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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

--Manuscript Draft--

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<b>Abstract:</b>	<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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Author Contributions: **Christopher Huong**: formal analysis, writing – original draft,  
methodology (equal). **Denver Brown**: conceptualization, methodology (equal), writing – review  
and editing

*Keywords*: mental health, well-being, physical activity, exercise, machine learning

## 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 publically 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 and female cohorts [4–10]. Collectively, it is clear that mental health problems and poor mental well-being are a growing issue in society today, but certain subgroups 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 [11,12]. 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 [13]. 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 [14]. 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 [15]. 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 [16–21], anxiety [22–24], and general mental health and well-being [25–27]. For example, in a large cross-sectional dataset of over 1.2M adults living in the United States, Chekroud et al [28] 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 [29]. 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 [30–33].

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 mental symptoms and disorders (e.g., bipolar disorder, schizophrenia), the evidence is less suggestive of benefits, or remains unclear [34–39]. 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 [40,41]. 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. At present, there is a paucity of literature in this area – to our knowledge only one study has investigated symptom-level effects [42]. Findings stemming from such studies have the potential to improve precision in the promotion of mental well-being and treatment of mental health problems and therefore may have important implications for clinical outcomes [43–45]. 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. [46]

**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 31<sup>st</sup>, 2021 and October 14<sup>th</sup>, 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 [47]. 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 ( $\leq -50$ ), 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 their development and full descriptions can be found elsewhere [47].

The MHQ has demonstrated high sample reliability when four randomly selected and demographically similar samples were compared on response distributions, and resulting MHQ distribution [48]. Internal consistency was demonstrated with conceptually similar items having higher correlations than unsimilar items. A subset of participants which took the MHQ twice at

least 3 days apart showed strong test-retest reliability as evidenced by a correlation of  $r = 0.84$ .

Validity was assessed by asking a subset of participants additional questions concerning days

missed from work and normal activities in the past month due to problems with their physical or

mental health. Those who were reporting being employed and scored an overall MHQ between

175 to 200 missed on average 0.2 days of work in the past month, while adults who reporting

being employed and who scored between -75 to -100 missed an average of 9.3 days of work.

**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 included in our statistical models: 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 dropped from our analyses. All items in which participants responded “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 [49] 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) [50,51], and implemented in the R Package *WeightIt* [52]. The propensity score is defined as “the conditional probability of assignment to a particular treatment given a vector of observed covariates” [53]. 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 [54]. 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) [53].

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 [50,55,56]. Several tuning

parameters were selected to achieve covariate balancing, as suggested by McCaffrey et al [50]. 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 [52]. Though unlikely to significantly improve the performance of our procedure [57] 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 [58,59].

First, we computed propensity score weighted regression models that included further adjustment for the full covariate set to allow for doubly robust estimation [60]. 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 [61]. 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%), post-secondary educated (47.5% with a bachelor's or graduate degree), employed (47.8%), married (42.5%), 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  $67.93 \pm 72.70$  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, and mental health can be found in 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 [62]. 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 1.

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 2) 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 [54], cognitive function [63,64], emotional skills [65], resilience [66], and quality of life [21,26]. 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

[67,68]. 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 [69,70], sleep [71,72], appetite regulation [73,74], and fatigue [75,76]. 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 [77–79]. 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.

293           This study also addressed a knowledge gap regarding a dearth of evidence investigating  
294 potential differential effects of physical activity on certain aspects of mental health and well-  
295 being across the adult lifespan. Evidence indicated that young and middle-aged adults may  
296 experience greater benefits for their overall mental health from physical activity engagement in  
297 comparison to older adults. It should be noted that adults 85+ years of age appear to be an  
298 exception; however, this group also had the largest confidence interval likely due to a relatively  
299 smaller sample. As average levels of physical activity tend to be higher among young and  
300 middle-aged adults than older adults [80,81], a more sedentary lifestyle may be especially  
301 indicative of impairment in younger cohorts. Core Cognition, Drive and Motivation, and  
302 Adaptability and Resilience followed the same trend as overall MHQ scores, and thus these  
303 specific aspects of mental health and well-being may be more amenable to benefits from  
304 adopting a more active lifestyle, whereas the other subcategories seem to demonstrate relatively  
305 consistent benefits from physical activity across the adult lifespan. Finally, differences between  
306 inactive and active groups across ages were most pronounced in the 85+ age group as evidenced  
307 by the largest average marginal effect across all subcategories. This finding makes it clear that  
308 physical activity engagement is especially important for maintaining better mental health and  
309 well-being in the latest stages of life.

310           As the body of literature examining associations between physical activity and mental  
311 health continues to grow, it is imperative that researchers adopt statistical best practices that can  
312 reduce bias and strengthen our inferences. Matching and weighting techniques have received  
313 little attention in the fields of exercise psychology and behavioral medicine to date. For example,  
314 an advantage of utilizing propensity scores over controlling for covariates in a traditional  
315 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 [58,59,61], 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 [22,82–84]. For example, previous meta-analyses of randomized controlled trials on exercise and depression found pooled effect sizes ranging from 0.62 to 0.98 [20,85,86]. Compared to previous intervention research however, our findings may underestimate the true effect of physical activity due to issues related with self-report (e.g., overestimating ones physical activity). Regardless, the present findings support and extend the existing literature on the benefits of physical activity engagement across various aspects of mental health.

Despite several strengths, there are several limitations with the current study. Firstly, unlike randomization, propensity score weighting does not adjust for unobserved covariates [87]. An unbiased treatment effect assumes that all potential confounders are observed, which is unlikely to be the case in any observational study. Additionally, the covariates included in this

analysis were restricted by what was included in the GMP survey. Adjusting for a partial set of confounders may reduce bias, but it is unknown to what extent. Second, the MHQ and its subcategories have yet, to our knowledge, been validated in an independent sample. It would be interesting, for example, to investigate whether the MHQ and its subcategories predict the onset or course of distinct mental disorders. Third, physical activity was self-reported, which can introduce recall errors – particularly among older adults who are more prone to cognitive decline – and social desirability effects [88]. However, researchers need to balance feasibility with practicality and therefore using a self-reported measure of physical activity may be best suited for data collection with a sample of this size and geographic dispersion. Lastly, the GMP has used convenience sampling to recruit participants, targeted towards individuals who used mental health-related search terms in Google and Facebook. Although the present sample includes individuals from over 200 countries, it may not truly be globally representative, as it would have also overlooked individuals living in regions with limited to no internet access.

