control (ATC) estimand, which is used to estimate the hypothetical average treatment effect on those who did not receive the treatment. In other words, it is the expected effect of physical activity on those in the sample who are inactive, which would help inform the clinical question of whether mental health practitioners should encourage physical activity in inactive patients. This research question is relevant for mental health practitioners given that individuals with mental health disorders have been shown to be more sedentary and

less active than population norms [40]. Treatment effects estimated with propensity score adjustment are unbiased when the strong ignorability assumption is met (i.e., when there are no unobserved confounders, and all observed confounders are included in the model) [39].

GBM is a non-parametric iterative machine learning method which, as implemented in the present study, combines boosting (the sequential combination of weak learners to improve predictions by adapting the errors of the previous model) and regression trees (the weak learners) to generate a smoothed function of estimated propensity scores. This method automatically accommodates non-linearity and complex interactions, and has been shown in previous studies to outperform traditional parametric models such as logistic regression [36,41,42]. Several tuning parameters were selected to achieve covariate balancing, as suggested by McCaffrey et al [36]. The Bernoulli distribution was chosen for the loss function the boosted model was to minimize, as our treatment variable was coded as a binary exposure. The number of trees was determined by minimizing the average standardized absolute mean difference in the covariates. The maximum number of trees was set to 10,000 by default, and increased to 20,000 if covariate balancing was not achieved. Missing data was handled by surrogate splitting as described in the *WeightIt* R package documentation [38]. Though unlikely to significantly improve the performance of our procedure [43] weights above 99% were winsorized to reduce potential bias from extreme values. Diagnostics were used to ensure covariates were adequately balanced by assessing the weighted absolute standardized difference in means of covariates between treatment and control group.

For our main analysis, propensity weights were fed into a regression model to estimate the ATC for physical activity on seven outcomes: overall MHQ score, and its six subcategories, Core Cognition, Adaptability and Resilience, Mood and Outlook, Drive and Motivation, Social

Self, and Mind-Body Connection. To explore whether the effect of physical activity on mental health differs across age groups, we performed the same analysis on each age group (18-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85+ years of age) for the MHQ and its six subcategories. Lastly, we estimated the marginal interaction effects of age and physical activity on MHQ to investigate whether an age gradient for mental health exists, and how this may be moderated by physical activity status. In all models, participants were nested within country to account for potential clustering effects.

Several sensitivity analyses were performed to determine whether the inferences of the main analyses were biased due to model misspecification or handling of missing data [44,45]. First, we computed propensity score weighted regression models that included further adjustment for the full covariate set to allow for doubly robust estimation [46]. Second, instead of handling covariate missingness by surrogate splitting, we first implemented multiple imputation (MI) before the GBM estimation of propensity scores. Third, we estimated ATCs using MI and covariate balancing propensity score (CBPS) weighting, which may outperform GBM if there is a non-complex relationship between treatment and outcome [47]. MI and CBPS are described in greater detail in the Supplementary Materials (Section A). Doubly robust estimation was also computed for these models by including the full covariate set in the multiply imputed, CBPS or GBM-weighted regression models. Akin to our main analyses, participants were nested within country for all models.

Results

Descriptive statistics. After dropping two cases due to Arabic responses not translating properly, the final sample included 341,956 participants, and was predominantly female (55.3%; 43.5% male, 0.2% other/intersex), post-secondary educated (47.5% with a bachelor's or graduate

degree; 32.6% high school or less), employed (47.8%; 32.1% studying or retired, 8.7% unemployed), married (42.5%; 24.9% single), and physically active to some degree (60.4%). The sample was also representative across the adult lifespan (18-24 and 55-64 were the most common age ranges selected at 18.91% and 18.50% of the sample, respectively). The mean score for the MHQ was 67.93 ± 72.70 SD, which would be considered “Managing” as per the MHQ’s six levels of functioning. Full descriptive statistics for the sample demographic characteristics, covariates, physical activity, MHQ, and the six subcategories for each age group can be found in Supplementary Materials Table 1.

After adjusting for propensity score weighting, the effective sample for the treated (active) group was reduced to 140,633.8 (68.13% of unadjusted), yielding an overall effective sample size of 276,158.8 (80.76% of original sample). The effective sample size is the “approximately the number of observations from a simple random sample that yields an estimate with sampling variation equal to the sampling variation obtained with the weighted comparison observation”, and can be interpreted as a conservative lower bound for the adjusted size of the weighted sample [48]. Diagnostics indicated that covariate balance was successfully achieved after GBM and CBPS weighting procedures were implemented (see Supplementary Materials, Section B).

Physical Activity. Propensity score weighted models demonstrated physical activity was associated with significant ($p < 0.01$) treatment effects on overall MHQ scores (ATC = 17.86; 95% CI: 15.07-20.64), which coincided with a small effect size calculated using standard deviations from the unweighted data (standardized mean difference (SMD) = 0.25). Physical activity was also associated with significant treatment effects for each of the six MHQ subcategories: Core Cognition (ATC = 16.33; 95% CI: 13.87-18.78; SMD = 0.25), Adaptability

and Resilience (ATC = 17.57; 95% CI: 14.83-20.31; SMD = 0.26), Drive and Motivation (ATC = 15.86; 95% CI: 12.87-18.86; SMD = 0.24), Mood and Outlook (ATC = 15.27; 95% CI: 12.53-18.01; SMD = 0.22), Social Self (ATC = 13.02; 95% CI: 10.18-15.85; SMD = 0.17), and Mind-Body Connection (ATC = 19.25; 95% CI: 16.66-21.84; SMD = 0.31).

Physical Activity and Age. Figures 1 and 2 show the effects of PA on overall MHQ scores and each subcategory by each age group. Briefly, overall trends showed significant beneficial effects of physical activity on overall MHQ scores and each MHQ subcategory across each age group. Larger effects were observed for young and middle-aged adults as well as those 85+ years of age. Inspection of the estimated effects on the six MHQ subcategories suggest that younger age groups may experience more favorable effects from physical activity for Core Cognition and Adaptability and Resilience, as compared to the other older age groups. All ATCs and standard errors can be found in Supplementary Materials Table 2.

