Global Mind Project data in the United States: A comparison with national statistics

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Abstract

Objectives: To assess whether large-scale data collected by the Global Mind Project through online recruitment, aligns demographically with national statistics from traditional probability-based surveys.

Methods: We compared data collected in the United States by the Global Mind Project (83,589 responses from 2020 to 2023) with time- and question-matched data from the American Community Survey, Household Pulse Survey, and American Trends Panel.

Results: Demographic trends in the Global Mind Project data matched national statistics within 5% to 10%. Slight biases were observed, including an overrepresentation of single individuals, those with fewer friends, and those seeking mental health treatment.

Conclusions: Online survey methods, when combined with quota-based recruitment and post-stratification, can yield data that closely reflect national demographic trends in census data. These findings support the utility of the Global Mind Project for real-time, scalable public health monitoring.

Key words: Population health; mental health; survey; methods; global mind project; MHQ; representativeness

Introduction

The Global Mind Project (GMP) was developed to leverage online sampling to provide a real time, global view of mental health and wellbeing and the social, technological and lifestyle factors that drive it. Since its launch in 2020, the GMP has collected data from 2 million individuals across 130 countries and in 21 languages[1,2]. The survey assesses a wide range of demographic, cultural, and experiential variables, including age, sex, ethnicity, education, employment status, and income, alongside 47 dimensions of mental function and feeling, rated on a 9-point scale. Its breadth and scale suggest numerous useful applications in understanding of public health trends in the United States.

Data for the GMP are obtained by recruiting participants anonymously via paid advertisements on the internet and social media platforms such as Facebook, Google Display, and Google AdSense, inviting users to complete a 15-minute online assessment in exchange for a free personalized mental wellbeing report[3].

Traditionally, population surveys have relied on mail, telephone or face to face recruitment of individuals selected through probability sampling within demographically stratified bands, typically by age, sex, geography and socioeconomics[4,5]. This approach is widely regarded as the gold standard for obtaining representative data samples of a target population. For example, in the United States (US), the Census Bureau draws multi-stage, stratified samples from the Master Address File (MAF) for surveys such as the American Community Survey (ACS)[6] and Household Pulse Survey (HPS)[7]. Similarly, Pew Research Center's American Trends Panel (ATP) recruits participants through random sampling of residential addresses from the US Postal Service Delivery Sequence File, inviting them to complete surveys online[8]. Although these methods are rigorous, they are also logistically complex and costly, making them difficult to scale, and resulting in time delays between data collection and data availability especially for global studies. As a result, many nongovernmental surveys use alternative methods such as Random Digit Dialing (RDD) based on landline or mobile phone databases[9,10]. However, RDD surveys often face low response rates and are constrained in length to secure real-time respondent cooperation[11–17]. Furthermore, both recruitment methods present challenges when addressing sensitive or stigmatized topics such as mental health which often require a high degree of anonymity to mitigate concerns over privacy and the risk of self-disclosure. In non-compulsory surveys, such concerns can further suppress participation and limit data quality.

The rapid expansion of internet and mobile phone usage worldwide[18] has opened the door to a new paradigm for sampling and recruitment in mental health research that enables large-scale, global reach at significantly lower cost and faster speed. Online recruitment methods such as digital advertisements on Google or Facebook offer the potential to access broad cross-sections of the population. However, these methods rely on non-probability sampling approaches driven by opaque platform-specific optimization algorithms. As a result, they may overrepresent certain demographics or interest groups, and are inherently limited to individuals with internet access and presence on the selected platforms. These limitations have prompted ongoing debate regarding the validity and generalizability of data obtained through such methods[19–30]. Further concerns arise from the anonymity of online surveys, which may increase the risk of fraudulent, misrepresentative, or bot-generated responses[31,32].

Here we evaluated how demographic and social trends in GMP data for the United States (US) compared with time-aligned trends from the ACS, HPS and ATP, for questions where there were exact or near-exact matches. This included educational attainment and marital status by age and biological sex (our target criteria), the percentage seeking treatment for mental health problems, and number of close friends. It was hypothesized that there would be broad alignment of demographic trends, while social and behavioral responses would differ more due to differences in nonresponse bias across surveys.

Methods

GMP data

Data from the Global Mind Project is freely available for nonprofit research purposes. Data collected between 2020 and 2023 in English and Spanish from individuals living in the US was downloaded from the database (Table 1).

Table 1: Number of data records from the GMP used in this analysis.