## Conclusion

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.

## References

1. Steel Z, Marnane C, Iranpour C, et al.: The global prevalence of common mental disorders: a systematic review and meta-analysis 1980–2013. *Int J Epidemiol.* 2014; 43:476–493.
2. Collaborators G 2019 MD, others: Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet Psychiatry.* 2022; 9:137–150.
3. Health TLG: Mental health matters. *Lancet Glob Health.* 2020; 8:e1352.
4. Samji H, Wu J, Ladak A, et al.: Mental health impacts of the COVID-19 pandemic on children and youth—a systematic review. *Child Adolesc Ment Health.* 2022; 27:173–189.
5. Patel K, Robertson E, Kwong AS, et al.: Psychological distress before and during the COVID-19 pandemic among adults in the United Kingdom based on coordinated analyses of 11 longitudinal studies. *JAMA Netw Open.* 2022; 5:e227629–e227629.
6. Panchal U, Salazar de Pablo G, Franco M, et al.: The impact of COVID-19 lockdown on child and adolescent mental health: systematic review. *Eur Child Adolesc Psychiatry.* 2021; 1–27.
7. Prati G, Mancini AD: The psychological impact of COVID-19 pandemic lockdowns: a review and meta-analysis of longitudinal studies and natural experiments. *Psychol Med.* 2021; 51:201–211.

8. Robinson E, Sutin AR, Daly M, Jones A: A systematic review and meta-analysis of longitudinal cohort studies comparing mental health before versus during the COVID-19 pandemic in 2020. *J Affect Disord.* 2022; 296:567–576.
9. Kauhanen L, Wan Mohd Yunus WMA, Lempinen L, et al.: A systematic review of the mental health changes of children and young people before and during the COVID-19 pandemic. *Eur Child Adolesc Psychiatry.* 2022; .
10. Santomauro DF, Mantilla Herrera AM, Shadid J, et al.: Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic. *The Lancet.* 2021; 398:1700–1712.
11. Oswalt SB, Lederer AM, Chestnut-Steich K, Day C, Halbritter A, Ortiz D: Trends in college students' mental health diagnoses and utilization of services, 2009–2015. *J Am Coll Health.* 2020; 68:41–51.
12. Keyes KM, Gary D, O'Malley PM, Hamilton A, Schulenberg J: Recent increases in depressive symptoms among US adolescents: trends from 1991 to 2018. *Soc Psychiatry Psychiatr Epidemiol.* 2019; 54:987–996.
13. Chen Y, Cowden RG, Fulks J, Plake JF, VanderWeele TJ: National data on age gradients in well-being among US adults. *JAMA Psychiatry.* 2022; 79:1046–1047.
14. Blanchflower DG, Oswald AJ: Is well-being U-shaped over the life cycle? *Soc Sci Med.* 2008; 66:1733–1749.

15. Solmi M, Radua J, Olivola M, et al.: Age at onset of mental disorders worldwide: large-scale meta-analysis of 192 epidemiological studies. *Mol Psychiatry*. 2022; 27:281–295.
16. Gordon BR, McDowell CP, Hallgren M, Meyer JD, Lyons M, Herring MP: Association of efficacy of resistance exercise training with depressive symptoms: meta-analysis and meta-regression analysis of randomized clinical trials. *JAMA Psychiatry*. 2018; 75:566–576.
17. Kvam S, Kleppe CL, Nordhus IH, Hovland A: Exercise as a treatment for depression: a meta-analysis. *J Affect Disord*. 2016; 202:67–86.
18. Pearce M, Garcia L, Abbas A, et al.: Association between physical activity and risk of depression: a systematic review and meta-analysis. *JAMA Psychiatry*. 2022; .
19. Schuch F, Vancampfort D, Firth J, et al.: Physical activity and sedentary behavior in people with major depressive disorder: a systematic review and meta-analysis. *J Affect Disord*. 2017; 210:139–150.
20. Schuch FB, Vancampfort D, Richards J, Rosenbaum S, Ward PB, Stubbs B: Exercise as a treatment for depression: a meta-analysis adjusting for publication bias. *J Psychiatr Res*. 2016; 77:42–51.
21. Schuch FB, Vancampfort D, Rosenbaum S, Richards J, Ward PB, Stubbs B: Exercise improves physical and psychological quality of life in people with depression: A meta-analysis including the evaluation of control group response. *Psychiatry Res*. 2016; 241:47–54.



22. Aylett E, Small N, Bower P: Exercise in the treatment of clinical anxiety in general practice—a systematic review and meta-analysis. *BMC Health Serv Res.* 2018; 18:1–18.
23. Biddle SJ, Ciaccioni S, Thomas G, Vergeer I: Physical activity and mental health in children and adolescents: An updated review of reviews and an analysis of causality. *Psychol Sport Exerc.* 2019; 42:146–155.
24. McDowell CP, Dishman RK, Gordon BR, Herring MP: Physical activity and anxiety: a systematic review and meta-analysis of prospective cohort studies. *Am J Prev Med.* 2019; 57:545–556.
25. Firth J, Solmi M, Wootton RE, et al.: A meta-review of “lifestyle psychiatry”: the role of exercise, smoking, diet and sleep in the prevention and treatment of mental disorders. *World Psychiatry.* 2020; 19:360–380.
26. Marquez DX, Aguiñaga S, Vásquez PM, et al.: A systematic review of physical activity and quality of life and well-being. *Transl Behav Med.* 2020; 10:1098–1109.
27. Rodriguez-Ayllon M, Cadenas-Sánchez C, Estévez-López F, et al.: Role of physical activity and sedentary behavior in the mental health of preschoolers, children and adolescents: a systematic review and meta-analysis. *Sports Med.* 2019; 49:1383–1410.
28. Chekroud SR, Gueorguieva R, Zheutlin AB, et al.: Association between physical exercise and mental health in 1· 2 million individuals in the USA between 2011 and 2015: a cross-sectional study. *Lancet Psychiatry.* 2018; 5:739–746.