Figures 3 and 4 show the predicted values of overall MHQ scores and each of the six subcategories as a function of age and physical activity engagement, demonstrating consistent increases in mental health with aging, with the exception of 75-84 to 85+ where mental health appears to plateau as evidenced by non-significant changes in both the Inactive and Active groups. Being physically active was associated with consistently higher mental health across all age groups.

Sensitivity analyses. Our sensitivity analyses (see Table 1) demonstrated convergence of the estimated treatment effects of physical activity on mental health across each of the alternative statistical techniques employed when compared to the main GBM results.

Discussion

The purpose of the present study was to estimate the treatment effects of physical activity engagement on a comprehensive indicator of mental health and its subcategories, and whether these effects may differ across age cohorts. Our findings revealed a significant small effect of self-reported physical activity on overall mental health and well-being. Sensitivity analyses revealed this effect was robust after adjusting for covariates using several different statistical methods. These findings are consistent with the existing evidence that has demonstrated beneficial associations between physical activity and various psychological outcomes including severe mental disorders [40], cognitive function [49,50], emotional skills [51], resilience [52], and quality of life [19,53]. Our results also align with previous work that has shown favorable effects of physical activity on indicators of mental health are consistent across the adult lifespan [54,55]. Taken together, these findings further underscore the importance of promoting a physically activity lifestyle to improve population mental health and well-being, which has the potential to significantly reduce the forecasted growing economic costs associated with poor mental health over the next decade.

Findings from the present study also contribute to the body of literature investigating associations between physical activity and mental health through examining specific subcategories of mental health and well-being. Our results showed robust and consistent beneficial effects of physical activity on each of the six subcategories of the MHQ, although it should be noted that physical activity appears to have a significantly stronger relationship with Mind-Body Connection compared to Social Self as evidenced by non-overlapping 95% CIs. The Mind-Body Connection subcategory, in which the largest effects were observed for physical activity, contains items assessing aspects of well-being with benefits robustly related to physical activity, such as pain [56,57], sleep [58,59], appetite regulation [60,61], and fatigue [62,63].

Conversely, the smallest effect was shown for Social Self, which includes aspects of well-being with less established and robust associations to physical activity such as empathy, communication skills and relationship building [64,65]. Although physical activity is a social pursuit for many, one potential explanation for a smaller effect of physical activity on Social Self is that some individuals prefer to engage in independent activities such as running or cycling alone, thus negating the potential social benefits associated with more group-oriented activities such as team sports and exercise classes. Nevertheless, these findings suggest that physical activity may confer benefits for all aspects of mental health and well-being, with small differences favoring psychophysiological over social aspects.

This study also addressed a knowledge gap regarding a dearth of evidence investigating potential differential effects of physical activity on certain aspects of mental health and well-being across the adult lifespan. Evidence indicated that young and middle-aged adults may experience greater benefits for their overall mental health from physical activity engagement in comparison to older adults. It should be noted that adults 85+ years of age appear to be an exception; however, this group also had the largest confidence interval likely due to a relatively smaller sample. As average levels of physical activity tend to be higher among young and middle-aged adults than older adults [66], a more sedentary lifestyle may be especially indicative of impairment in younger cohorts. Core Cognition, Drive and Motivation, and Adaptability and Resilience followed the same trend as overall MHQ scores, and thus these specific aspects of mental health and well-being may be more amenable to benefits from adopting a more active lifestyle, whereas the other subcategories seem to demonstrate relatively consistent benefits from physical activity across the adult lifespan. Finally, differences between inactive and active groups across ages were most pronounced in the 85+ age group as evidenced by the largest

average marginal effect across all subcategories. This finding makes it clear that physical activity engagement is especially important for maintaining better mental health and well-being in the latest stages of life.

As the body of literature examining associations between physical activity and mental health continues to grow, it is imperative that researchers adopt statistical best practices that can reduce bias and strengthen our inferences. Matching and weighting techniques have received little attention in the fields of exercise psychology and behavioral medicine to date. For example, an advantage of utilizing propensity scores over controlling for covariates in a traditional multivariable linear regression is that the propensity model can deal with non-linear relationships between the covariates and outcome, as well as higher order interactions, and the GBM can handle these interaction terms non-parametrically when estimating the propensity score. As different propensity score estimation methods may perform differentially based on different assumptions and approaches to handle missing data [44,45,47], we utilized several combinations of methods in our sensitivity analyses. Our sensitivity analysis revealed minimal deviance in the estimated effects of physical activity on overall MHQ scores across the various covariate adjustment and missing data procedures that were implemented – effect sizes were equivalent ranging from an SMD of 0.25 to 0.26. Using these various propensity score estimation techniques helped to improve our confidence that the estimated effect was not biased due to misspecification of the propensity model. In doing so, these estimates strengthen the inferences we can make about the relationship between physical activity and mental health. Though strong causal inferences are not indicated by cross-sectional observations, our results converge with existing intervention studies. For example, previous meta-analyses of randomized controlled trials on exercise and depression found pooled effect sizes ranging from 0.62 to 0.98 [16,67,68].

This cross-sectional study estimated treatment effects of physical activity on several aspects of mental health among a large global sample of adults using advanced covariate balancing techniques to reduce bias in our estimates. Our results demonstrate a significant small effect of self-reported physical activity on a comprehensive measure of overall mental health and well-being, in addition to similar benefits across several specific subcategories of mental health. The strongest associations between physical activity and mental health appear to occur during the early and middle-aged adult life stages, with effects becoming weaker into old age. These findings further support the growing body of evidence promoting the benefits of physical activity on various aspects of mental health and well-being among the population.

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Tables and Figures

Table 1. Sensitivity analysis. Reported ATC effects and standard errors on MHQ

MHQ	GBM	Doubly Robust		Doubly Robust		Doubly Robust MI	
		GBM	MI + GBM	MI + GBM	MI + CBPS	+ CBPS	
ATC	17.86	17.74	17.75	17.77	18.15	17.87	
SE	1.43	0.99	0.28	0.23	0.28	0.22	
SMD	0.25	0.25	0.25	0.25	0.26	0.25	

Figure 1. ATC's of physical activity on overall MHQ and subcategories scores across age groups. Error bars represent 95% CIs.

