National Wellbeing Survey (NWS), 2024

Methodology Report

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CONTENT

Overview

The National Wellbeing Survey (NWS) is a non-probability cross-sectional survey of non-institutionalized adults aged 18 to 64 in the United States. The 2024 NWS was administered online from June 4 to August 23, 2024. The sample frame included non-institutionalized adults in the United States who ranged in age from 18 to 64 years old and who were able to read English. NWS sample participants were recruited online through Qualtrics Panels. Respondents were asked to complete a 25-minute survey. The survey was available only in English. Survey topics included psychosocial wellbeing, social relationships and support, participation in social activities, physical health, mental health, health behaviors, health care use, employment quality and experiences, COVID-19 experiences, socioeconomic measures, political orientation, and demographic measures. The final sample included 7,027 respondents. The restricted use version of the data includes geographic identifiers for states (N=51) and counties (N=1,721). Survey design and post-stratification weights are included to adjust for the NWS non-probability sampling approach, using a separate large-scale, nationally representative survey (the National Health Interview Survey) as the reference. Additional details about the NWS methodology are provided in the sections below.

Motivation

Although there are several existing national health surveys that collect data from the U.S. working-age population (e.g., Behavioral Risk Factor Surveillance System, National Health Interview Survey, National Survey of Drug Use and Health), none include all three of the following features:

1. A comprehensive array of physical health, mental health, and psychosocial wellbeing measures.
2. A large enough sample of nonmetropolitan respondents to enable metro-nonmetro and within-nonmetro comparisons and a measure to identify a respondent's rural-urban continuum code.
3. State and county geographic identifiers to enable linkage to contextual data.

The NWS includes all three features. The NWS was designed to support research to assess population-level wellbeing, broadly defined (physical health, mental health, psychosocial wellbeing, social relationships, employment quality, financial wellbeing) and identify how wellbeing varies by demographic group and geography. Given that the 2023 NWS was administered in the aftermath of the COVID-19 pandemic, the survey also includes a module to assess respondents experiences during – as well as impacts/consequences of – the pandemic on their lives.

Sampling and Survey Administration

Overview

Respondents were sampled from Qualtrics Panels. The sample source and procedures are described in the following sections. NWS 2024 aimed to have completed surveys from at least 7,000 respondents based on sampling quota described below. The final sample included 7,027 respondents.

Sample Quotas

The target population for the NWS is the U.S. population ages 18-64. To create a demographically representative sample of adults ages 18-64 by age, sex, race, Hispanic ethnicity, and educational attainment, quotas were determined using the 2018-2022 American Community Survey estimates from the U.S. Census Bureau for each of these demographic characteristics.

In addition, we created quotas to recruit a sufficient sample of nonmetropolitan residents to enable statistical power to conduct robust metro-nonmetro and within-nonmetro analysis. We defined metropolitan status at the county level using the 2023 Rural-Urban Continuum Code (RUCC) classification from the USDA Economic Research Service (https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/). Note that this is a departure from prior years of the NWS, where we used the 2013 RUCCs.

Below is the list of RUCC codes. We merged quotas for RUCCs 4 & 5, 6 & 7, and 8 & 9.

Metro counties:

1 Counties in metro areas of 1 million population or more
2 Counties in metro areas of 250,000 to 1 million population
3 Counties in metro areas of fewer than 250,000 population

Nonmetro counties:

4 Counties in nonmetro areas with urban population of 20,000 or more, adjacent to a metro area
5 Counties in nonmetro areas with urban population of 20,000 or more, not adjacent to a metro area
6 Counties in nonmetro areas with urban population of 2,500 to 19,999, adjacent to a metro area
7 Counties in nonmetro areas with urban population of 2,500 to 19,999, not adjacent to a metro area
8 Completely rural or less than 2,500 urban population, adjacent to a metro area
9 Completely rural or less than 2,500 urban population, not adjacent to a metro area

We sought to include an oversample of residents of nonmetropolitan counties, so that at least 28% of completed surveys would be from residents of nonmetropolitan counties as defined by the U.S. Department of Agriculture Economic Research Service (USDA ERS 2023). The final sample included 1,947 (27.7%) respondents whose reported county of residence was classified as nonmetropolitan.