29. Ekkekakis P: Why Is exercise underutilized in clinical practice despite evidence it is effective? Lessons in pragmatism from the inclusion of exercise in guidelines for the treatment of depression in the British National Health Service. *Kinesiol Rev.* 2020; 10:29–50.
30. Kendrick T, Pilling S, Mavranouzouli I, et al.: Management of depression in adults: summary of updated NICE guidance. *BMJ.* 2022; 378:o1557.
31. Canadian Network for Mood and Anxiety Treatments (CANMAT) 2016 Clinical Guidelines for the Management of Adults with Major Depressive Disorder: Section 5. Complementary and Alternative Medicine Treatments - Arun V. Ravindran, Lynda G. Balneaves, Guy Faulkner, Abigail Ortiz, Diane McIntosh, Rachel L. Morehouse, Lakshmi Ravindran, Lakshmi N. Yatham, Sidney H. Kennedy, Raymond W. Lam, Glenda M. MacQueen, Roumen V. Milev, Sagar V. Parikh, , the CANMAT Depression Work Group, the CANMAT Depression Work Group, 2016: no date; .
32. Stubbs B, Vancampfort D, Hallgren M, et al.: EPA guidance on physical activity as a treatment for severe mental illness: a meta-review of the evidence and Position Statement from the European Psychiatric Association (EPA), supported by the International Organization of Physical Therapists in Mental Health (IOPTMH). *Eur Psychiatry.* 2018; 54:124–144.
33. Malhi GS, Bassett D, Boyce P, et al.: Royal Australian and New Zealand College of Psychiatrists clinical practice guidelines for mood disorders. *Aust N Z J Psychiatry.* 2015; 49:1087–1206.

34. Firth J, Cotter J, Elliott R, French P, Yung AR: A systematic review and meta-analysis of exercise interventions in schizophrenia patients. *Psychol Med.* 2015; 45:1343–1361.
35. Dauwan M, Begemann MJ, Heringa SM, Sommer IE: Exercise improves clinical symptoms, quality of life, global functioning, and depression in schizophrenia: a systematic review and meta-analysis. *Schizophr Bull.* 2016; 42:588–599.
36. Brokmeier LL, Firth J, Vancampfort D, et al.: Does physical activity reduce the risk of psychosis? A systematic review and meta-analysis of prospective studies. *Psychiatry Res.* 2020; 284:112675.
37. Brondino N, Rocchetti M, Fusar-Poli L, et al.: A systematic review of cognitive effects of exercise in depression. *Acta Psychiatr Scand.* 2017; 135:285–295.
38. Ashdown-Franks G, Firth J, Carney R, et al.: Exercise as medicine for mental and substance use disorders: a meta-review of the benefits for neuropsychiatric and cognitive outcomes. *Sports Med.* 2020; 50:151–170.
39. Melo MCA, Daher EDF, Albuquerque SGC, de Bruin VMS: Exercise in bipolar patients: a systematic review. *J Affect Disord.* 2016; 198:32–38.
40. Borsboom D, Cramer AO, Schmittmann VD, Epskamp S, Waldorp LJ: The small world of psychopathology. *PloS One.* 2011; 6:e27407.
41. Newson JJ, Pastukh V, Thiagarajan TC: Poor separation of clinical symptom profiles by DSM-5 disorder criteria. *Front Psychiatry.* 2021; 12:775762.

42. Murri MB, Ekkekakis P, Menchetti M, et al.: Physical exercise for late-life depression: Effects on symptom dimensions and time course. *J Affect Disord.* 2018; 230:65–70.
43. Uher R, Perlis R, Henigsberg N, et al.: Depression symptom dimensions as predictors of antidepressant treatment outcome: replicable evidence for interest-activity symptoms. *Psychol Med.* 2012; 42:967–980.
44. Iniesta R, Malki K, Maier W, et al.: Combining clinical variables to optimize prediction of antidepressant treatment outcomes. *J Psychiatr Res.* 2016; 78:94–102.
45. Fried EI, Nesse RM: Depression sum-scores don't add up: why analyzing specific depression symptoms is essential. *BMC Med.* 2015; 13:1–11.
46. Von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP: The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. *The Lancet.* 2007; 370:1453–1457.
47. Newson JJ, Thiagarajan TC: Assessment of population well-being with the mental health quotient (MHQ): development and usability study. *JMIR Ment Health.* 2020; 7:e17935.
48. Newson JJ, Pastukh V, Thiagarajan TC: Assessment of Population Well-being With the Mental Health Quotient: Validation Study. *JMIR Ment Health.* 2022; 9:e34105.
49. R Core Team: R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing, 2022.

50. McCaffrey DF, Ridgeway G, Morral AR: Propensity score estimation with boosted regression for evaluating causal effects in observational studies. *Psychol Methods*. 2004; 9:403.
51. Friedman JH: Greedy function approximation: a gradient boosting machine. *Ann Stat*. 2001; 1189–1232.
52. Greifer N: *WeightIt: Weighting for Covariate Balance in Observational Studies*. 2022.
53. Rosenbaum PR, Rubin DB: The central role of the propensity score in observational studies for causal effects. *Biometrika*. 1983; 70:41–55.
54. Vancampfort D, Firth J, Schuch FB, et al.: Sedentary behavior and physical activity levels in people with schizophrenia, bipolar disorder and major depressive disorder: a global systematic review and meta-analysis. *World Psychiatry*. 2017; 16:308–315.
55. Tu C: Comparison of various machine learning algorithms for estimating generalized propensity score. *J Stat Comput Simul*. 2019; 89:708–719.
56. Lee BK, Lessler J, Stuart EA: Improving propensity score weighting using machine learning. *Stat Med*. 2010; 29:337–346.
57. Lee BK, Lessler J, Stuart EA: Weight trimming and propensity score weighting. *PloS One*. 2011; 6:e18174.
58. Cham H, West SG: Propensity score analysis with missing data. *Psychol Methods*. 2016; 21:427.

59. Coffman DL, Zhou J, Cai X: Comparison of methods for handling covariate missingness in propensity score estimation with a binary exposure. *BMC Med Res Methodol.* 2020; 20:1–14.
60. Funk MJ, Westreich D, Wiesen C, Stürmer T, Brookhart MA, Davidian M: Doubly robust estimation of causal effects. *Am J Epidemiol.* 2011; 173:761–767.
61. Setodji CM, McCaffrey DF, Burgette LF, Almirall D, Griffin BA: The right tool for the job: Choosing between covariate balancing and generalized boosted model propensity scores. *Epidemiol Camb Mass.* 2017; 28:802.
62. Ridgeway G, McCaffrey DF, Morral AR, et al.: Toolkit for weighting and analysis of nonequivalent groups: a tutorial for the R TWANG package. Rand Santa Monica, Calif, 2022.
63. Bidzan-Bluma I, Lipowska M: Physical Activity and Cognitive Functioning of Children: A Systematic Review. *Int J Environ Res Public Health.* 2018; 15:800.
64. Carvalho A, Rea IM, Parimon T, Cusack BJ: Physical activity and cognitive function in individuals over 60 years of age: a systematic review. *Clin Interv Aging.* 2014; 661–682.
65. Laborde S, Dosseville F, Allen MS: Emotional intelligence in sport and exercise: A systematic review. *Scand J Med Sci Sports.* 2016; 26:862–874.
66. Shanahan L, Steinhoff A, Bechtiger L, et al.: Emotional distress in young adults during the COVID-19 pandemic: evidence of risk and resilience from a longitudinal cohort study. *Psychol Med.* 2022; 52:824–833.