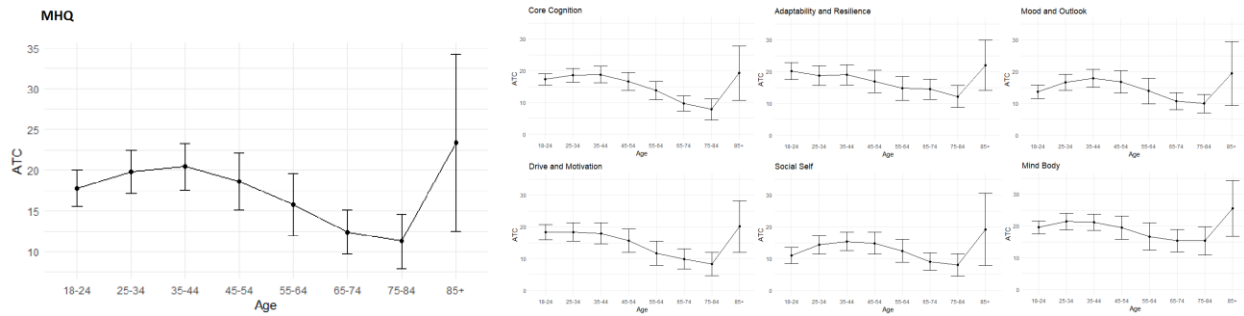


Figure 2. Marginal effects on MHQ and subcategories by age for inactive and active groups with 95% CIs. Levels of subcategory scores ranged from -100 to +200.