Overview of Qualtrics Panels

Qualtrics Panels comprise partner-based databases of several million U.S. adults who volunteer to participate in surveys. Qualtrics recruits participants from various sources, including website intercept recruitment, member referrals, targeted email lists, gaming sites, customer loyalty web portals, permission-based networks, and social media. Consumer panel members' names, addresses, and dates of birth are typically validated via third-party verification measures prior to their joining a panel. Some panel participants (e.g. via B2B) are subject to additional quality control measures such as LinkedIn matching, phone calls to the participant's place of business, and other third-party verification methods (TrueSample, RelevantID, Verity, etc.). Qualtrics compensates respondents in various ways (e.g., airline miles, gift cards) agreed upon when the member joins the panel. Online panels are increasingly used in social science research due to efficiency, cost, timeliness, and data quality (Hays 2015).

Sample Recruitment

Panel members received an email invitation to complete the NWS from Qualtrics. Qualtrics targeted respondents based on demographics to meet our quotas. Qualtrics conducted all respondent recruitment in batches. Qualtrics first targeted populations that are more difficult to reach via online surveys, including Hispanic and rural respondents. As quotas for these populations were reached, recruitment shifted to easier to reach populations. Participants were only compensated for complete surveys, a condition agreed to before they began the survey. Qualtrics survey administrators determined whether a survey was completed to a satisfactory level to earn compensation.

Survey Administration

Data collection occurred from June 4 to August 23, 2024. The NWS survey was administered via Qualtrics using Syracuse University's branded Qualtrics account. We enabled the "prevent ballot box stuffing" feature to prevent multiple responses from the same device. We also used the "Bot Detection" feature that uses Google's reCAPTCHA to identify and flag responses that are likely generated by bots. Qualtrics removed these responses from the data set. While the Qualtrics platform enables collection of personal and location identifiers, Qualtrics does not share that information with us. This helps protect respondent anonymity.

Sample Quality Control

Qualtrics conducted quality checks at multiple points during survey collection. These included checking for and deleting:

1. <u>Flatliners</u>: This measures for attention by evaluating respondents' selections to matrix style questions. Respondents are flagged for straight-lining when the same answer choice is selected across most or all of the entire grid(s).
2. <u>Multi-Response Check</u>: Respondents selected almost all options in at least one select-all-that-apply, displaying click-through behavior.
3. <u>Inattentive</u>: Respondents who take an inordinate amount of time (600+ minutes) completing the survey compared to others, provide signs of contradictory responses, or show signs of excessive selection in a multi-response set are flagged for inattention.
4. <u>Speeder</u>: Respondents who speed through the survey. This includes respondents who took less than the median time to complete the survey (a point set by Qualtrics based upon the median survey completion time during pre-launch – the first 100 surveys).
5. <u>Garbage and Profane Responses</u>: Respondents who entered gibberish (keyboard banging), repetitive verbatims, and profanity to the text response options are flagged for signs of poor quality.
6. <u>Suspicious Responses</u>: Respondents who entered suspicious open-ended responses (e.g. irrelevant or similar responses across multiple text response options).

Qualtrics gives respondents an overall score, or "bad rate" based on the quality checks above. For example, if a respondent showed patterns of straight-lining for grid questions that would be expected to have varying response for the average individual, that offense would contribute to a higher "bad rate" than in a case where it's reasonable that someone might "Agree" with 5 statements in a row.

Following Qualtrics screening, we conducted additional internal data screening that involved identifying mismatches across several groups of items and straightliners in specific sections. We removed from the sample all survey respondents who failed these screenings.

