Cross-sectional associations between physical activity and subdomains of mental wellbeing: A global propensity score-weighted study

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**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]. Global burden of mental disorders in 2019 is estimated at 125.3 million disability-adjusted life-years (DALY) – 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 wellbeing 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].

Emerging evidence in addition to recent findings from the COVID-19 pandemic suggests certain age cohorts across the lifespan may be at greater risk for poor mental health and wellbeing than others [11]. For example, a recent report 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 wellbeing observed with increased age [12]. These findings are in contrast to previous work that had demonstrated an inverted-U relationship between age and mental wellbeing in which mental wellbeing was lowest in middle adulthood [13]. Further, an estimated half of first mental disorder onsets occur by age 18 [14]. Evidently, more research is needed to better understand these trends from a global perspective, including a focus on protective factors that may moderate the relationship between age, mental health, and wellbeing.

Physical activity is one aspect of our lifestyle that has received increasing attention for its potential to promote mental wellbeing as well as assist in the prevention and management of mental health disorders. Observational and experimental evidence consistently shows a relationship between higher levels of physical activity and benefits across various mental health outcomes, including, but not limited to depression [15-20], anxiety [21-23], and general mental health [24-26]. For example, using non-parametric matching in a large cross-sectional dataset, Chekroud, et al. (27) showed that engaging in physical exercise 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 [28]. 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 [29-32].

While evidence supports the importance of physical activity for preventing and/or reducing a range of mental health problems and improving overall wellbeing, for some other mental symptoms and disorders (e.g., bipolar disorder, schizophrenia), the evidence is less suggestive of benefits, or remains unclear [33-38]. More recently, however, researchers have observed considerable overlap in symptomology across the most commonly classified mental health disorders, which illustrates the complexity and heterogeneous nature of mental health as a construct [39, 40]. 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 [41]. Findings stemming from such studies have the potential to improve precision in the promotion of mental wellbeing and treatment of mental health problems and therefore may have important implications for clinical outcomes [42-44]. 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 purpose of the present study was to estimate the treatment effect of regular physical activity engagement on overall mental health in a large global sample, as well as various subdomains of mental health, while statistically accounting for a range of observed covariates using a machine learning technique underutilized in exercise psychology and behavioral medicine.

**Study Sample and Data Collection**

This cross-sectional study used data from the Mental Health Million (MHM) project, an on-going study with the purpose of assessing global mental wellbeing through administration of the Mental Health Quotient. The sample for our present study included 341,956 participants from 229 countries who completed the MHQ from December 31st, 2021 to Oct 14th, 2022; This start of this period coincided with the launch of Version 3 of the MHQ. Additional information concerning the MHM project and recruitment strategy may be found elsewhere [45]. This study involved secondary analysis of existing 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 wellbeing 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 assessed the 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 mental health and wellbeing score. 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 wellbeing were computed: Core Cognition (ability for executive functioning), Adaptability and Resilience (decision making, creativity, and tolerance to change), Mood and Outlook (ability to effectively regulate ones emotions), Drive and Motivation (ability to achieve goals in the face of obstacles), Social Self (social functioning), and Mind-Body (physical functioning and psychosomatic health). 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 [45].

The MHQ has demonstrated high sample reliability when four randomly selected and demographically similar samples were compared on response distributions (p = 0.99), and resulting MHQ distribution (p = 0.18) [46]. 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 a test-retest reliability 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. Those who were employed and scored an overall MHQ between 175 to 200 missed on average 0.2 days of work in the past month, while those employed 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. (27), 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 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%), 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 [47] and RStudio version XXX (ref). First, distributions of covariates were balanced between the non-exposure and exposure groups using propensity score weights estimated with generalized boosted modeling (GBM) [48], and implemented in the R-Package WeightIt [49]. The propensity score is defined as “the conditional probability of assignment to a particular treatment given a vector of observed covariates” [50]. Weighting procedures were preferred over matching procedures for the purpose of preserving sample size. Propensity scores weights were computed based on the Average Treatment effect on the Treated (ATT) estimand, which is used to estimate the hypothetical effect (i.e., counterfactual) of physical activity exposure on the control (i.e. inactive) group, and is unbiased when the strong ignorability assumption is met (i.e., when there are no unobserved covariates related to both treatment and outcome) [50]. GBM is a non-parametric iterative machine learning method which utilizes regression trees to generate predicted values of propensity scores. As suggested by McCaffrey, et al. (48) the number of iterations was determined by minimizing the average standardized absolute mean difference in the covariates. The number of trees was set to 10,000 by default, and increased to 20,000 if covariate balancing was not achieved. GBM handles missing data by the surrogate splitting method as described in the WeightIt R-package documentation [49]. Though unlikely to significantly improve performance of inferences for our estimation procedure [51] weights above 99% were trimmed to reduce potential bias from extreme values. Diagnostics were used to ensure covariates were adequately balanced.

For our main analysis, we estimated the ATT for physical activity on seven outcomes: overall MHQ score, and its six subdomains: Core Cognition, Adaptability and Resilience, Mood and Outlook, Drive and Motivation, Social Self, and Mind-Body. Using the same procedures, we also tested whether age moderates the relationship between physical activity and the seven mental health outcomes. In all models, participants were nested within country to account for potential clustering effects. ATTs were presented as beta coefficients with 95% confidence intervals.