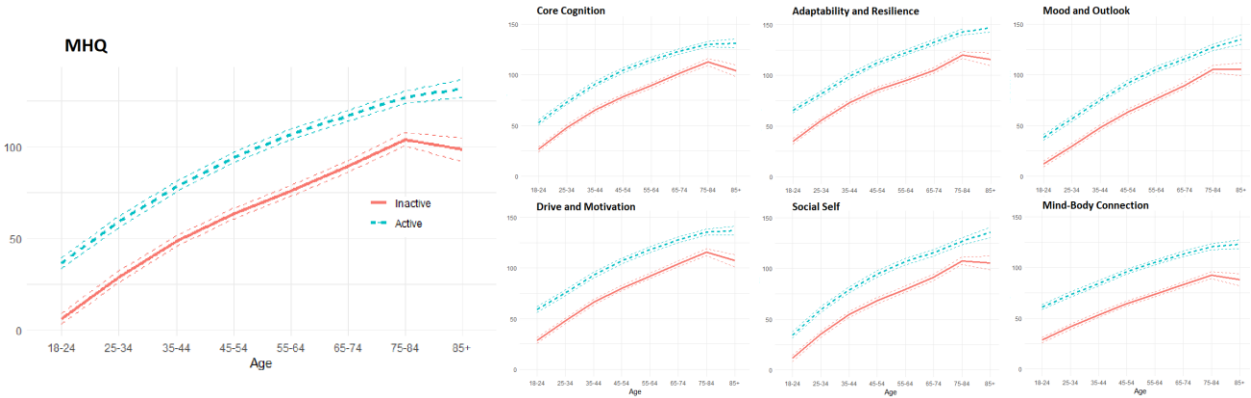


Figure 1

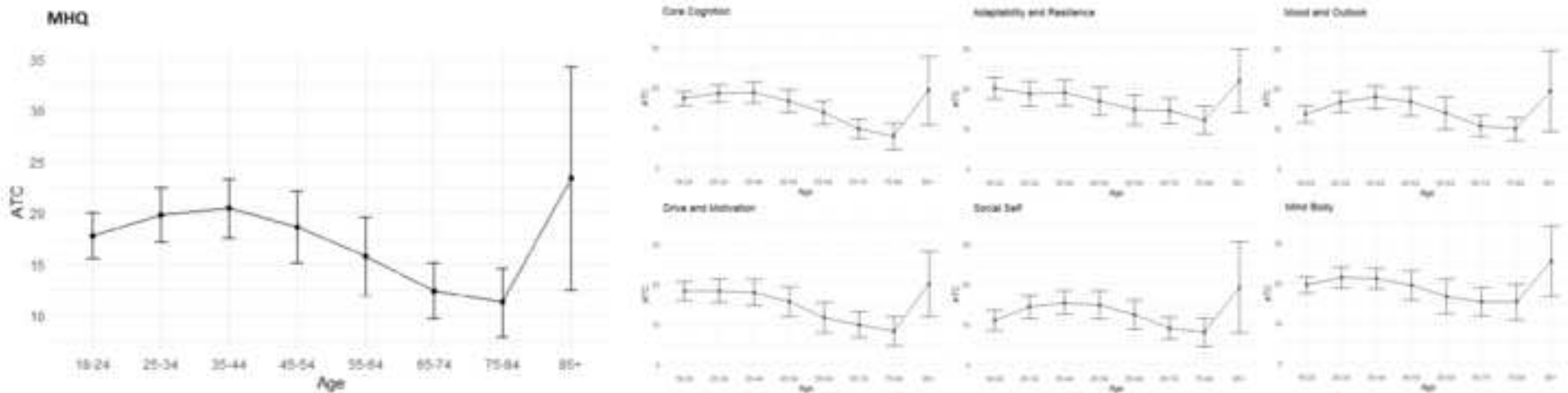
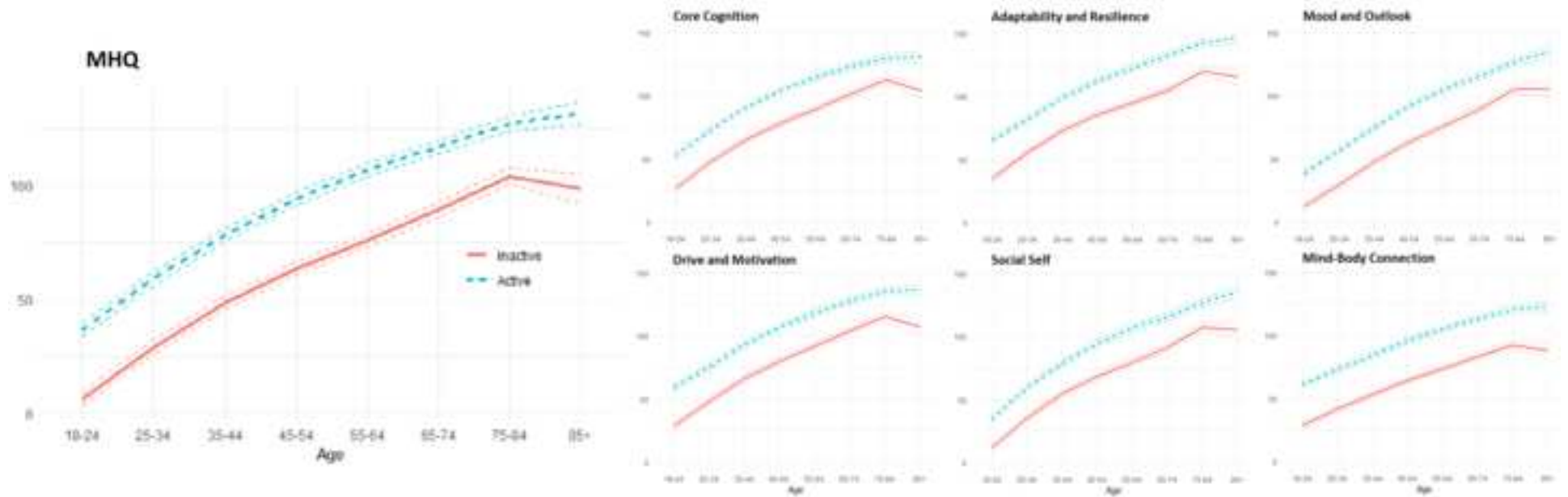
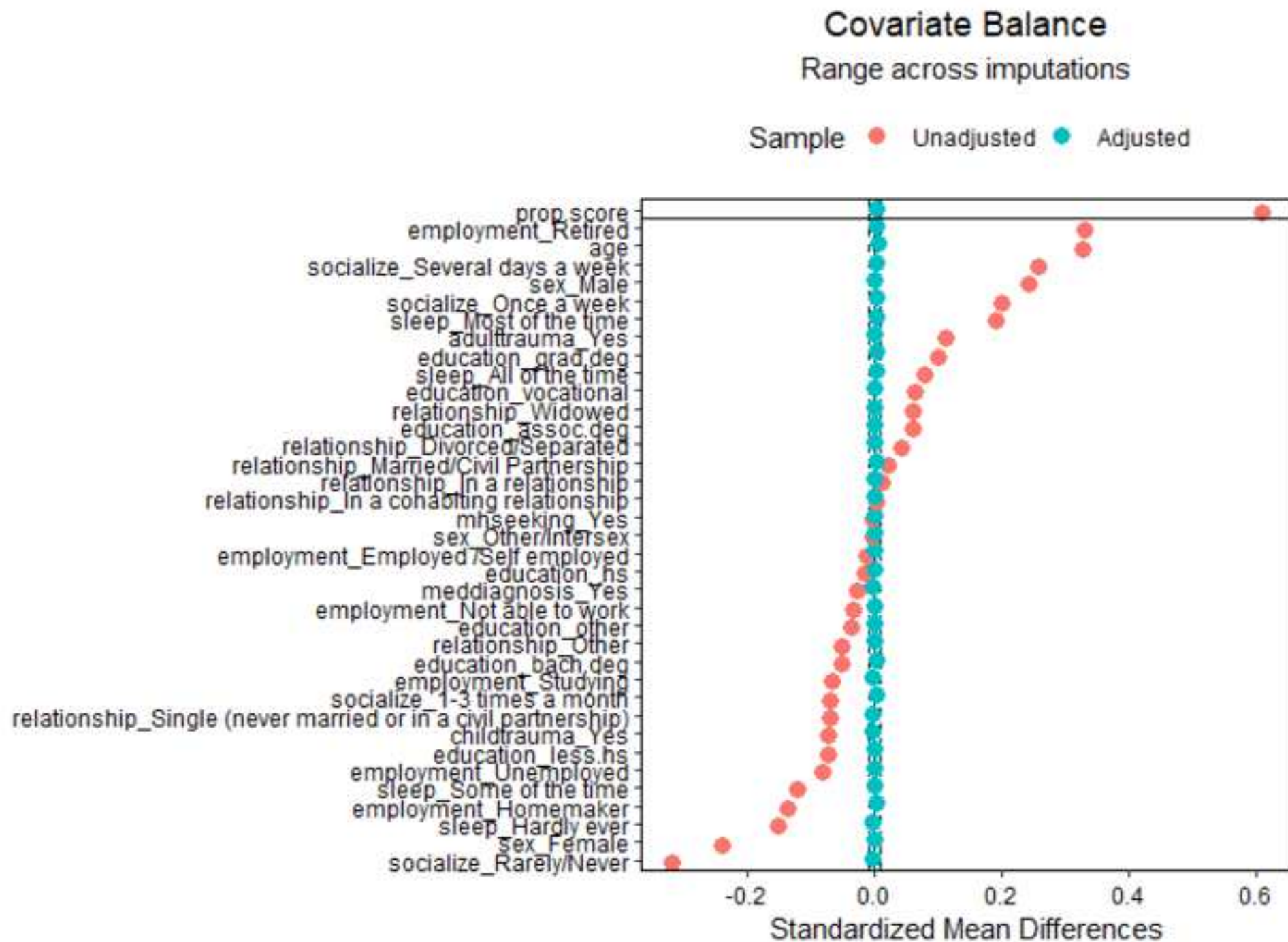


Figure 2

[Click here to access/download;Figure;Figure 2.png](#)