Response Rate

The traditional response rate is not a useful measure for opt-in online panels because they use passive recruitment (e.g., invitation could be embedded in a longer email, repeated invitations are not sent). Qualtrics aggregates many online panel resources, and most use what are called “dynamic surveys” that are distributed in a dashboard style where respondents see a dashboard of surveys for which they likely to qualify. This can also include app-based recruitment, and a multitude of other methods. Some people may receive email notifications, but this is an older system of distributing surveys that is no longer widely used. Qualtrics starts tracking the respondent as soon as they choose to engage with the NWS, but they do not have a specific survey invite that everyone sees across the project. Because of this inability to track respondents prior to them entering the survey, Qualtrics is unable to provide a confirmed number of people who simply see the invitation and choose not to attempt the survey.
In the 2024 survey administration, 16,184 respondents clinked on the link to enter the survey landing page. Of those, 3,035 participants were screened out due to not qualifying (e.g., due to age) and 4,655 were screened out due to sample quota requirements (i.e., they represented a demographic category for which we had already achieved our sample quota). Therefore, 8,494 people who entered the survey landing page were eligible. From there, 7,670 people completed the survey. Of those, 643 respondents were dropped due to data quality issues (e.g., speeding, straight lining), typically removing people in real time who did not pass data quality checks. The final number of quality completed surveys was 7,027.

Survey Design

Overview

The NWS was designed by Principal Investigator Shannon Monnat and affiliates of the Syracuse University Lerner Center for Public Health Promotion and Population Health. Several survey questions were taken from gold standard surveys, such as the Behavioral Risk Factor Surveillance System, the National Health Interview Survey, and the Survey on Drug Use and Health, enabling comparisons of responses with those other surveys. The final NWS survey instrument was submitted for review (IRB #20-290) to the Institutional Review Board at Syracuse University. It received approval as an Exempt Protocol in December 2020.

Pretesting

We pretested a draft of the survey on a convenience sample of 10 individuals we identified. Pretesters included Syracuse University faculty members, graduate students, and staff. We asked pretesters to identify any issues or errors in the survey, including inaccurate skip patterns and confusing questions. Many of the items on the 2024 NWS are the same as those on the 2021 NWS, which we pretested with 50 respondents.

Survey Components

The 2024 NWS is divided into one consent and one screener component and six thematic modules (shown below). While demographic information was reserved for the end of the survey, seven questions (age, sex, Hispanic ethnicity, race, education, state of residence, and county of residence) were moved to the screener component to filter respondents based on characteristics that met specific demographic quotas.

Domains

1. *Global Life Satisfaction and Psychological Wellbeing*. Several measures are adapted from “World Values Survey” (Haerpfer et al., 2020), “McArthur Scale of Subjective Social Status” (Adler et al., 2000), “The Cantril Self-Anchoring Striving Scale” (Gallup, 2012), “Gallup”

(Gallup, 2018), “The Satisfaction With Life Scale (Diener, Emmons, Larsen, & Griffin, 1985)”, and “The Brief Resilience Scale” (Smith et al., 2008).