	Total records				Clean Records			
DEMOGRAPHIC	2020	2021	2022	2023*	2020	2021	2022	2023*
18-24 F	1776	2707	2761	1705	1641	2426	2482	1536
18-24 M	927	1730	1406	1139	857	1548	1286	1056
25-34 F	666	1434	1285	917	620	1326	1202	852
25-34 M	435	950	789	679	413	894	745	638

35-44 F	612	1139	1029	904	580	1079	969	828
35-44 M	388	677	657	635	366	629	624	593
45-54 F	927	1469	1213	996	890	1375	1141	943
45-54 M	552	885	881	735	527	840	833	692
55-64 F	1641	2179	2203	1847	1594	2098	2108	1764
55-64 M	1139	1839	1968	1790	1103	1777	1891	1719
65-75 F	2146	2955	3238	3282	2090	2869	3134	3162
65-75 M	1418	2757	2773	3135	1391	2673	2681	3013
75+ F	1163	2327	2639	3777	1141	2257	2550	3651
75+ M	598	1449	1898	2764	577	1414	1842	2659
TOTAL	14388	24497	24740	24305	13790	23205	23488	23106
			TOTAL	87930			TOTAL	83589

*partial year; data recorded for this analysis ended in November 2023

GMP Data Processing and Quality Checks

As the data was downloaded in its raw form, multiple data cleaning criteria were applied to the data based on previously reported criteria[3]. First, responses that were completed in under 7 minutes or over 60 were excluded from the analysis. Second, those who had responses with a standard deviation of less than 0.2, representing people who answered with the same rating value across all 47 rating items (e.g. 111… or 5555…), were excluded. Finally, records where the respondent answered ‘No’ to the question ‘Did you find this assessment easy to understand?’ were removed. Completions arising from organic traffic, including peer referrals, were also excluded as they lay outside of the managed targeting criteria. As a result, 5% of responses were excluded from the analysis. After cleaning, the data sample size was 13,790 in 2020, 23,205 in 2021, 23,488 in 2022 and 23,106 in 2023. However, N values for individual analyses varied due to the removal of blanks or ‘Prefer not to say’ responses.

Comparison against the ACS, HPS and ATP Data

GMP US survey data was compared against data from the ACS, HPS and ATP. As the GMP collects data on a wide variety of demographics, cultural, lifestyle and life experience factors, only questions where there was an exact or near-exact match to questions in the ACS, HPS and ATP were selected for inclusion in this study to ensure an accurate comparison. This included educational attainment and marital status by age and biological sex from GMP and ACS obtained in 2022; the percentage seeking treatment for mental health problems from GMP and HPS from 2020 to 2023; and number of close friends from GMP and ATP for 2023.

For each of these data elements within GMP, the percentage of respondents selecting each answer option were computed for each age and biological sex group. In all cases, this was done by first computing averages for each age-sex group and then computing a weighted average based on the proportion of the population in each age group as provided by the United Nations (UN) Population Statistics[33]. For each of the comparison surveys (ACS, HPS, ATP), precalculated numbers by age and biological sex or national aggregates were directly downloaded from the respective survey sites.

Comparison of marital and education status data in GMP and ACS

ACS 2022 data was downloaded from the ACS data site[34]. The specific ACS tables downloaded were S1501 (Educational Attainment; N~3 million) and B12002 (Marital Status; N=~3 million). ACS Table S1501 reports education attainment as percentage with High School or Higher and percentage with Bachelor's or Higher. To create a comparable metric from the equivalent 2022 GMP data (n=22,396), the percentage with Bachelor's degree, Master's Degree and PhD degree were summed as percentage Bachelor's or higher, while percentage with High School and Associate degree were added to this to arrive at percentage High School or Higher.

ACS marital status options provided were: Never Married, Married/Spouse Present, Married/Separated, Married, Spouse absent, Divorced, Widowed while GMP marital status options provided were: Single (Never Married), In a relationship, Married/Civil Partnership, Divorced/Separated, Widowed, Prefer not to say (n=22,396). Given the slight differences, the data were aggregated and compared as follows: (i) ACS Never Married to GMP Single (Never Married) + In a relationship; (ii) ACS Divorced + Married but Separated to GMP Divorced/Separated; (iii) ACS Married/Spouse present to GMP Married/Civil Partnership; (iv) ACS Widowed to GMP Widowed.