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Article Title Estimating treatment effects of physical activity on subcategories of mental health: A propensity score analysis among a global sample of 341,956 adults

Author Signature 

Date 6/10/2023

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Author Name Denver Brown

Article Title Estimating treatment effects of physical activity on subcategories of mental health: A propensity score analysis among a global sample of 341,956 adults

Author Signature 

Date 06/10/2023

SUPPLEMENTARY MATERIALS

Section A

For the sensitivity analysis we handled missing data with Multiple Imputation using Fully Conditioned Specification as implemented in the R Package *mice* [1] with number of imputations set to 5. Multiple imputation preserves the sample size while accounting for uncertainty by incorporating randomness in missing value estimation with multiple data sets. Covariate balancing propensity scores [2] were used to estimate propensity weights on each imputed dataset as implemented in the R Package *WeightThem* [3], and the results were combined using the *Within* approach where weights are estimated for each imputed data set, exposure effects are computed for each individual data set and then the coefficients and standard errors are subsequently pooled using Rubin's Rules [4] to produce a point estimate of the exposure effect. The within approach demonstrates unbiased estimates when compared to other approaches [5,6].

Section B

Covariate balancing was assessed using the R package *cobalt* [7]. Pre-weighting and pre-imputation assessment indicated 26/41 covariate levels were unbalanced. After GBM weighting, perfect balance was achieved across all covariate levels using a difference threshold of > 0.01 . After multiple imputation and covariate balancing propensity score weighting, perfect covariate balance was also achieved. Both love plots are shown in Figures 1 & 2 to visualize the standardized mean differences of covariates before and after weighting.

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46 Figure 1. Love plot displaying covariate balance before and after GBM adjustment.

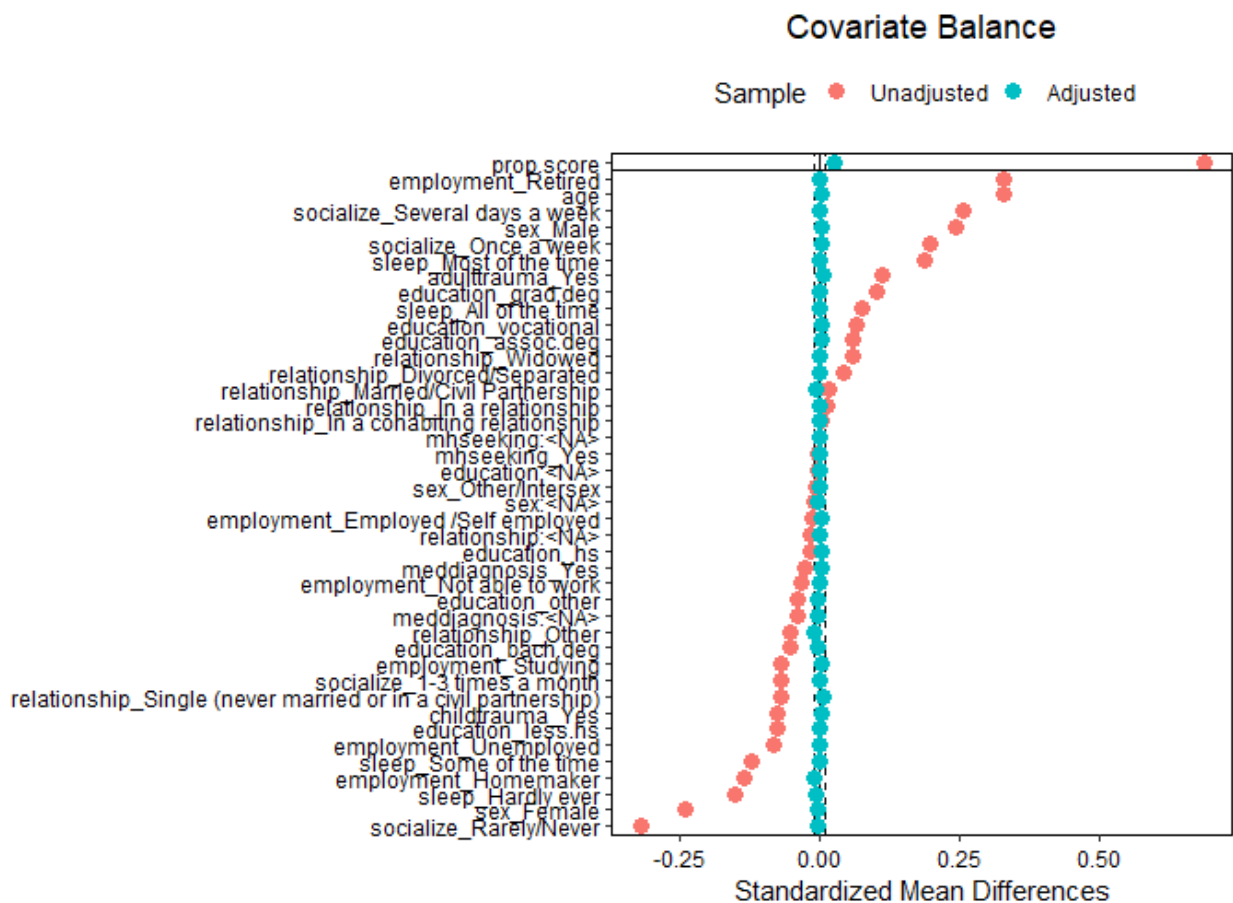


Figure 2. Love plot displaying covariate balance before and after multiple imputation and covariate balancing propensity score adjustment.