2. *Social Relationships and Support*. All measures are adapted from “UCLA 20-Item Loneliness Scale & UCLA 3-Item Loneliness Scale” (Russell, 1996), “Pew Research Center 2014 Religious Landscape Study (RLS-II)” (Pew Research Center, 2022), “Fragile Families and Child Wellbeing Study” (McLanahan & Garfinkel, 2000), “Changing Lives of Older Couples” (Nesse et al., 2003), and “National Social Life, Health, and Aging Project (NSHAP)” (Waite et al., 2011).
3. *Physical and Mental Health*. Several measures are adapted from “Midlife in the United States (MIDUS 2), 2004-2006” (Barger, 2006), “Behavioral Risk Factor Surveillance System” (Centers for Disease Control and Prevention, 2020), “Canadian Community Health Survey and Medical Expenditure Survey” (Ahmad, Jhajj, Stewart, Burghardt, & Bierman, 2014), “Household Pulse Survey” (Fields et al., 2020), “Health and Retirement Study” (Health and Retirement Study, 2020), and “PHQ-4: The Four-Item Patient Health Questionnaire for Anxiety and Depression” (Kroenke, Spitzer, Williams, & Löwe, 2009).
4. *Health Behaviors*. Measures are adapted from “National Health Interview Survey Adult Questionnaire” (National Center for Health Statistics, 2016; 2019), “National Health and Nutrition Examination Survey (NHANES)” (Centers for Disease Control and Prevention & National Center for Health Statistics, 2020), (Centers for Disease Control and Prevention, 2020), “National Survey on Drug Use and Health” (U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, 2021), and “Health Behavior in School-Aged Children (HBSC), 2005-2006” (Iannotti, 2012).
5. *Employment and Income*. Measures are adapted from “2018 National Panel Survey of Demographic, Structural, Cognitive, and Behavioral Characteristics” (Bruce, Wu, Lustig, Russell, & Nemecek, 2019), “Current Population Survey” (U.S. Census Bureau, 2020), “National Health Interview Survey Adult Questionnaire” (National Center for Health Statistics, 2022), “National Compensation Survey” (U.S. Bureau of Labor Statistics, 2022), “Survey of Income and Program Participation” (U.S. Census Bureau, 2022), “The Shift Project” (Schneider & Harknett, 2024), and “American Community Survey” (U.S. Census Bureau, 2022)
6. *Demographic Information*. All measures are adapted from “Behavioral Risk Factor Surveillance System” (Centers for Disease Control and Prevention, 2020), “National Survey of Veterans” (U.S. Department of Veterans Affairs, 2017), “American Community Survey” (U.S. Census Bureau, 2022), “National Health Interview Survey” (National Center for Health Statistics, 2019), and “2018 Pew Research Center’s American Trends Panel” (Pew Research Center, 2018).

   Politics. Measures are adapted from “General Social Survey” (Davern et al., 2021).

Comparability to Prior Years of the NWS

We repeated several questions from the 2021-2023 surveys in the 2024 survey. However, there are items where the question wording or response set is different across the years. In cases where there is a slight difference in question wording, we maintain the same variable name but include a note with the variable in the codebook to indicate what changed. In cases where there is a large difference in question wording or the response set, we use a different variable name. Users should take caution in combining variables across years when wording or response sets have changed.

Data Cleaning

We completed the following data cleaning procedures:

Removing Potentially Identifiable Text: While the survey did not ask questions intended to elicit identifiable information, it was possible for respondents to insert such information into the textual responses. Therefore, we combed the text responses to delete any such instances should they occur. No identifiable information was provided in any text response.

Recoding Missing Values: For questions that asked responses to 'select all' response options that apply to them, we created separate variables for each response option. In most cases, missing values originally indicated that the response was not chosen. We recoded these missing values to 0. In addition, due to skip patterns (see codebook), some questions were not asked of all respondents. In these cases, we assigned a value of '96' to respondents who were outside of the universe (i.e., were not asked the question). In cases where there was a skip pattern for a 'select all that apply' question, a '96' indicates the respondent is outside of the universe, and a '0' indicates that the response option was not selected.

Recoding Other Options: For several survey questions, respondents had the option to choose 'Other' and provide a follow-up text response. In some cases, the answer provided in the text box clearly aligned with one of the available response options. In these cases, we recoded the respondent's answer from 'Other' to the aligned response option. In all cases where we recoded a respondent from 'Other' to an available response option, we created a _FLAG variable, where respondents are coded '1' if we changed the response from 'Other' to an available option.

Derived Variables

We created the following additional variables from other information available in the dataset. Additional information about each variable can be found in the codebook.