Comparison of mental health treatment status in GMP and HPS

The percentage seeking treatment for mental health problems captured as part of the HPS from January 2020 to October 2023 (N=2,036,992) was compared to the equivalent information captured by GMP across the same time period (N=70,800 after removal of those answering 'Prefer not to say'). The HPS asked the following questions:

HPS1: At any time in the last 4 weeks, did you take prescription medication to help you with any emotions or with your concentration, behavior, or mental health? Yes/No

HPS2: At any time in the last 4 weeks, did you receive counseling or therapy from a mental health professional such as a psychiatrist, psychologist, psychiatric nurse, or clinical social worker? Include counseling or therapy online or by phone. Yes/No

While GMP asked:

Project GMP1: Are you presently undergoing treatment for any mental health challenges? Yes/No/Prefer not to say

Specifically, the percentage of those who answered ‘Yes’ to GMP1 above was compared to the percentage who answered ‘Yes’ to either HPS1 or HPS2. Age-sex weighted national estimates from 2020 to 2023 were also compared, as well as the age-wise break-up for 2023 alone. Calculated results for those who answered ‘Yes’ to either HPS1 or HPS2 by age and year were downloaded directly from the CDC site[35]. Annual estimates were arrived at by averaging results across multiple time periods of the HPS survey reported during the same year. The HPS reported aggregated data by age bands 18-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80 years and above, while GMP captured age data in bands 18-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84. 85+. Since only pre-aggregated results were available for the HPS this did not afford a perfectly age-aligned comparison.

Comparison of number of close friends in GMP and ATP

The average percentage of the population with each number of close friends from 0 to 5+ in the ATP, obtained during July 2023 (N=5,057) was compared against the equivalent GMP data obtained between January 1st and November 30th 2023 (N=19,857 after removal of blanks and values over 100). The results from the ATP used responses to the question: ‘Not counting your family, how many close friends do you have?’ with answer options 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 or more. The average percentages of the population reporting each number of close friends in the ATP were weighted to be representative of the US adult population by sex, race, ethnicity, education, and other categories. Equivalent percentages were computed from GMP data for the similar question: ‘How many close friends do you have?’ with a numerical response field. These were age-sex weightings used national statistics from UN to reflect their proportions in the population.

Results

Demographic Trends in the ACS are mirrored in GMP data

Figure 1 shows a comparison of educational attainment and marital status by age group for data obtained by ACS (N=~3.5M) and GMP (N=22,396) in 2022. Overall, trends for both educational attainment (Figure 1A) and marital status (Figure 1B) in GMP data closely matched trends in the ACS data. However, a few differences were noted. For educational attainment, the proportion of High school or higher was 12% higher in GMP than ACS in the 18-24 age group. For other age groups, the difference ranged from ±0% to ±3% (average ±1%). The GMP age question captures 18-24 as a group, therefore it is possible that this group either contained a smaller proportion of 18-year-olds (the majority of whom are still in high school) or that 18-year-olds close to completing high school choose "High School" for educational attainment in preference to 'Some High School' which was the alternative option available. Presently, those still in high school are directed to a youth version of the survey. For marital status, GMP data showed a higher proportion of never married respondents across all ages except 18-24 (average difference 6%; range ±1% to ±9%) and a correspondingly lower proportion of married respondents (average difference 7%; range ±1% to ±10%). For 18–24-year-olds, there was a higher proportion of never married respondents in ACS data (7%), while the proportion married was similar (1% difference). 3% chose 'Prefer not to say' in GMP and were not included which may explain some of the difference between married and never married.