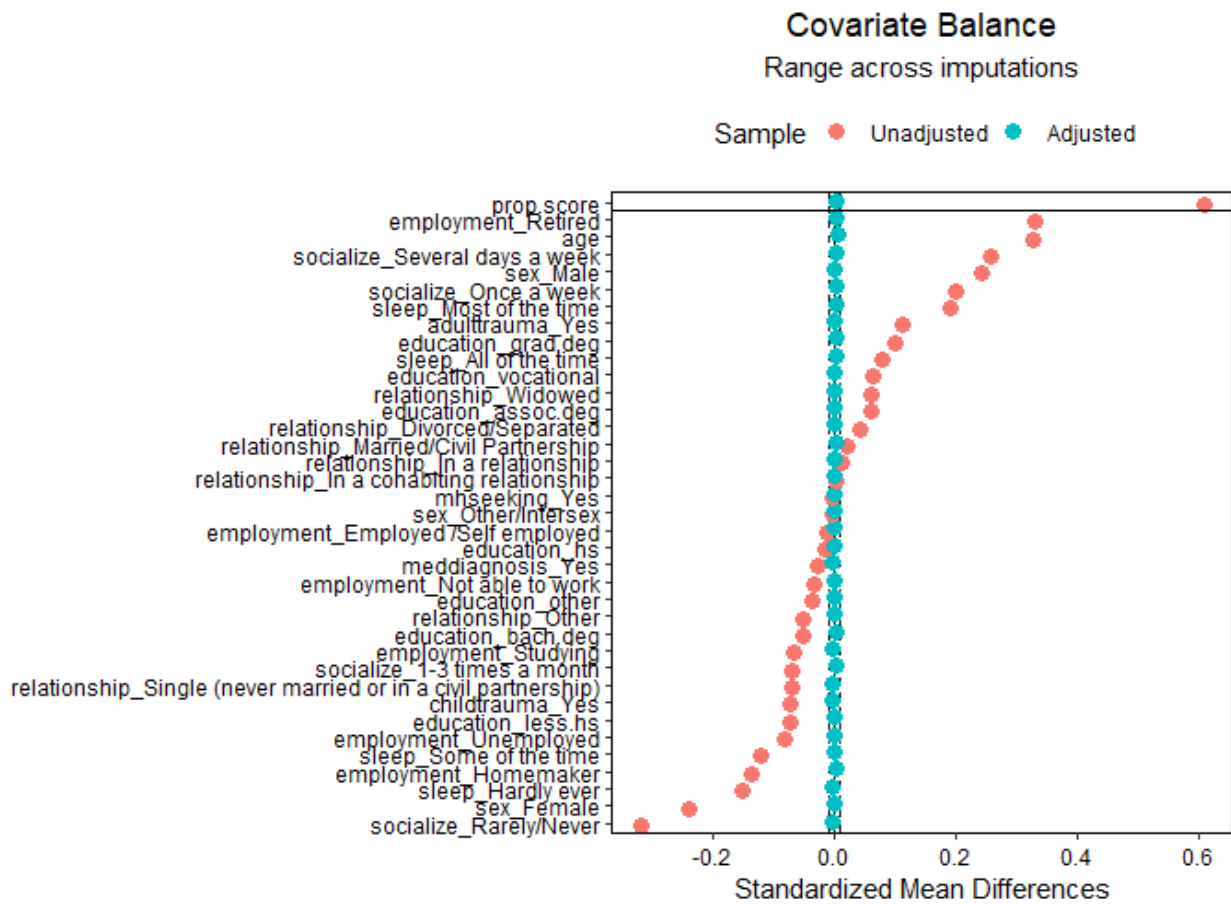


Table 1. Descriptive statistics for the full sample and by each age group

		1	3	4	5	6	7	8	
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years
	(((((((((
	N =	n =	n =	n =	n =	n =	n =	n =	n =
	341,956	64,648)	47,24	55,241)	57,259)	63,113	40,88	12,02	1,536)
)	9))	1)	9)		
x	Se								
	Fe	1	3	3	3	5			8
male	89226	9831	7344	1203	0890	2729	0256	141	32
	(55.3%)	(61.6%	(57.9	(56.5%	(53.9%	(51.9	(49.5	(51.1	(54.2
)	%)))	%)	%)	%)	%)	%)
M	1	2		2	2	5			6
ale	48624	3206	9427	3584	5815	9827	0299	807	59
	(43.5%)	(35.9%	(41.1	(42.7%	(45.1%	(47.3	(49.7	(48.3	(42.9
)	%)))	%)	%)	%)	%)	%)
Ot	8	2		9	1	1			2
her/Interse	19	68	3	2	63	36	3	4	0
x	(0.2%)	(0.4%)	(0.1	(0.2%)	(0.3%)	(0.2%)	(0.2	(0.1	(1.3%)
			%)				%)	%)	

		1	3	4	5	6	7	8	
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	total	years	years	years	years	years	years	years	years
Mi	3	1		3	3	4			2
ssing	287	343	15	62	91	21	63	7	5
	(1.0%)	(2.1%)	(0.9	(0.7%)	(0.7%)	(0.7%)	(0.6	(0.6	(1.6%)
			%)				%)	%)	
Ed									
ucation									
As	2	3		2	3	4			1
sociate's	1259	921	512	643	174	381	398	093	37
Degree	(6.2%)	(6.1%)	(5.3	(4.8%)	(5.5%)	(6.9%)	(8.3	(9.1	(8.9%)
			%)				%)	%)	
Ba	1	1		2	1	1			2
achelor's	05724	7800	9818	0404	8197	7066	753	455	31
Degree	(30.9%)	(27.5%	(41.9	(36.9%	(31.8%	(27.0	(23.9	(20.4	(15.0
)	%)))	%)	%)	%)	%)
Gr	5	3		1	1	1			2
aduate	6764	386	580	1690	1725	1671	423	038	51
Degree	(16.6%)	(5.2%)	(18.2	(21.2%	(20.5%	(18.5	(18.2	(16.9	(16.3
			%)))	%)	%)	%)	%)