1. Variable Name: rucc_2023
   This variable assigns each respondent a Rural-Urban Continuum Code based on the 2023 designation (USDA ERS 2023 designations) based on their responses to the state and county of residence questions.
2. Variable Name: rucc_2013
   This variable assigns each respondent a Rural-Urban Continuum Code based on the 2013 designation (USDA ERS 2013 designations) based on their responses to the state and county of residence questions.
3. Variable Name: racerec
   This variable used responses to the HISPANIC and RACE_ questions to create a combined Race/Ethnicity variable.
4. Variable Names: fips, stfips, stfips_preCOVID, fips_preCOVID
   These variables were created to allow users to link respondents to other county- and state-level datasets. These variables are available only in the restricted use version of the data.
5. Variable Name: county_state
   This variable allows respondents to see the full county and state names associated with each respondent's residence. This variable is available only in the restricted use version of the data.
6. Variable Name: rucc_preCOVID
   This variable assigns each respondent a Rural-Urban Continuum Code (USDA ERS 2013 designations) based on their responses to their state and county of residence in early March 2020.

Weights and Sample Representativeness

Qualtrics-Derived Post-Stratification Weight (original_weight)

Screening questions were used to ensure a demographically representative sample by age, sex, race, Hispanic ethnicity, and education. However, because we oversampled nonmetropolitan residents, Qualtrics created a survey weight (original_weight). When the weight is applied to the analysis, the results are *demographically* representative of the U.S. population ages 18-64 by age, sex, race/ethnicity, educational attainment, and RUCC. This was the only weight available until May 2025. Therefore, papers published in 2025 or earlier used this weight. While demographically representative, this weight does not account for any bias or non-representativeness introduced from the NWS being a non-probability sample. A separate weight – which we recommend users incorporate in their analyses – was derived in May 2025 to correct for the NWS survey design (final_weight). The rationale for and derivation of this weight is described below, as well as guidance on how users should incorporate it in their analyses.

Final Global Survey Weight (final_weight)

The National Wellbeing Survey (NWS) is a non-probability sample of U.S. adults ages 18-64 with an oversample of respondents living in nonmetropolitan counties. Therefore, unweighted estimates – particularly for the means and prevalence of specific outcomes – may not be generalizable to the underlying population of adults ages 18-64. To help account for potential biases in estimates, we contracted with the University of Michigan Population Dynamics and Health Program (PDHP) to create full-sample, general-purpose survey weights based on a quasi-randomization (QR) approach (Elliott and Valliant 2017). This methodology requires finding a reference sample that: (a) is probability-based with corresponding survey weights; (b) contains key covariates that are shared with the selected sample; and, ideally, (c) arises from the same population as the selected sample. The 2023 National Health Interview Survey (NHIS) was determined to be a reference survey with these key properties, in addition to being a "gold standard" survey in U.S. population health research. The team used the 2023 NHIS because the 2024 NHIS data were not yet available at the time of weight construction. In brief, these weights use data from the 2023 NHIS respondents ages 18-64 as a reference to first create a "design weight" (i.e., an estimated probability of selection for each survey respondent) and then calibrate this design weight to reflect differences in the makeup of the NWS and the 2021 NHIS (which we use as a stable reference population across all NWS waves). Consequently, the resulting weight serves the dual purpose of helping to correct for the non-probability design of the NWS, as well as maximize national representativeness, based on the sampling design and weighting of the comparable NHIS sample. The steps are detailed below.

<u>Protocol</u>

First, data on key covariates that are shared between NWS and NHIS and are useful predictors of key outcome variables in the NWS were harmonized. Key sociodemographic predictors – including sex, race/ethnicity, educational attainment, employment/work status, poverty ratio, urbanicity, among others (18 total) – were coded to exactly match in both the NWS and NHIS samples.

Second, these harmonized data were "stacked" to create a single dataset with cases from both samples, including original survey weights from the NHIS (coded as "1" for NWS) and an indicator variable of cases belonging to a non-probability sample (i.e., 1 = NWS; 0 = NHIS). These stacked data were used to develop initial design weights, fitting a weighted logistic regression model with membership in the non-probability sample (i.e., the NWS) as the dependent variable. For each of the NWS respondents, this approach computed an estimated probability of the respondent being included in the NWS sample from the common population, based on their observed characteristics, if the NWS had used a probability sampling approach similar to the NHIS. The inverse of each estimated probability from the model then served as the estimated design weight for that case ($\hat{w}_i = 1/\hat{p}_i$). Thus, NWS cases that were estimated to have a lower probability of being included in a probability sample from this population (like the NHIS) received a higher relative weight, and vice versa.