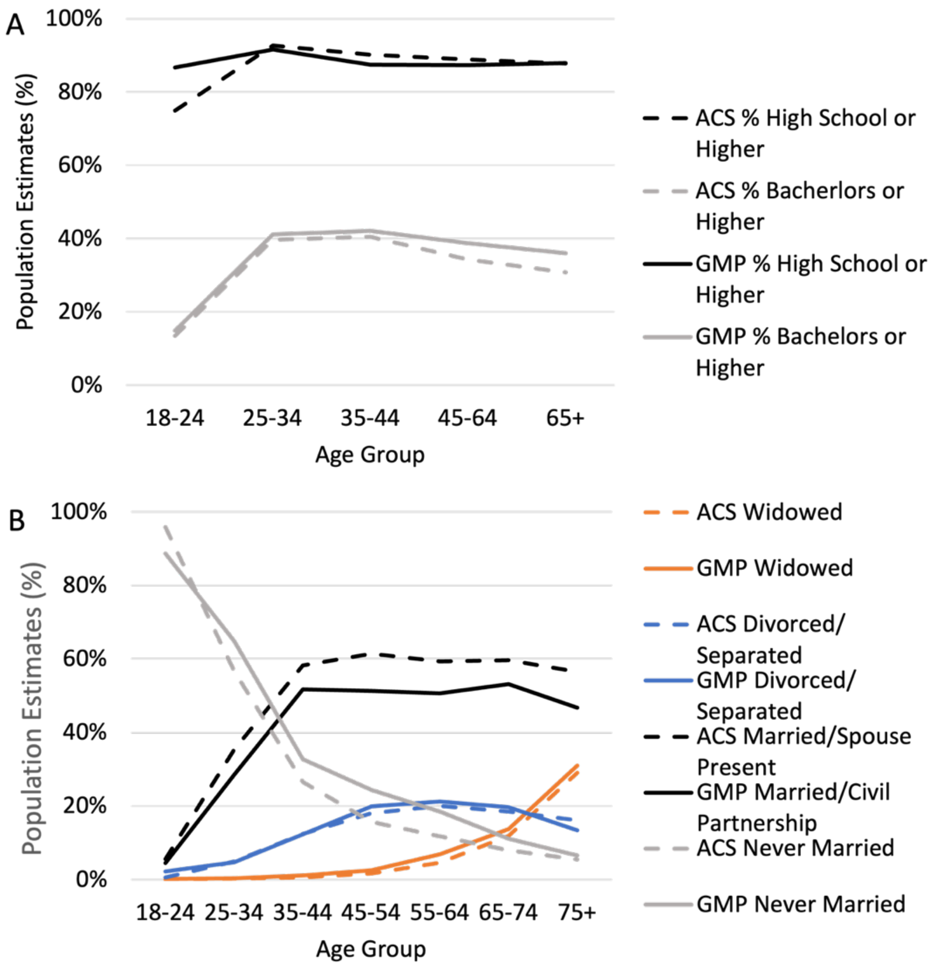

Figure 1. Comparison of population estimates (%) for educational attainment (A) and marital status (B) by age group for data obtained by ACS (N= ~3.5 M; dotted lines) and GMP (N=22,396; solid lines) in 2022.

Reported mental health treatment seeking behavior captured in the HPS was mirrored in GMP

Figure 2 compares trends of the percentage of the adult population seeking professional treatment for a mental health problem over time from 2020 to 2023, and by age for 2023, between the HPS and GMP. The specific questions asked by the HPS and GMP surveys were similar but not identical. While GMP asks about ‘current’ treatment for mental health challenges without specifying which type of treatment, HPS asks specifically whether prescription medication and/or therapy/counseling were taken in the past 4 weeks. Nonetheless, it provides a broadly similar comparison that can determine if GMP oversamples for individuals with mental health problems. Figure 2A shows that the age-sex weighted national estimates of GMP were within ±1% of the national estimates of the HPS for all years other than 2021 where it was 5% higher. The estimates by age for 2023 data are shown for HPS and GMP in Figures 2B and 2C respectively. HPS data tables use different age categories (e.g. 30-39, 40-49 rather, than 35-44, 45-54 etc.) precluding a direct comparison. However, broadly, the percentage seeking treatment in GMP data was generally higher for ages 25-54 by an average of 8% (range 6% to 10%) and lower for ages 70 and above by an average of 5% (range 4% to 7%). This difference could arise because GMP responses consider any treatment beyond prescription medication and therapy/counseling. However, it may also arise from a nonresponse bias where younger people in treatment were more likely to take part in GMP while older people in treatment may be less likely to be on the Internet.