67. Cunningham C, O'Sullivan R, Caserotti P, Tully MA: Consequences of physical inactivity in older adults: A systematic review of reviews and meta-analyses. *Scand J Med Sci Sports*. 2020; 30:816–827.
68. de Oliveira L da SSCB, Souza EC, Rodrigues RAS, Fett CA, Piva AB: The effects of physical activity on anxiety, depression, and quality of life in elderly people living in the community. *Trends Psychiatry Psychother*. 2019; 41:36–42.
69. Rice D, Nijs J, Kosek E, et al.: Exercise-induced hypoalgesia in pain-free and chronic pain populations: state of the art and future directions. *J Pain*. 2019; 20:1249–1266.
70. Shiri R, Falah-Hassani K: Does leisure time physical activity protect against low back pain? Systematic review and meta-analysis of 36 prospective cohort studies. *Br J Sports Med*. 2017; 51:1410–1418.
71. Lederman O, Ward PB, Firth J, et al.: Does exercise improve sleep quality in individuals with mental illness? A systematic review and meta-analysis. *J Psychiatr Res*. 2019; 109:96–106.
72. Kredlow MA, Capozzoli MC, Hearon BA, Calkins AW, Otto MW: The effects of physical activity on sleep: a meta-analytic review. *J Behav Med*. 2015; 38:427–449.
73. Beaulieu K, Hopkins M, Blundell J, Finlayson G: Homeostatic and non-homeostatic appetite control along the spectrum of physical activity levels: An updated perspective. *Physiol Behav*. 2018; 192:23–29.

74. Beaulieu K, Hopkins M, Blundell J, Finlayson G: Does habitual physical activity increase the sensitivity of the appetite control system? A systematic review. *Sports Med.* 2016; 46:1897–1919.
75. Pilutti LA, Greenlee TA, Motl RW, Nickrent MS, Petruzzello SJ: Effects of exercise training on fatigue in multiple sclerosis: a meta-analysis. *Psychosom Med.* 2013; 75:575–580.
76. Bower JE: Cancer-related fatigue—mechanisms, risk factors, and treatments. *Nat Rev Clin Oncol.* 2014; 11:597–609.
77. Pels F, Kleinert J: Loneliness and physical activity: A systematic review. *Int Rev Sport Exerc Psychol.* 2016; 9:231–260.
78. Shima T, Nakao H, Tai K, et al.: The influences of changes in physical activity levels with easing restriction of access to the University campus on empathy and social supports in college students during the covid-19 pandemic. *Asia Pac J Public Health.* 2022; 34:406–410.
79. Shima T, Jesmin S, Nakao H, et al.: Association between self-reported empathy and level of physical activity in healthy young adults. *J Phys Fit Sports Med.* 2021; 10:45–49.
80. Westerterp K: Changes in physical activity over the lifespan: impact on body composition and sarcopenic obesity. *Obes Rev.* 2018; 19:8–13.
81. Van Der Zee MD, Van Der Mee D, Bartels M, De Geus EJ: Tracking of voluntary exercise behaviour over the lifespan. *Int J Behav Nutr Phys Act.* 2019; 16:1–11.
82. Bernstein EE, McNally RJ: Acute aerobic exercise helps overcome emotion regulation deficits. *Cogn Emot.* 2017; 31:834–843.



83. Buffart LM, Kalter J, Sweegers MG, et al.: Effects and moderators of exercise on quality of life and physical function in patients with cancer: an individual patient data meta-analysis of 34 RCTs. *Cancer Treat Rev.* 2017; 52:91–104.
84. Rosenbaum S, Sherrington C, Tiedemann A: Exercise augmentation compared with usual care for post-traumatic stress disorder: A randomized controlled trial. *Acta Psychiatr Scand.* 2015; 131:350–359.
85. Cooney GM, Dwan K, Greig CA, et al.: Exercise for depression. *Cochrane Database Syst Rev.* 2013; .
86. Josefsson T, Lindwall M, Archer T: Physical exercise intervention in depressive disorders: Meta-analysis and systematic review. *Scand J Med Sci Sports.* 2014; 24:259–272.
87. Joffe MM, Rosenbaum PR: Invited commentary: propensity scores. *Am J Epidemiol.* 1999; 150:327–333.
88. Sallis JF, Saelens BE: Assessment of physical activity by self-report: status, limitations, and future directions. *Res Q Exerc Sport.* 2000; 71:1–14.

### Tables and Figures

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

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	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)	
Sex									
Female	189226	39831	2734	31203	30890	32729	2025	6141	832
	(55.3%)	(61.6%	4	(56.5%	(53.9%	(51.9	6	(51.1	(54.2
		)	(57.9	)	)	%)	(49.5	%)	%)
			%)				%)		
Male	148624	23206	1942	23584	25815	29827	2029	5807	659
	(43.5%)	(35.9%	7	(42.7%	(45.1%	(47.3	9	(48.3	(42.9
		)	(41.1	)	)	%)	(49.7	%)	%)
			%)				%)		
Other/Inte	819	268	63	92	163	136	63	14	20
rsex	(0.2%)	(0.4%)	(0.1	(0.2%)	(0.3%)	(0.2%)	(0.2	(0.1	(1.3%)
			%)				%)	%)	