Third, this initial design weight was "calibrated" using a post-stratification adjustment based on covariates that were predictive across five key NWS outcomes of interest (self-rated mental health, self-rated physical health, current smoking, the Cantril Ladder present standing score, and an index of life satisfaction), based on machine learning approaches. Age, educational attainment, and marital status emerged as consistent, significant predictors of these outcomes. Those variables were then cross-classified to create 12 unique post-strata (age: 18-32, 33-47, 48-65; education: four-year college degree or higher, no 4-year college degree; marital status: currently married, other). The initial design weight was then re-scaled to account for differences in the relative size of the population in each stratum between the two samples (i.e., the ratio of the weighted population in the NHIS to the design weighted population in the NWS). Thus, the final, calibrated NWS weight was estimated by multiplying the initial design weight, $\hat{w}$, by the stratum-specific scalar. This calibration means that the weighted NWS sample will exactly match the "known" population totals from the NHIS for each individual post-stratum, as well as the estimated population size in total (based on the 2021 NHIS) across the entire dataset. The final calibrated NWS full sample-weight provided in the data is named 'final_weight'. The weighted percentages and means shown in the NWS codebook are based on the 'final_weight'.

Replicate Weights (weight1—weight200)

To properly estimate sampling variance for estimates based on the "weighted" NWS sample, a bootstrapping technique was employed that created 200 replicate weights. This bootstrapping process took the original NWS respondents and drew a simple random sample of the same size, with replacement. Each such sample is one replicate sample, which then went through a custom weighting and calibration phase using the bootstrap sample of the NWS and the fixed NHIS sample. Due to sampling with replacement, some cases will not appear in any given bootstrap sample, and some will appear multiple times. However, prior to post-stratification adjustment, each bootstrap sample was weighted back to the original sample size, with cases that were not selected in a specific bootstrap sample given a weight of zero, and those selected multiple times given a weight that is scaled based on the number of times that case was selected in the bootstrap sample. This process was then repeated 200 times per survey wave (year) to result in a set of 200 replicate weights for each case, enabling data users to mimic the sampling variance that would arise from repeating this non-probability sampling and weighting approach many times.

When properly incorporated into an analysis, the final NWS weights (final_weight) enable computation of approximately unbiased point estimates (based on the QR approach), and the replicate weights allow for proper estimation of the *variability* of those weighted estimates, resulting in better estimates of sampling variability that would not be possible with a single weight variable only (Elliott and Valliant, 2017).

Sample code for how to use the full-sample and replicate weights as part of a bootstrapped analysis is:

svyset _n [pweight=final_weight], poststrata(stratum_ID) postweight(total_NHIS_weight) vce(bootstrap) bsrw(weight1-weight200)

Estimates obtained using the final, adjusted person-weight alone are comparable – if not almost identical – to those obtained using replicate weights with bootstrapped analysis. Thus, in instances where bootstrapped analysis may not be possible and/or cause issues with estimation, the person-weight may suffice. However, while this is true for estimates of prevalence and/or means, we cannot guarantee this comparability holds for more complex analyses with multiple variables. Users should carefully compare results under different weighting scenarios to ensure consistency in their findings.

Doubly Robust Estimation Technique

The full-sample weights (final_weight) and replicate weights (weight1—weight200) are designed to improve the quality of estimates in most standard design-based analyses of NWS data. However, users should be aware that other methods may be used to obtain outcome-specific estimates, such as the Doubly Robust (DR) estimation technique. This DR estimation technique employs a carefully specified model for the sample selection mechanism and a carefully specified model for the key outcome of interest, and as long as one of the models is correctly specified, point estimates will be approximately unbiased and have greater efficiency than the QR approach (Chen et al., 2020). The downside of this approach is that it requires a separate model for each individual outcome, unlike the general-purpose weights described above. We generally find that estimates using the general-purpose weights are nearly identical to those obtained from the DR approach; however, users should carefully consider which approach is most appropriate for their research goals.