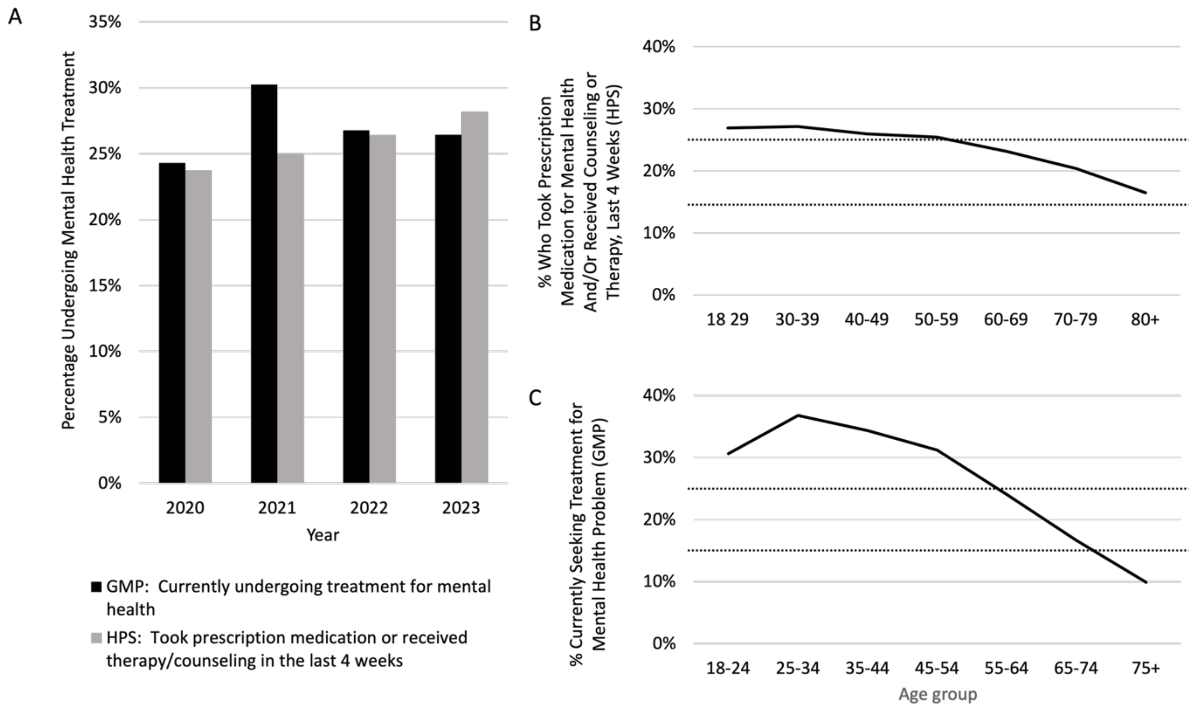

Figure 2. Comparison of trends for the percentage of the adult population seeking professional treatment for a mental health problem over time and by age between the HPS and GMP. (A) Comparison of the percentage currently undergoing treatment for mental health problem (GMP, blue) and the percentage who took prescription medication or received therapy/counseling in the last 4 weeks (HPS, red) from 2020 to 2023. (B) HPS data across different age groups for the percentage who took prescription medication for mental health conditions and/or received counseling or therapy in last 4 weeks in 2023. (C) GMP data across different age groups for the percentage currently seeking treatment for mental health problem in 2023.

National trends of close friendships in the ATP compared to GMP

Figure 3 shows a comparison of the number of close friends reported in the ATP in July 2023 compared to the annual GMP data for 2023. While the pattern across number of friends was similar, there were some key differences. Respondents in GMP sample were more likely to report only 2 close friends or less (average 15%) compared the ATP (average 10%; difference 5%) and correspondingly less likely to report 5+ friends (28%) compared to the ATP (38%; difference 10%). The differences may arise for multiple reasons including differences in the estimation methods or differences in the nature of nonresponse bias between the two surveys.

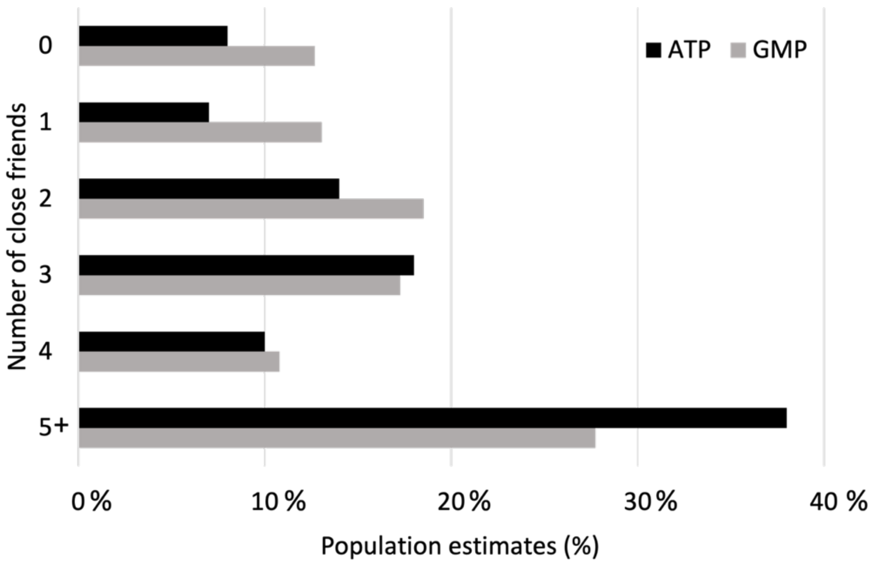

Figure 3: Comparison of population estimates (%) for the number of close friends (0 to 5+) reported in the ATP in July 2023 (black) compared to the annual GMP data for 2023 (grey).

Discussion

Principal results

The Global Mind Project (GMP) data from the United States provides a potentially valuable public health resource. Here we demonstrate that data from the GMP in the United States closely aligns with national trends obtained from various rigorously stratified and randomly sampled US based surveys such as the ACS and HPS conducted by the US Census Bureau, and the ATP conducted by Pew Research Centre. This includes demographic factors of marital status and educational attainment, mental healthcare trends and friendship, which represent a diverse range of variables. This alignment suggests that despite relying on nonprobability online recruitment, GMP can yield nationally representative insights with appropriate post-stratification.