In case the inferences of the main analyses were biased due to model misspecification or handling of missing data, we performed several sensitivity analyses. First, we computed propensity score weighted linear regression models that included further adjustment for the full covariate set to allow for doubly robust estimation [52]. Second, we estimated ATTs using multiple imputation (MI) and covariate balancing propensity score (CBPS) weighting, which may outperform GBM if there is a non-complex relationship between treatment and outcome [53]. This procedure is 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 weighted linear regression models. Lastly, we computed a (non-covariate balanced) linear regression model to examine the mean difference in MHQ scores between the physical activity exposure and non-exposure groups, adjusted for covariates. Akin to our main analyses, participants were nested within country for all models.

**Results:**

**Descriptive statistics**

Descriptive statistics for the sample demographics characteristics, physical activity and mental health can be found in Table 1. Provide a brief description of the sample here. The mean score for the MHQ in the full sample was 67.93 ± 72.70 SD. Diagnostics indicated that covariate balance was successfully achieved after GBM weighting procedures were implemented (Supplementary Materials, Section B).

**Physical activity**

Propensity score weighted models demonstrated physical activity was associated with significantly (p < 0.01) higher MHQ scores (B = 18.45; 95% CI: 15.52-21.37), which coincided with a small effect size (Cohen’s *d* = 0.26). Physical activity was also associated with significantly higher scores for each of the six MHQ subdomains: Core Cognition (B = 16.44; 95% CI: 13.77-19.10; *d* = 0.25), Adaptability and Resilience (B = 18.14; 95% CI: 15.40-20.88; *d* = 0.27), Drive and Motivation (B = 15.75; 95% CI: 12.62-18.87; *d* = 0.24), Mood and Outlook (B = 16.32; 95% CI: 13.44-19.20; *d* = 0.24), Social Self (B = 14.03; 95% CI: 11.12-16.93; *d* = 0.19), and Mind-Body (B = 19.81; 95% CI: 17.23-22.36; *d* = 0.32).

**Physical Activity by Age**

The propensity score weighted moderation models revealed a significant (p < 0.05) physical activity by age interaction for overall MHQ scores (B = -2.04; 95% CI: -3.18 - -0.90), Core Cognition (B = -2.09; 95% CI: -3.10 - -1.08), Adaptability and Resilience (B = -1.16; 95% CI: -2.30 - -0.02), Mood and Outlook (B = -2.04; 95% CI: -3.20 - -0.89), Drive and Motivation (B = -2.15; 95% CI: -3.42 - -0.88), and Mind-Body (B = -2.20; 95% CI: -3.49 - -0.91), but not Social Self (). These results indicate younger age cohorts experience more favorable benefits for mental health (except for Social Self) from physical activity. Significant main effects of age were observed for overall MHQ scores (B = 14.94; 95% CI: 13.43-16.44) as well as the INSERT INFORMATION subdomains. Similarly, significant main effects of physical activity were observed for overall MHQ scores (B = XXXX; 95% CI: XXX) as well as the INSERT INFORMATION subdomains.

**Sensitivity analyses**

Our sensitivity analyses showed convergence of the estimated treatment effects of physical activity on mental health across each of the alternative statistical analysis techniques employed when compared to the main GBM results (B = 18.45): doubly robust GBM (B = 18.07), MI + CBPS (B = 18.04), doubly robust CBPS (B = 17.87), non-covariate balanced linear regression model (B = 18.07).

**Discussion**

* Favorable benefits of physical activity on overall mental health as well as several subdomains (Main effect of PA)
  + How does this compare to chekroud
  + Supports general body of literature demonstrating the benefits of PA
  + Ours results compared to RCTs (compare effect sizes?)
* PE strongest effect on Adaptability and Resilience, lowest on Social Self (is this in line with current literature? Comments on different exercise modalities?) (How PA differed across each subdomain – where are the strongest/weakest effects – why may this be)
  + Implications for precision medicine – PA stands to provide greatest benefits for some outcomes, maybe other behaviors provide greater benefits for others – to be determined in future use of the instrument (MHQ)
* Relatively poor MH in younger ages, confirming Chen 2022 (main effect of age)
* Interaction effects exist, stronger benefits for PA among younger adults.
  + This may be due to them having more to gain due to poorer mental health
  + Comment on implications for population level interventions potentially
* Propensity weighting methods allow us to make stronger causal inferences compared to common regression models (using more advanced techniques)
* Limitations
* Conclusion

There are several limitations with the current study. Firstly, unlike randomization, propensity score weighting does not adjust for unobserved covariates (Joffe & Rosenbaum, 1999). An unbiased treatment effect assumes that all potential confounders are observed, which is unlikely to be the case in any observational study. Adjusting for partially observed confounders may reduce bias, but it is unknown to what extent.

Limitations:

Self-reported physical activity behavior – can introduce bias and recall errors

Cross-sectional design – cannot infer causality

Convenience sampling – not truly globally representative despite over 200 countries included

Strong ignorability assumption; propensity scoring assumes all potentially confounding covariates are observed

Dropped ethnicity and gender identity

Self reported PA

Cross sectional

Volunteer online survey

Ordinal nature of PA questions = difficult to assess exact non-linear effects

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