Pooling NWS Waves

Unique general-purpose weights, and corresponding replicate weights, are included in the data for each wave of NWS. However, users may be interested in pooling data *across* NWS waves (survey years) to increase sample sizes and/or provide multi-year estimates, among other methodological or substantive reasons. In these cases, users should continue to use the wave-specific weights in their analyses, without any additional adjustment.

However, if a user aims to use the NWS data to provide any estimates of "population" totals or counts across years, then additional rescaling of the weights is needed to avoid inflating these totals/counts. We generally do not recommend that NWS data are used for these purposes – and thus offer no specific guidance on rescaling – but users may consult National Health and Nutrition Examination Survey (NHANES) protocols for pooling data across years for the purposes of generating population totals:
https://wwwn.cdc.gov/nchs/nhanes/analyticguidelines.aspx.

Sample Representativeness

The sampling frame was adults ages 18-64 residing in the United States. Table 1 presents weighted bootstrapped NWS estimates based on the final survey design weight and replicate weights, as well as the corresponding poststratification weights (applying the sample code shown on page 8). Note that the NWS codebook uses only the 'final_weight', so there are slight differences in weighted percentages in the codebook versus the tables below. Table 1 shows that, when weighted, the NWS sample is demographically representative of the overall U.S. population ages 18-64, based on weighted 2023 American Community Survey 1-year estimates (we applied ACS person weights and strata). Sex and race/ethnicity are comparable across surveys. With respect to educational attainment, the largest discrepancies are in the "less than high school" category (where NWS respondents are underrepresented) and the "some college/AA" category (where NWS respondents are overrepresented). Educational attainment is not asked identically in the NWS and ACS, so this may account for discrepancies. There is a lower percentage of never married and separated/divorced adults in NWS than ACS, though the lack of a “member of unmarried couple” response in ACS may affect comparisons. Finally, rural-urban continuum distributions are generally comparable across the surveys.

Table 1. Distribution of NWS (2024) Respondents Compared to Overall U.S. Population ages 18-64

	NWS Unweighted N (%)	NWS Weighted %	U.S. Population (ages 18-64) %
SEX			
Male	3,415 (48.6)	51.0	50.1
Female	3,579 (50.9)	49.0	49.9
Non-binary	33 (0.5)	0.0	unknown
RACE/ETHNICITY			
Non-Hispanic White	4,126 (58.9)	57.2	56.0
Non-Hispanic Black	913 (13.0)	13.5	12.3
Hispanic	1,267 (18.0)	17.4	19.9
Other Race	699 (10.0)	12.0	11.8
AGE			
18-24	1,056 (15.0)	16.7	15.0
25-34	1,472 (21.0)	21.3	22.3
35-44	1,536 (21.9)	21.7	22.1
45-54	1,423 (20.3)	19.6	20.0
55-64	1,540 (21.9)	20.8	20.6
EDUCATIONAL ATTAINMENT (ages 25-64)			
<High School	681 (11.4)	6.0	9.7
HS Grad	1,638 (27.4)	25.2	24.6
Some College/AA	1,994 (33.4)	32.7	27.7
4-year degree+	1,658 (27.8)	36.1	38.0
MARITAL STATUS			
Never Married	2,955 (42.1)	29.7	38.2
Currently Married	2,131 (30.4)	51.9	48.8
Separated/Divorced	1,104 (15.7)	8.3	11.5
Widowed	252 (3.6)	1.5	1.5
Member of Unmarried Couple	580 (8.3)	8.6	NA[a]
CHILDREN IN HOUSEHOLD			
No children under age 18 in household[b]	4,785 (68.1)	62.4	59.2
RURAL-URBAN CONTINUUM CODE, 2023[c]			
1 Counties in metro areas of 1 million population or more	3,314 (47.2)	57.2	58.0
2 Counties in metro areas of 250,000 to 1 million population	1,127 (16.0)	18.3	20.1