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Missing	3287	1343	415	362	391	421	263	67	25
	(1.0%)	(2.1%)	(0.9	(0.7%)	(0.7%)	(0.7%)	(0.6	(0.6	(1.6%)
			%)				%)	%)	
Education									
Associate'	21259	3921	2512	2643	3174	4381	3398	1093	137
s Degree	(6.2%)	(6.1%)	(5.3	(4.8%)	(5.5%)	(6.9%)	(8.3	(9.1	(8.9%)
			%)				%)	%)	
Bachelor'	105724	17800	1981	20404	18197	17066	9753	2455	231
s Degree	(30.9%)	(27.5%	8	(36.9%	(31.8%	(27.0	(23.9	(20.4	(15.0
		)	(41.9	)	)	%)	%)	%)	%)
			%)						
Graduate	56764	3386	8580	11690	11725	11671	7423	2038	251
Degree	(16.6%)	(5.2%)	(18.2	(21.2%	(20.5%	(18.5	(18.2	(16.9	(16.3
			%)	)	)	%)	%)	%)	%)
High	77434	23451	7871	9293	10880	12985	9321	3155	478
School	(22.6%)	(36.3%	(16.7	(16.8%	(19.0%	(20.6	(22.8	(26.2	(31.1
		)	%)	)	)	%)	%)	%)	%)
Less than	34040	6836	2902	4720	5674	7249	4811	1620	228
High	(10.0%)	(10.6%	(6.1	(8.5%)	(9.9%)	(11.5	(11.8	(13.5	(14.8
School		)	%)			%)	%)	%)	%)

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Other	16246	3578	2248	2552	2733	2997	1649	412	77
	(4.8%)	(5.5%)	(4.8	(4.6%)	(4.8%)	(4.7%)	(4.0	(3.4	(5.0%)
			%)				%)	%)	
Vocationa	21823	1922	2613	3054	3842	5487	3762	1043	100
l	(6.4%)	(3.0%)	(5.5	(5.5%)	(6.7%)	(8.7%)	(9.2	(8.7	(6.5%)
Certificati			%)				%)	%)	
on									
Missing	8666	3754	705	885	1034	1277	764	213	34
	(2.5%)	(5.8%)	(1.5	(1.6%)	(1.8%)	(2.0%)	(1.9	(1.8	(2.2%)
			%)				%)	%)	
Employment									
Employed	163401	12630	2904	39198	41026	33075	7391	960	81
/Self	(47.8%)	(19.5%	0	(71.0%	(71.6%	(52.4	(18.1	(8.0	(5.3%)
employed	)	(61.5	)	)	%)	%)	%)		
		%)							
Homemak	31570	2260	5383	8198	7162	5874	2124	478	91
er	(9.2%)	(3.5%)	(11.4	(14.8%	(12.5%	(9.3%)	(5.2	(4.0	(5.9%)
			%)	)	)		%)	%)	

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Not able to work	7210 (2.1%)	1212 (1.9%)	806 (1.7%)	966 (1.7%)	1444 (2.5%)	2193 (3.5%)	473 (1.2%)	81 (0.7%)	35 (2.3%)
Retired	61333 (17.9%)	102 (0.2%)	93 (0.2%)	317 (0.6%)	1924 (3.4%)	17194 (27.2%)	3003 (8.0%)	1038 (0.0%)	1285 (83.7%)
Studying	48583 (14.2%)	40925 (63.3%)	4306 (9.1%)	1476 (2.7%)	1101 (1.9%)	574 (0.9%)	149 (0.4%)	30 (0.2%)	22 (1.4%)
Unemployed	29859 (8.7%)	7519 (11.6%)	7621 (16.1%)	5086 (9.2%)	4602 (8.0%)	4203 (6.7%)	706 (1.7%)	100 (0.8%)	22 (1.4%)
Relationship Status									
Divorced/Separated	32484 (9.5%)	876 (1.4%)	2137 (4.5%)	4738 (8.6%)	6849 (12.0%)	9677 (15.3%)	6535 (16.0%)	1536 (12.8%)	136 (8.9%)

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
In a cohabiting relationship	15388 (4.5%)	1318 (2.0%)	2861 (6.1%)	3170 (5.7%)	3062 (5.3%)	3022 (4.8%)	1576 (3.9%)	345 (2.9%)	34 (2.2%)
In a civil partnership	32066 (9.4%)	12729 (19.7%)	7347 (15.5%)	3650 (6.6%)	3146 (5.5%)	3103 (4.9%)	1669 (4.1%)	390 (3.2%)	32 (2.1%)
Married/Civil Partnership	145166 (42.5%)	2022 (3.1%)	1423 5 (30.1%)	31501 (57.0%)	33622 (58.7%)	35037 (55.5%)	2229 5 (54.5%)	5897 (49.0%)	557 (36.3%)
Other	2313 (0.7%)	803 (1.2%)	470 (1.0%)	439 (0.8%)	339 (0.6%)	208 (0.3%)	46 (0.1%)	5 (0.0%)	3 (0.2%)
Single (never married or in a civil partnership)	85117 (24.9%)	42004 (65.0%)	1827 9 (38.7%)	9084 (16.4%)	6653 (11.6%)	5955 (9.4%)	2583 (6.3%)	508 (4.2%)	51 (3.3%)

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Widowed	14744	139	158	557	1490	3860	4895	2984	661
	(4.3%)	(0.2%)	(0.3	(1.0%)	(2.6%)	(6.1%)	(12.0	(24.8	(43.0
			%)				%)	%)	%)
Missing	14678	4757	1762	2102	2098	2251	1282	364	62
	(4.3%)	(7.4%)	(3.7	(3.8%)	(3.7%)	(3.6%)	(3.1	(3.0	(4.0%)
			%)				%)	%)	
Socialize									
Frequency									
Rarely/Ne	86212	14926	1406	16429	16052	15390	7446	1683	223
ver	(25.2%)	(23.1%	3	(29.7%	(28.0%	(24.4	(18.2	(14.0	(14.5
		)	(29.8	)	)	%)	%)	%)	%)
			%)						
1-3 times	79457	13115	1198	12973	13545	15310	9591	2655	279
a month	(23.2%)	(20.3%	9	(23.5%	(23.7%	(24.3	(23.5	(22.1	(18.2
		)	(25.4	)	)	%)	%)	%)	%)
			%)						
Once a	63389	11242	8055	9235	9847	12275	9352	3019	364
week	(18.5%)	(17.4%	(17.0	(16.7%	(17.2%	(19.4	(22.9	(25.1	(23.7
		)	%)	)	)	%)	%)	%)	%)