Nonresponse bias and limitations

Understanding nonresponse bias is important as every survey will have its own form of nonresponse bias based on the survey topic and mode of delivery. GMP aims to target a general population rather than specifically those who have mental health problems, but by necessity it mentions mental health and wellbeing in its outreach which raises the possibility of bias related to interest in these aspects. In this context, although GMP data closely mirrored national trends, it is important to note some differences arising between the datasets. In GMP data, we observed a bias towards single people (as compared to the ACS), more people seeking treatment in the age groups between 25-54 (as compared to the HPS) and a higher proportion with fewer friends (as compared to the ATP). These differences were on an order of magnitude of 5-7%. This suggests the possibility that those who were more inclined to take part in GMP were single people with fewer friends who were seeking mental health treatment or, conversely, a nonresponse bias towards married people with lots of friends who are not seeking mental health treatment (or both). This latter finding aligns with other studies involving mental health surveys that report a greater representation of people with mental health problems within the sample[36,37]. However, other explanations are also possible. For example, GMP considers all treatments for mental health and not just prescription medication and therapy/counseling as included in the HPS. Some fraction of the difference may therefore reflect those undergoing other types of treatment (e.g. brain stimulation, neurofeedback). With respect to the differences in trends for the number of close friends, one explanation for the difference might be that people who frequent social media channels may have fewer close friends. Alternatively, as the ATP recruits participants for a broader survey of civic trends it is possible that those who agree to participate in the ATP are more civic minded which biases towards people with more friends. Nonetheless, while these differences could explain and mitigate some of the differences observed, a small nonresponse bias in GMP data favoring individuals with greater risk factors for mental health challenges cannot be ruled out.

One of the primary goals of GMP is to track country level trends across the globe, particularly with respect to mental health status. The question therefore arises as to how much a 5-7% bias towards single people, those with few friends and/or those taking prescription medication or in therapy would shift these estimates. For example, the difference in the percentage of those who are mentally distressed or struggling [as measured by the MHQ score, see [38] for more details on the MHQ and how it is calculated] among those seeking treatment versus those not seeking treatment is only 14% (40% vs 26%). The average percentage of those distressed or struggling (MHQ scores<0) re-weighted by the proportions of those single and seeking treatment in each age group, as per the ACS and HPS respectively, results in a value 1-2% lower for most age groups, providing an estimate of the magnitude of this potential bias. Altogether, this suggests that national trends of the percentage distressed or struggling in GMP are overestimated by up to 2%, particularly for middle age groups. However, as the recruitment methods are relatively stable each year, changes over time would still provide a reliable estimate of the magnitude of change.

Global Mind methodology as an alternative to traditional surveys

The alignment of Global Mind data with national statistics has particular importance given the challenges with many probability survey approaches[12,14–16,39]. Probability-based sampling, while rigorous, is often logistically complex, time-intensive, expensive, and increasingly hampered by declining response rates. Such approaches are also difficult to scale globally. By contrast, GMP's online recruitment methodology, enables rapid data collection (1000-2000 people take part globally every day); has global scalability (currently active in 130 countries); is adaptive to changing societal trends and events; is readily able to target specific populations of interest; and can explore sensitive or stigmatized topics with greater anonymity. Together, these strengths position GMP as a complementary and, in many contexts, preferable alternative for capturing mental health and wellbeing data, particularly at scale, and in settings where traditional survey methods may be impractical.

Furthermore, the consistency of recruitment methods and real-time nature of the program positions GMP as an easily scalable and flexible platform for tracking national trends, as well as detecting emerging trends in the face of widespread societal, technological, and environmental change. The findings also contribute to the growing body of literature that highlights the opportunity of using online channels such as Facebook and Google Ads and careful targeting to recruit participants for health-related studies[28,29,36,40].

GMP data beyond the United States

GMP presently operates in 21 languages across 130 countries although sample sizes vary across countries. While it is not possible to directly extrapolate these conclusions to all other countries, we note that the same methodology is used across the world, suggesting the potential for similar outcomes. However, it must be noted that GMP recruits only from the Internet-enabled population. With 94% of the US population Internet-enabled, most of the population in the US are covered and may be invited to participate. In contrast, GMP data will increasingly deviate from national statistics with decreasing Internet penetration and, for countries with substantially lower internet penetration. Nonetheless, as the world becomes more digitally connected, and as traditional survey infrastructures struggle to keep pace with urgent data needs, the Global Mind Project provides a compelling model for a new generation of mental health monitoring that is real-time, inclusive, and adaptive.

Conclusion

The Global Mind Project represents a scalable, real-time approach to understanding mental health and its drivers at a national and global level. This analysis shows that GMP data collected online in the US shows good alignment with large surveys using more rigorous sampling techniques, suggesting that GMP data from the US are likely to be broadly reflective of the national population. Altogether, with rising rates of mental health conditions around the world, especially in younger populations[41–43], and growing nonresponse rates with traditional surveys, there is an urgent need for a new paradigm of data collection within the field of mental health, something also noted by Sanchez and colleagues[44] who stated *"Developing new strategies to increase recruitment for mental health research is essential to addressing the field's most pressing problems"*.