		1	3	4	5	6	7	8	
	Total	18-24 years	25-34 years	35-44 years	45-54 years	55-64 years	65-74 years	75-84 years	85+ years
High School	7434	3451	871	293	1088	2985	321	155	78
	(22.6%)	(36.3%)	(16.7%)	(16.8%)	(19.0%)	(20.6%)	(22.8%)	(26.2%)	(31.1%)
Less than High School	4040	836	902	720	674	249	811	620	28
	(10.0%)	(10.6%)	(6.1%)	(8.5%)	(9.9%)	(11.5%)	(11.8%)	(13.5%)	(14.8%)
Other	6246	578	248	552	733	997	649	12	7
	(4.8%)	(5.5%)	(4.8%)	(4.6%)	(4.8%)	(4.7%)	(4.0%)	(3.4%)	(5.0%)
Vocational Certification	1823	922	613	1054	842	487	762	1043	100
	(6.4%)	(3.0%)	(5.5%)	(5.5%)	(6.7%)	(8.7%)	(9.2%)	(8.7%)	(6.5%)
Missing	666	754	105	85	1034	277	64	13	4
	(2.5%)	(5.8%)	(1.5%)	(1.6%)	(1.8%)	(2.0%)	(1.9%)	(1.8%)	(2.2%)

		1		3	4	5			8
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years
E									
mploymen									
t									
	E	1	1		3	4	5		8
mployed	63401	2630	9040	9198	1026	3075	391	60	1
/Self	(47.8%)	(19.5%	(61.5	(71.0%	(71.6%	(52.4	(18.1	(8.0	(5.3%)
employed)))))))))
Ho	3	2		8	7	5			9
memaker	1570	260	383	198	162	874	124	78	1
	(9.2%)	(3.5%)	(11.4	(14.8%	(12.5%	(9.3%)	(5.2	(4.0	(5.9%)
)))))	
No	7	1		9	1	2			3
t able to	210	212	06	66	444	193	73	1	5
work	(2.1%)	(1.9%)	(1.7	(1.7%)	(2.5%)	(3.5%)	(1.2	(0.7	(2.3%)
)))	
Re	6	1		3	1	1			1
tired	1333	02	3	17	924	7194	0038	0380	285
	(17.9%)	(0.2%)	(0.2	(0.6%)	(3.4%)	(27.2	(73.5	(86.3	(83.7
)))))

		1			3		4		5		6		7		8	
		T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+						
		total	years	years	years	years	years	years	years	years						
St		4	4			1	1	4			2					
dying	8583	0925	306	476	101	74	49	0	2							
	(14.2%)	(63.3%)	(9.1	(2.7%)	(1.9%)	(0.9%)	(0.4	(0.2	(1.4%)							
))					%)	%)								
Un		2	7			5	4	4			2					
employed	9859	519	621	086	602	203	06	00	2							
	(8.7%)	(11.6%)	(16.1	(9.2%)	(8.0%)	(6.7%)	(1.7	(0.8	(1.4%)							
))					%)	%)								
Relationship Status																
Di		3	8			4	6	9			1					
vorded/ Separated	2484	76	137	738	849	677	535	536	36							
	(9.5%)	(1.4%)	(4.5	(8.6%)	(12.0%)	(15.3	(16.0	(12.8	(8.9%)							
))	%)	%)	%)								
In		1	1			3	3	3			3					
a cohabiting relationshi p	5388	318	861	170	062	022	576	45	4							
	(4.5%)	(2.0%)	(6.1	(5.7%)	(5.3%)	(4.8%)	(3.9	(2.9	(2.2%)							
)					%)	%)							

[illegible]

		1	3	4	5	6	7	8	
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years
Wi	1	1	5	1	2	2	2	2	6
dowed	4744	39	58	57	490	860	895	984	61
	(4.3%)	(0.2%)	(0.3	(1.0%)	(2.6%)	(6.1%)	(12.0	(24.8	(43.0
			%)				%)	%)	%)
Mi	1	4	2	2	2	2	2	2	6
ssing	4678	757	762	102	098	251	282	64	2
	(4.3%)	(7.4%)	(3.7	(3.8%)	(3.7%)	(3.6%)	(3.1	(3.0	(4.0%)
			%)				%)	%)	
So									
cialize									
Frequency									
Ra	8	1	1	1	1	1	1	1	2
rely/Never	6212	4926	4063	6429	6052	5390	446	683	23
	(25.2%)	(23.1%	(29.8	(29.7%	(28.0%	(24.4	(18.2	(14.0	(14.5
)	%)))	%)	%)	%)	%)
1-	7	1	1	1	1	1	1	1	2
3 times a	9457	3115	1989	2973	3545	5310	591	655	79
month	(23.2%)	(20.3%	(25.4	(23.5%	(23.7%	(24.3	(23.5	(22.1	(18.2
)	%)))	%)	%)	%)	%)

		1	3	4	5	6	7	8	9
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years
On	6	1	1	9	9	1	1	1	3
ce a week	3389	1242	055	235	847	2275	352	019	64
	(18.5%)	(17.4%	(17.0	(16.7%	(17.2%	(19.4	(22.9	(25.1	(23.7
)	%)))	%)	%)	%)	%)	%)
Se	1	2	1	1	2	2	2	2	6
veral days	12898	5365	3142	6604	7815	0138	4492	672	70
a week	(33.0%)	(39.2%	(27.8	(30.1%	(31.1%	(31.9	(35.4	(38.8	(43.6
)	%)))	%)	%)	%)	%)	%)
Ad									
equate									
Sleep									
Frequency									
Ha	4	1	7	7	5	5	5	5	1
rdly ever	2262	0071	175	270	113	180	498	36	19
	(12.4%)	(15.6%	(13.1	(13.2%	(12.4%	(11.4	(8.6	(6.9	(7.7%)
)	%)))	%)	%)	%)	%))
So	1	2	2	2	1	1	1	1	2
me of the	17966	5492	8234	1289	0129	9465	0499	569	89
time	(34.5%)	(39.4%	(38.6	(38.5%	(35.2%	(30.8	(25.7	(21.4	(18.8
)	%)))	%)	%)	%)	%)	%)