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Several	112898	25365	1314	16604	17815	20138	1449	4672	670
days a	(33.0%)	(39.2%	2	(30.1%	(31.1%	(31.9	2	(38.8	(43.6
week	)	(27.8	)	)	%)	(35.4	%)	%)	%)
			%)				%)		
Adequate									
Sleep									
Frequency									
Hardly	42262	10071	6175	7270	7113	7180	3498	836	119
ever	(12.4%)	(15.6%	(13.1	(13.2%	(12.4%	(11.4	(8.6	(6.9	(7.7%)
	)	%)	)	)	%)	%)	%)	%)	
Some of	117966	25492	1823	21289	20129	19465	1049	2569	289
the time	(34.5%)	(39.4%	4	(38.5%	(35.2%	(30.8	9	(21.4	(18.8
	)	(38.6	)	)	%)	(25.7	%)	%)	%)
			%)				%)		
Most of	140096	22792	1786	21383	23592	27803	1979	6106	755
the time	(41.0%)	(35.3%	6	(38.7%	(41.2%	(44.1	9	(50.8	(49.2
	)	(37.8	)	)	%)	(48.4	%)	%)	%)
			%)				%)		





		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Yes	50606	12028	8183	8221	8181	8732	4192	979	90
	(14.8%)	(18.6%	(17.3	(14.9%	(14.3%	(13.8	(10.3	(8.1	(5.9%)
		)	%)	)	)	%)	%)	%)	
Missing	3832	850	434	586	624	725	450	134	29
	(1.1%)	(1.3%)	(0.9	(1.1%)	(1.1%)	(1.1%)	(1.1	(1.1	(1.9%)
			%)				%)	%)	

Experienc  
ed  
Childhood  
Trauma  
(Y/N)

Yes	210952	48130	3196	33581	33036	35712	2164	6071	816
	(61.7%)	(74.4%	0	(60.8%	(57.7%	(56.6	6	(50.5	(53.1
		)	(67.6	)	)	%)	(52.9	%)	%)
			%)				%)		

Experienc  
ed Adult  
Trauma  
(Y/N)

Core  
Cognition

		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
Mean	81.4	39.5	61.0	78.6	92.3	104	113	119	116
(SD)	(67.0)	(63.2)	(64.7	(64.7)	(63.0)	(60.4)	(54.7	(51.3	(58.3)
		)				)	)		
Adaptability and Resilience									
Mean	89.8	50.7	70.6	88.3	101	110	118	125	123
(SD)	(67.4)	(67.5)	(66.7	(64.6)	(62.7)	(61.3)	(55.2	(49.7	(55.4)
		)				)	)		
Drive and Motivation									
Mean	83.4	43.5	62.6	80.4	94.3	105	114	118	114
(SD)	(66.6)	(64.7)	(65.2	(63.9)	(62.4)	(60.1)	(53.8	(49.7	(57.1)
		)				)	)		
Mood and Outlook									
Mean	67.2	24.4	44.1	62.0	78.1	91.2	102	111	114
(SD)	(71.1)	(64.8)	(66.3	(67.1)	(67.6)	(66.2)	(61.5	(57.2	(61.7)
		)				)	)		

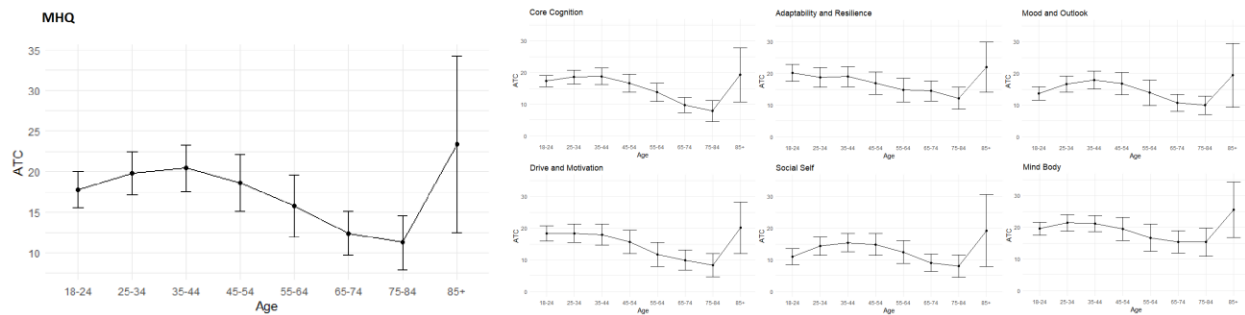
		18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
	Total	years	years	years	years	years	years	years	years
<b>Social</b>									
<b>Self</b>									
Mean	70.7	23.1	50.2	69.7	83.5	94.3	103	112	116
(SD)	(76.6)	(69.5)	(72.5)	(72.8)	(72.8)	(71.8)	(68.2)	(64.6)	(67.3)
		)				)	)		
<b>Mind-</b>									
<b>Body</b>									
Mean	73.4	44.6	57.7	68.7	80.5	90.1	98.5	102	99.3
(SD)	(64.7)	(64.3)	(63.8)	(63.8)	(62.9)	(60.8)	(55.5)	(52.0)	(57.0)
		)				)	)		

**Table 2. Sensitivity analysis. Reported ATC effects and standard errors on MHQ**

		Doubly		Doubly		Doubly
		Robust		Robust		Robust MI
MHQ	GBM	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.