References:

1. Newson JJ, Pastukh V, Thiagarajan TC. Assessment of Population Well-being With the Mental Health Quotient: Validation Study. *JMIR Ment Health*. 2022;9(4):e34105. doi:10.2196/34105

2. Newson JJ, Thiagarajan TC. Assessment of Population Well-Being With the Mental Health Quotient (MHQ): Development and Usability Study. *JMIR Ment Health*. 2020;7(7):e17935. doi:10.2196/17935

3. Taylor J, Topalo O, Newson JJ, Thiagarajan TC. Data Collection and Management Infrastructure of the Global Mind Project. *Preprint*. Published online 2025.

4. Banerjee A, Chaudhury S. Statistics without tears: Populations and samples. *Ind Psychiatry J*. 2010;19(1):60-65. doi:10.4103/0972-6748.77642

5. Levy PS, Lemeshow S. *Sampling of Populations: Methods and Applications*. John Wiley & Sons; 2013.

6. US Census Bureau. American Community Survey (ACS). 2023. https://www.census.gov/programs-surveys/acs

7. US Census Bureau. Household Pulse Survey: Measuring Emergent Social and Economic Matters Facing U.S. Households. 2024. https://www.census.gov/data/experimental-data-products/household-pulse-survey.html

8. Pew Research Foundation. The American Trends Panel. https://www.pewresearch.org/our-methods/u-s-surveys/the-american-trends-panel/

9. Hartge P, Brinton LA, Rosenthal JF, Cahill JI, Hoover RN, Waksberg J. Random digit dialing in selecting a population-based control group. *Am J Epidemiol*. 1984;120(6):825-833. doi:10.1093/oxfordjournals.aje.a113955

10. Wolter K, Chowdhury S, Kelly J. Chapter 7 - Design, Conduct, and Analysis of Random-Digit Dialing Surveys. In: Rao CR, ed. *Handbook of Statistics*. Vol 29. Handbook of Statistics. Elsevier; 2009:125-154. doi:10.1016/S0169-7161(08)00007-2

11. Boland M, Sweeney M, Scallan E, Harrington M, Staines A. Emerging advantages and drawbacks of telephone surveying in public health research in Ireland and the U.K. *BMC Public Health*. 2006;6:208. doi:10.1186/1471-2458-6-208

12. Brick JM, Williams D. Explaining Rising Nonresponse Rates in Cross-Sectional Surveys. *The ANNALS of the American Academy of Political and Social Science*. 2013;645(1):36-59. doi:10.1177/0002716212456834

13. Dillon A, Glazerman S, Rosenbaum M. Understanding Response Rates in Random Digit Dial Surveys. Published online April 1, 2021. doi:10.2139/ssrn.3836024

14. Keeter S, Kennedy C, Dimock M, Best J, Craighill P. Gauging the Impact of Growing Nonresponse on Estimates from a National RDD Telephone Survey. *Public Opinion Quarterly*. 2006;70(5):759-779. doi:10.1093/poq/nfl035

15. Kohut A, Keeter S, Doherty C, Dimock M, Christian L. Assessing the Representativeness of Public Opinion Surveys. *Pew Research Centre For the People and the Press*. Published online 2012.

16. Leeper TJ. Where Have the Respondents Gone? Perhaps We Ate Them All. *Public Opinion Quarterly*. 2019;83(S1):280-288. doi:10.1093/poq/nfz010

17. Vercruyssen A, Roose H, Carton A, Putte BVD. The effect of busyness on survey participation: being too busy or feeling too busy to cooperate? *International Journal of Social Research Methodology*. 2014;17(4):357-371. doi:10.1080/13645579.2013.799255

18. Data Reportal. Digital around the world. 2023. https://datareportal.com/global-digital-overview

19. Baker R, Brick JM, Bates NA, et al. Summary Report of the AAPOR Task Force on Non-probability Sampling. *Journal of Survey Statistics and Methodology*. 2013;1(2):90-143. doi:10.1093/jssam/smt008

20. Birnbaum MH. Human Research and Data Collection via the Internet. *Annu Rev Psychol*. 2004;55(1):803-832. doi:10.1146/annurev.psych.55.090902.141601

21. Cornesse C, Blom AG. Response Quality in Nonprobability and Probability-based Online Panels. *Sociological Methods & Research*. Published online May 6, 2020:004912412091494. doi:10.1177/0049124120914940

22. Couper MP. Review: Web Surveys: A Review of Issues and Approaches*. *Public Opinion Quarterly*. 2000;64(4):464-494. doi:10.1086/318641