3 Counties in metro areas of fewer than 250,000 population	639 (9.1)	10.6	8.7
4-5 Counties in nonmetro areas with urban population of 20,000 or more	766 (10.9)	5.9	5.1
6-7 Counties in nonmetro areas with urban population of 2,500 to 19,999	764 (10.9)	5.4	5.0
8-9 Completely rural or less than 2,500 urban population	417 (5.9)	2.6	3.0

Notes: *Notes*: U.S. population comparisons are based on 2023 American Community Survey 1-year estimates; NWS values are weighted based on the final survey design weight and replicate weights, as well as the corresponding poststratification weights. ACS estimates are weighted based on the person weight and strata.
a. The Census Bureau's marital status distribution does not include a breakdown for members of an unmarried couple.
b. The NWS asks about the presence of any children under age 18 in the household, while the ACS asks about "own" children. Therefore, the NWS and ACS are not directly comparable.
c. Population percentages by RUCC are based on the 2018-2022 American Community Survey 5-year estimates merged with the USDA Economic Research Service Rural-Urban Continuum Codes (2023).

Table 2 compares the demographic characteristics (means) between all counties in the U.S. and the 1,721 counties in which NWS (2024) respondents live. Although differences are not large, most differences are statistically significant at p<.05. Counties represented by NWS respondents have a higher percentage NH Black population, lower percent Hispanic population, lower percentage age 65+ population, lower percentage with less than high school education, higher percentage with a 4-year college degree or more, higher percentage employed, lower percentage not in the labor force, higher median household income, lower percentage of families in poverty, and lower percentage of owner-occupied housing units.

Table 2. Comparison of Counties Represented in 2024 NWS versus all U.S. Counties

County Characteristic	All U.S. Counties N=3,143 (Means)	Counties Represented in NWS N=1,721 (Means)
Racial/Ethnic Composition		
Percent non-Hispanic White	72.8	72.4
Percent non-Hispanic Black	8.5	10.2*
Percent Hispanic	12.2	10.8*
Age Composition		
Percent under age 18	21.9	22.0
Percent age 65+	20.1	19.0*
Educational Composition		
Percent 25+ with less than high school	9.9	9.5*
Percent 25+ with a 4-year college degree or more	24.1	25.9*
Employment Composition		
Percent employed (among ages 16+)	63.7	65.2*
Percent not in labor force (among ages 16+)	32.8	31.0*
Socioeconomic Composition		
Median household income	$65,145	$68,224*

Percent families in poverty	14.3	14.1*
Percent owner-occupied housing units	72.8	71.2*

Note: County characteristics are from the 2019-2023 American Community Survey; *difference is statistically significant at p<.05 based on t-test.

Caution against geographic aggregation: Although restricted data users are able to identify respondents' states and counties of residence, data users should not attempt to produce state- or county-level aggregated estimates from the survey data. The sampling procedure was not designed to attain within-state or within-county quotas. The quotas and survey weights are designed to make results demographically representative *only at the national level*. Any state- or county-level estimates derived from the individual-level survey data would be prone to bias.

Comparisons to Other National Surveys

We will update this section of the Methodology report when comparison survey data (i.e., National Health Interview Survey, Behavioral Risk Factor Surveillance System, National Survey on Drug Use and Health) for 2024 become available. Until then, users can rely on comparisons presented in the 2021, 2022, and 2023 Methodology Reports.

Data Dissemination

The data, questionnaire, and codebook are available through the ICPSR National Addiction & HIV Data Archive Program (NAHDAP). There are two versions of the data available. The public use version does not include any geographic identifiers except the USDA ERS Rural-Urban Continuum Codes (RUCCs). The public-use data files in this collection are available for access by the general public. Access does not require affiliation with an ICPSR member institution. The restricted use version includes state and county identifiers.

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