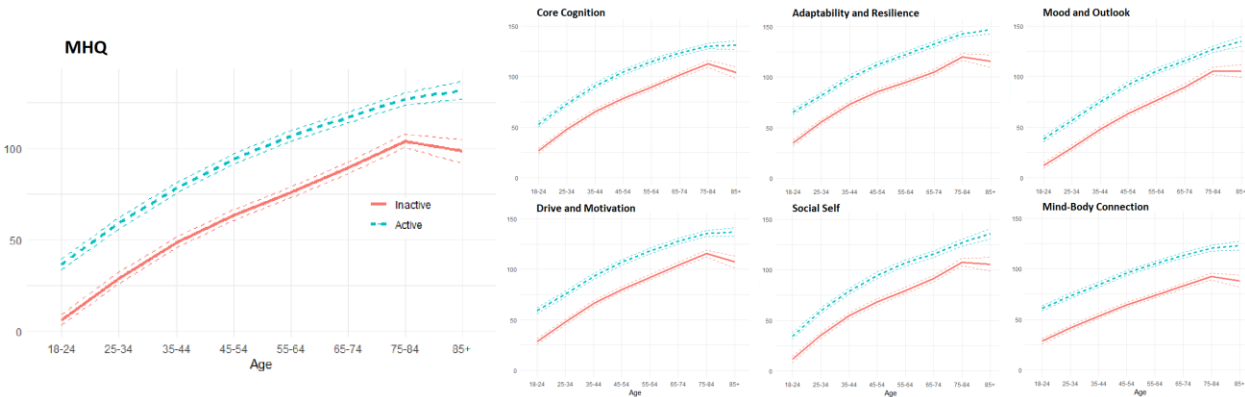


Figure 1

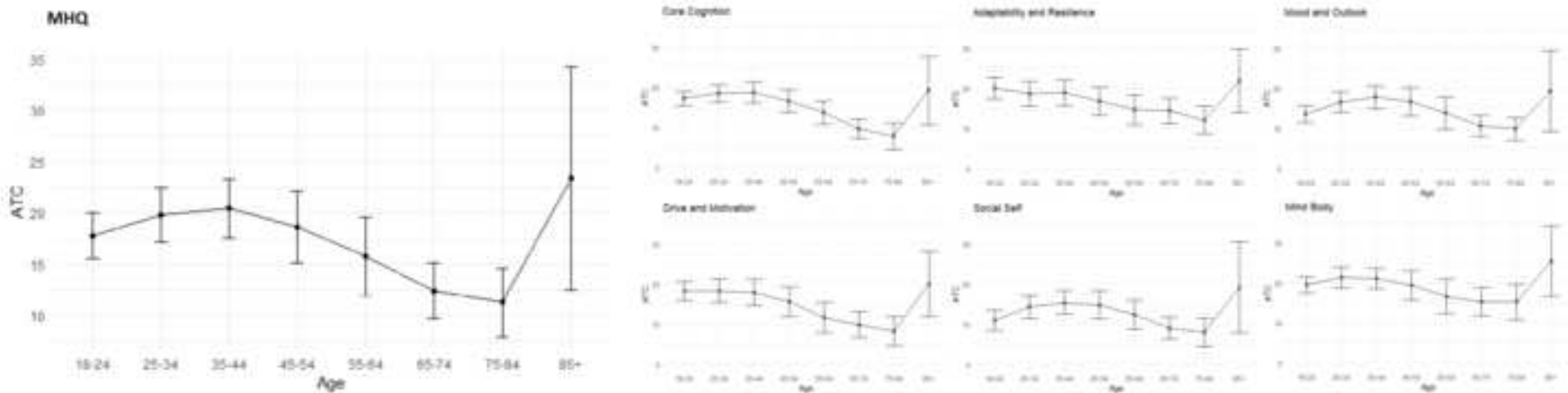
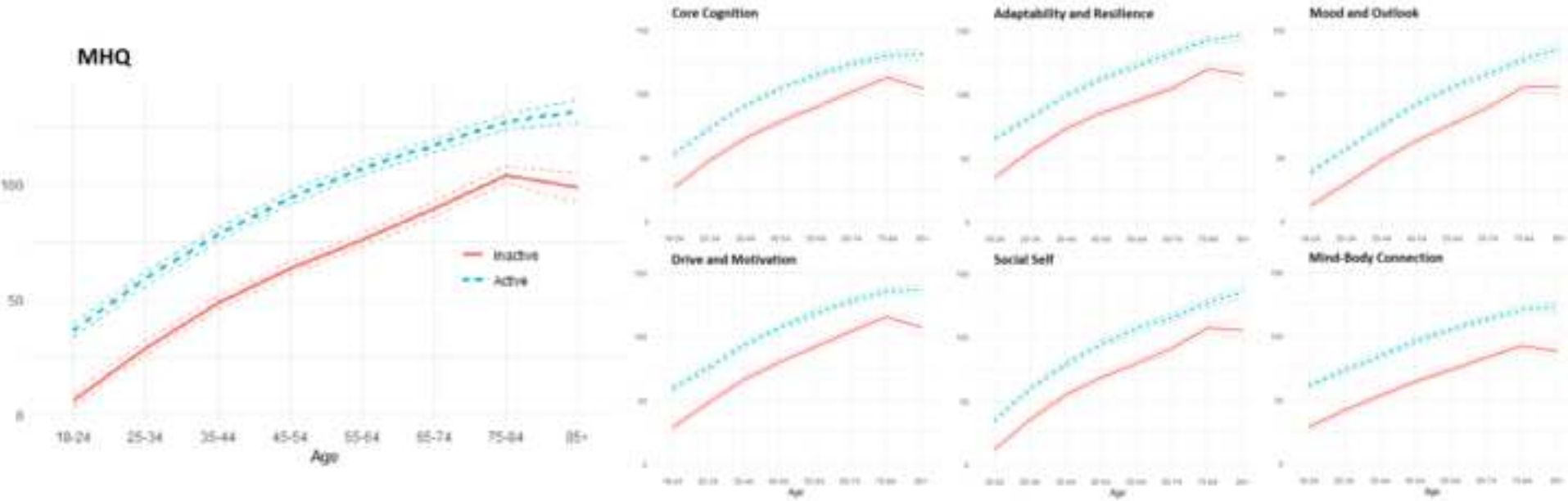
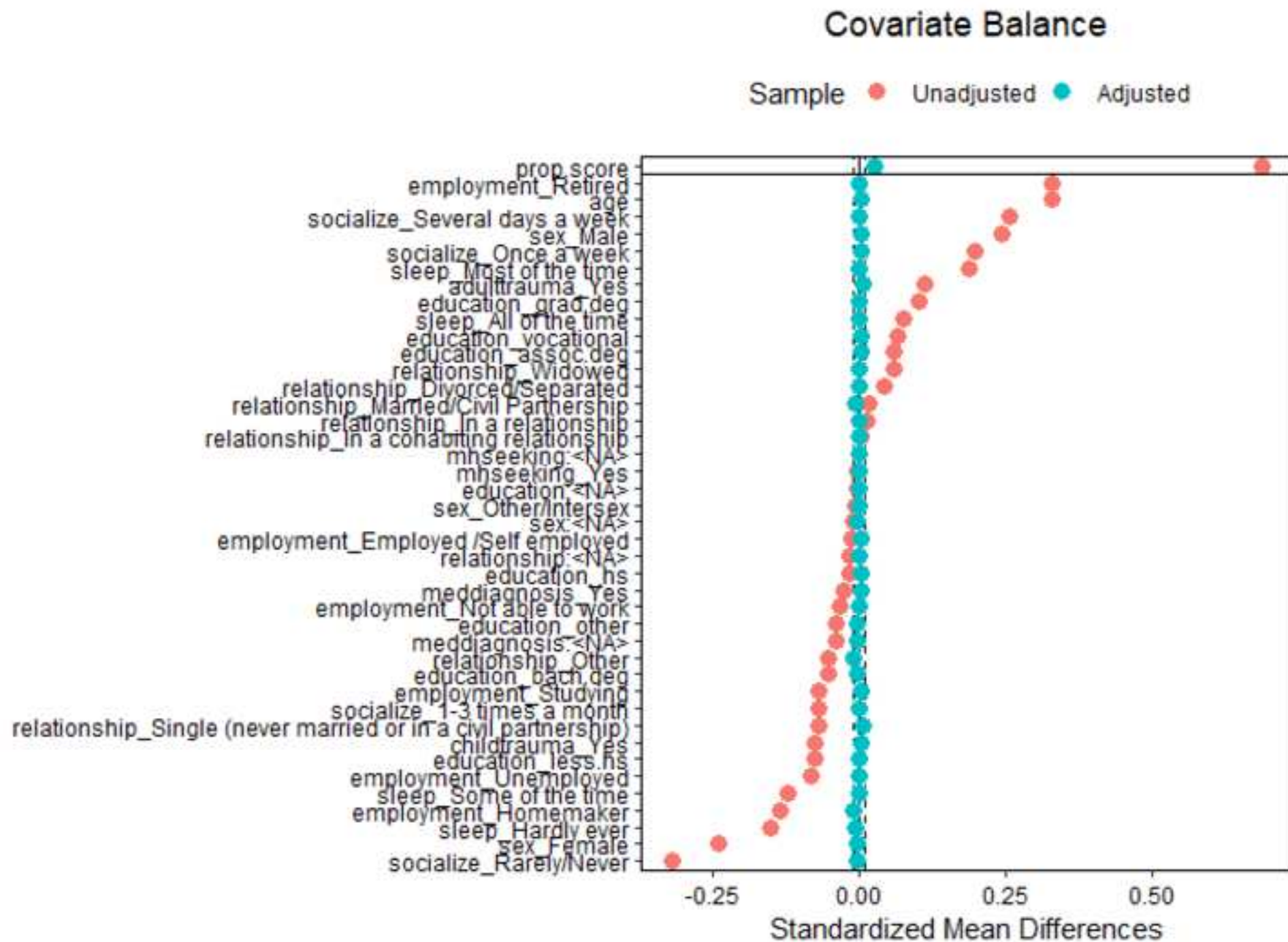
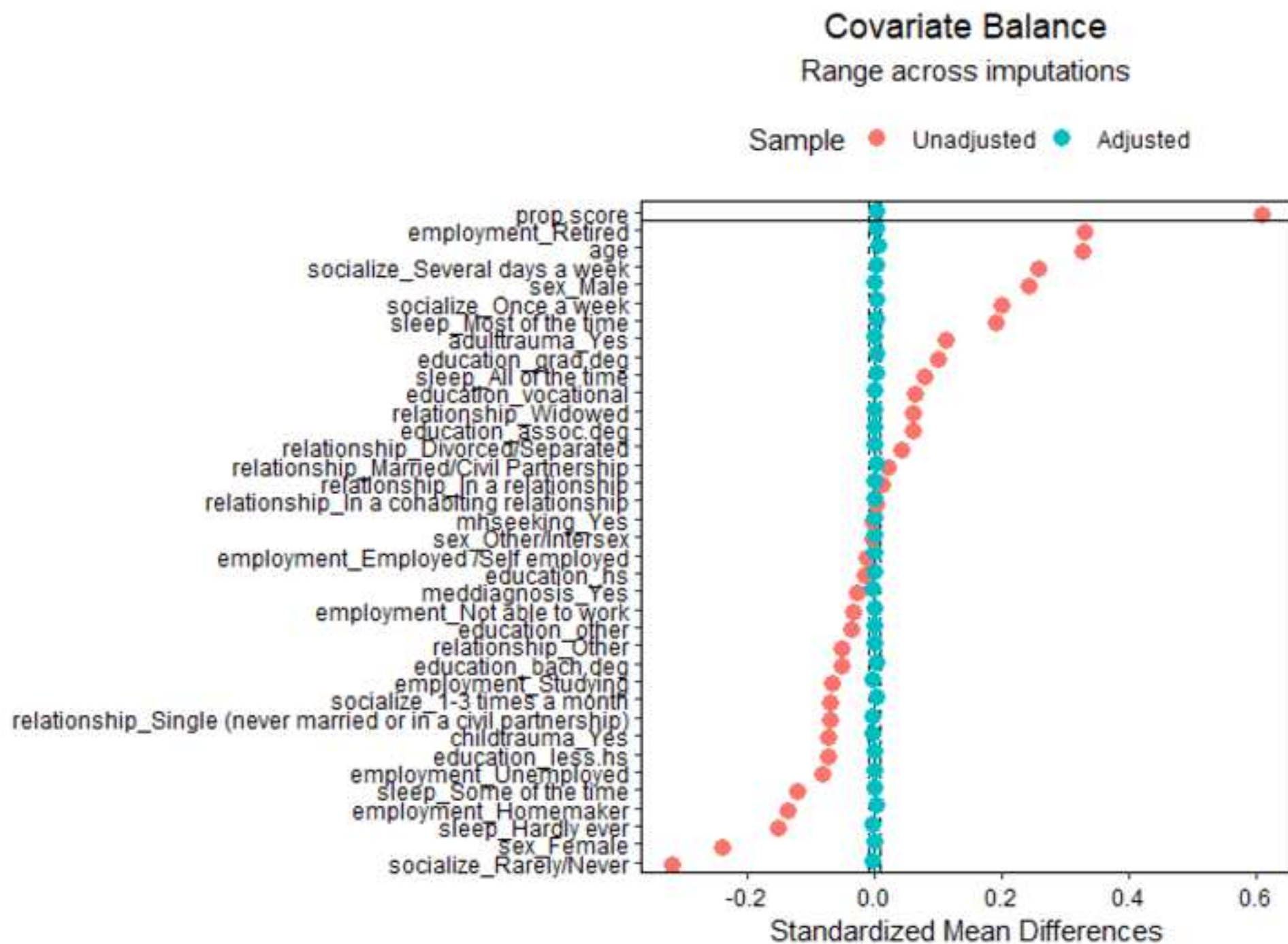


Figure 2









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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

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