		1		3	4	5		8	
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	total	years	years	years	years	years	years	years	years
M	1	2		2	2	2			7
ost of the	40096	2792	7866	1383	3592	7803	9799	106	55
time	(41.0%)	(35.3%	(37.8	(38.7%	(41.2%	(44.1	(48.4	(50.8	(49.2
)	%)))	%)	%)	%)	%)	%)
All	4	6		5	6	8			3
of the	1632	293	974	299	425	665	085	518	73
time	(12.2%)	(9.7%)	(10.5	(9.6%	(11.2%	(13.7	(17.3	(20.9	(24.3
			%))	%)	%)	%)	%)	%)
M									
edical									
Diagnosis									
(Y/N)									
Ye	5	7		6	8	1			4
s	3164	584	438	702	628	2133	917	286	76
	(15.5%)	(11.7%	(11.5	(12.1%	(15.1%	(19.2	(21.8	(27.3	(31.0
)	%)))	%)	%)	%)	%)	%)
Mi	8	2		1	1	1			6
ssing	080	187	98	203	212	290	74	55	1
	(2.4%)	(3.4%)	(2.1	(2.2%	(2.1%	(2.0%)	(2.1	(2.1	(4.0%)
			%)				%)	%)	

		1		3		4		5		8	
		T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+	
		otal	years	years	years	years	years	years	years	years	
Mental Health Treatment in Past Year (Y/N)											
Yes		5	1	8		8	8	8	9		
s		0606	2028	183	221	181	732	192	79	0	
		(14.8%)	(18.6%	(17.3	(14.9%	(14.3%	(13.8	(10.3	(8.1	(5.9%)	
)	%)))	%)	%)	%)	%)		
Missing		3	8	5		6	7	2			
ssing		832	50	34	86	24	25	50	34	9	
		(1.1%)	(1.3%	(0.9	(1.1%)	(1.1%)	(1.1%)	(1.1	(1.1	(1.9%)	
				%)				%)	%)		
Experienced Childhood Trauma (Y/N)											

		1		3	4	5			8
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years
Ye	2	4		3	3	5			8
s	10952	8130	1960	3581	3036	5712	1646	071	16
	(61.7%)	(74.4%	(67.6	(60.8%	(57.7%	(56.6	(52.9	(50.5	(53.1
)	%)))	%)	%)	%)	%)	%)

Ex									
perienced									
Adult									
Trauma									
(Y/N)									
Ye	2	4		3	4	4			1
s	52869	7240	4676	8578	1473	7681	1854	0030	337
	(73.9%)	(73.1%	(73.4	(69.8%	(72.4%	(75.5	(77.9	(83.4	(87.0
)	%)))	%)	%)	%)	%)	%)

Ph									
ysical									
Activity									
Ina	1	2		2	2	2			4
ctive	35525	7949	3082	7178	4080	0054	828	883	71
	(39.6%)	(43.2%	(48.9	(49.2%	(42.1%	(31.8	(24.0	(24.0	(30.7
)	%)))	%)	%)	%)	%)	%)

		1	3	4	5	6	7	8	9
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years

and Resilience									
M	8	5	8	1	1	1	1	1	1
ean (SD)	9.8	0.7	0.6	8.3	01	10	18	25	23
	(67.4)	(67.5)	(66.7	(64.6)	(62.7)	(61.3)	(55.2	(49.7	(55.4)
)))		

Dr ive and Motivatio n									
M	8	4	8	9	1	1	1	1	1
ean (SD)	3.4	3.5	2.6	0.4	4.3	05	14	18	14
	(66.6)	(64.7)	(65.2	(63.9)	(62.4)	(60.1)	(53.8	(49.7	(57.1)
)))		

M ood and Outlook									
M	6	2	6	7	9	9	9	9	1
ean (SD)	7.2	4.4	4.1	2.0	8.1	1.2	02	11	14
	(71.1)	(64.8)		(67.1)	(67.6)	(66.2)			(61.7)

		1		3	4	5		8	
	T	8-24	5-34	5-44	5-54	5-64	5-74	5-84	5+
	otal	years	years	years	years	years	years	years	years
			(66.3				(61.5	(57.2	
)))	
So									
cial Self									
	M	7	2		6	8	9		1
ean (SD)	0.7	3.1	0.2	9.7	3.5	4.3	03	12	16
	(76.6)	(69.5)	(72.5	(72.8)	(72.8)	(71.8)	(68.2	(64.6	(67.3)
)))	
Mi									
nd-Body									
	M	7	4		6	8	9		9
ean (SD)	3.4	4.6	7.7	8.7	0.5	0.1	8.5	02	9.3
	(64.7)	(64.3)	(63.8	(63.8)	(62.9)	(60.8)	(55.5	(52.0	(57.0)
)))	

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Table 2. *ATC's of physical activity across age groups and subcategories*

	18- 24	25- 34	35- 44	45- 54	55- 64	65- 74
MHQ						
ATC	17.77	19.79	20.41	18.65	15.76	12.37
SE	1.23	1.35	1.462	1.78	1.93	1.38
SMD	0.26	0.29	0.30	0.28	0.24	0.20
Core Cognition						
ATC	17.29	18.56	18.79	16.66	13.78	9.74
SE	0.92	1.11	1.32	1.45	1.45	1.22
SMD	0.28	0.29	0.30	0.27	0.23	0.17
Adaptability and Resilience						
ATC	20.10	18.71	18.96	16.87	14.79	14.50
SE	1.37	1.59	1.60	1.79	1.90	1.60

SMD	0.30	0.28	0.30	0.27	0.24	0.25
Mood and Outlook						
ATC	13.71	16.64	17.94	16.81	13.90	10.74
SE	1.06	1.31	1.44	1.79	2.03	1.36
SMD	0.22	0.26	0.27	0.25	0.21	0.17
Drive and Motivation						
ATC	18.27	18.34	17.94	15.65	11.71	9.88
SE	1.21	1.47	1.66	1.87	1.93	1.61
SMD	0.29	0.29	0.29	0.25	0.19	0.18
Social Self						
ATC	10.96	14.33	15.42	14.84	12.45	9.04
SE	1.28	1.49	1.48	1.76	1.84	1.39
SMD	0.16	0.20	0.21	0.21	0.17	0.13
Mind-Body						
ATC	19.54	21.38	21.12	19.46	16.67	15.38
SE	1.03	1.33	1.29	1.86	2.17	1.79
SMD	0.31	0.34	0.34	0.32	0.28	0.27