23. Couper MP. Issues of Representation in eHealth Research (with a Focus on Web Surveys). *American Journal of Preventive Medicine*. 2007;32(5, Supplement):S83-S89. doi:10.1016/j.amepre.2007.01.017

24. Dutwin D, Buskirk TD. Apples to Oranges or Gala versus Golden Delicious?: Comparing Data Quality of Nonprobability Internet Samples to Low Response Rate Probability Samples. *Public Opinion Quarterly*. 2017;81(S1):213-239. doi:10.1093/poq/nfw061

25. Fricker RD. Sampling Methods for Online Surveys. In: *The SAGE Handbook of Online Research Methods*. SAGE Publications Ltd; 2017:162-183. doi:10.4135/9781473957992.n10

26. Goel S, Obeng A, Rothschild D. Non-Representative Surveys: Fast, Cheap, and Mostly Accurate. *Working Paper*. Published online 2016.

27. Kennedy C, Mercer A, Keeter S, Hatley N, McGeeney K, Gimenez A. Evaluating Online Nonprobability Surveys. Published online 2016.

28. Schneider D, Harknett K. What's to Like? Facebook as a Tool for Survey Data Collection. *Sociological Methods & Research*. 2022;51(1):108-140. doi:10.1177/0049124119882477

29. Thornton L, Batterham PJ, Fassnacht DB, Kay-Lambkin F, Calear AL, Hunt S. Recruiting for health, medical or psychosocial research using Facebook: Systematic review. *Internet Interventions*. 2016;4:72-81. doi:10.1016/j.invent.2016.02.001

30. Whitaker C, Stevelink S, Fear N. The Use of Facebook in Recruiting Participants for Health Research Purposes: A Systematic Review. *Journal of Medical Internet Research*. 2017;19(8):e7071. doi:10.2196/jmir.7071

31. Glazer JV, MacDonnell K, Frederick C, Ingersoll K, Ritterband LM. Liar! Liar! Identifying eligibility fraud by applicants in digital health research. *Internet Interv*. 2021;25:100401. doi:10.1016/j.invent.2021.100401

32. Wang J, Calderon G, Hager ER, et al. Identifying and preventing fraudulent responses in online public health surveys: Lessons learned during the COVID-19 pandemic. *PLOS Glob Public Health*. 2023;3(8):e0001452. doi:10.1371/journal.pgph.0001452

33. United Nations. World Population Prospects 2022. 2022. https://population.un.org/wpp/

34. US Census Bureau. American Community Survey Data. 2023. https://www.census.gov/programs-surveys/acs/data.html

35. CDC. Mental Health Care: Household Pulse Survey. 2022. https://www.cdc.gov/nchs/covid19/pulse/mental-health-care.htm

36. Batterham PJ. Recruitment of mental health survey participants using Internet advertising: content, characteristics and cost effectiveness. *Int J Methods Psychiatr Res*. 2014;23(2):184-191. doi:10.1002/mpr.1421

37. Lee S, Torok M, Shand F, et al. Performance, Cost-Effectiveness, and Representativeness of Facebook Recruitment to Suicide Prevention Research: Online Survey Study. *JMIR Ment Health*. 2020;7(10):e18762. doi:10.2196/18762

38. Newson JJ, Sukhoi O, Thiagarajan TC. MHQ: constructing an aggregate metric of population mental wellbeing. *Population Health Metrics*. 2024;22(1):16. doi:10.1186/s12963-024-00336-y

39. US Government Accountability Office. The American Community Survey: Accuracy and Timeliness Issues. 2002. https://www.gao.gov/products/gao-02-956r

40. Astley CM, Tuli G, Mc Cord KA, et al. Global monitoring of the impact of the COVID-19 pandemic through online surveys sampled from the Facebook user base. *Proc Natl Acad Sci U S A*. 2021;118(51):e2111455118. doi:10.1073/pnas.2111455118

41. Sapien Labs. *Mental State of the World 2020*.; 2021. https://mentalstateoftheworld.report/msw-2020/

42. Twenge JM, Cooper AB, Joiner TE, Duffy ME, Binau SG. Age, period, and cohort trends in mood disorder indicators and suicide-related outcomes in a nationally representative dataset, 2005–2017. *Journal of Abnormal Psychology*. 2019;128(3):185-199. doi:10.1037/abn0000410

43. CDC. *Youth Risk Behavior Survey: Data Summary & Trends Report*.; 2023. https://www.cdc.gov/media/releases/2023/p0213-yrbs.html

44. Sanchez C, Grzenda A, Varias A, et al. Social media recruitment for mental health research: A systematic review. *Compr Psychiatry*. 2020;103:152197. doi:10.1016/j.comppsych.2020.152197