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State-level variation in the prevalence of child psychopathology symptoms in the US: Results from the ABCD study

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ABSTRACT

Objective: To estimate the prevalence of clinically meaningful youth mood, anxiety, behavioral, and attention symptoms across US states.

Method: Data are drawn from the Adolescent Brain Cognitive Development (ABCD) study baseline wave, which included 11,876 children ages 9–10. Statistical weighting strategies generated projected state-specific prevalence estimates for the 17 states where ABCD collected data based on state socio-demographics. Twenty dimensions of mental health were assessed with the Child Behavior Checklist using recommended cut-scores to assess clinical and sub-threshold symptoms.

Results: Psychopathology symptom prevalence varied by state and outcome. Projected prevalence of internalizing problems ranged from 11.0% [95% CI: 9.8%, 12.2%; Oklahoma] to 7.9% [95% CI: 6.9%, 9.0%; Maryland] across states. Projected prevalence of externalizing problems ranged from 6.9% [95% CI: 6.1%, 7.8%; South Carolina] to 4.5% [95% CI: 3.7%, 5.4%; California]. Regions with high symptoms included sections of the South (e.g., Oklahoma, South Carolina) and Vermont. Conduct problems had the most variability across states (i.e., greatest state-level prevalence 91% higher than the lowest). Attention problems had the least variability across states (greatest state-level prevalence 26% higher than the lowest).

Conclusions: Clinically meaningful psychopathology symptoms are common in children across the US, with substantial state-level variability in prevalence. Understanding variability in the prevalence of psychopathology symptoms across the US can help to inform resource allocation to increase the availability of youth mental health services.

1. Introduction

Mental disorders are common in US children, and the social environment influences disorder onset and persistence (Kirkbride et al., 2024). The prevalence of child psychiatric disorders may differ substantially across US states given variation in social environmental factors that influence psychopathology risk, including economic resources and social safety nets. For instance, in 2022, 16.3% of children in the US were living in poverty, with substantial variation by US state and higher levels of concentrated child poverty in the US South (Benson, 2023). Understanding potential state-level heterogeneity in psychopathology risk is an urgent priority, seeing as psychopathology symptoms have risen and mental health has worsened among youth in recent years (US Census Bureau, 2018a; US Census Bureau, 2018b; Bhandari and Gupta, 2024; Keyes and Platt, 2024; Lebrun-Harris et al., 2022). States and regions with particularly severe psychiatric outcomes would be important areas of focus in combatting the ongoing “national emergency in child and adolescent mental health” (American Community Survey, 2021).

Differences in the prevalence of child psychopathology symptoms across US states remain inadequately understood (Whitney and Peterson, 2019). National estimates of child psychopathology obscure state-to-state variation that may be relevant to both resource allocation and the identification of social environmental factors that contribute to higher risk for youth psychopathology. The data that do exist on state differences in the prevalence of mental disorders such as depression indicate significant variation (Whitney and Peterson, 2019). Whether similar variation exists for other symptom types is largely unexplored.

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The Adolescent Brain Cognitive Development (ABCD) study, the largest long-term study of children's health and neural development in the United States, includes structured, validated instruments to assess a broad range of psychopathology symptoms in children (Leeb et al., 2020; Price and Khubchandani, 2022; Shim et al., 2022). ABCD conducted data collection across 17 states, and these data are a potentially useful resource in identifying state-level differences in child psychopathology symptoms. However, several issues require interrogation. Selection into the sample was based on both the geographic considerations of site locations as well as a range of participant characteristics (Compton et al., 2019). Some sites oversampled certain racial/ethnic groups, for example, and over and under selected participants based on other factors as well (e.g. twins) (Garavan et al., 2018; Karcher and Barch, 2021). Previous studies have noted discrepancies between the 9–10 year old ABCD sample and the demographic characteristics of 9–10 year old children in the US, particularly regarding socio-economic status, that can be magnified in ABCD subsamples (Cosgrove et al., 2022; Gard et al., 2023).

Existing literature has already begun to address matters of bias and representativeness within ABCD, acknowledging the potential for generalizability issues to influence findings (Compton et al., 2019; Cosgrove et al., 2022; Gard et al., 2023; White et al., 2023). Given the significant heterogeneity in state population compositions across sex, race, ethnicity, and other socioeconomic factors including household income and resources, all of which are differentially associated with the likelihood of developing psychopathology symptoms (Hodgkinson et al., 2017; Lee and Wong, 2020; Udalova et al., 2022), maximizing the utility of ABCD for population neuroscience and epidemiological research requires both transparency about the lack of representativeness and specialized methods to generate state-specific estimates. While ABCD provides sample weights to estimate nationally representative distributions and correlates of mental health outcomes, further work is needed to generate state-level estimates and assess heterogeneity across the US.

The present study aims to estimate variability in the state-level prevalence of child psychopathology symptoms utilizing data from the ABCD study. By deploying novel weighting strategies, we describe the heterogeneity of clinical and sub-threshold psychopathology symptoms across US states, developing and applying state-level statistical weights to generate state-specific prevalence estimates for the 17 states where ABCD collected data based on the demographic characteristics of each state. Additionally, we provide detailed maps of the US based on these analyses that summarize projected US state prevalence of clinical mood, anxiety, behavioral, and attention symptoms.

2. Material and methods

This study used data from the baseline wave of the Adolescent Brain Cognitive Development (ABCD) study (N = 11,876 children ages 9/10). Recruitment spanned between September 1st, 2016 and August 31st, 2018, with baseline assessment data completed and disseminated in 2018 (Garavan et al., 2018). This longitudinal, multi-site US study collects data from 17 states with 21 sites operating across the US; sites reside in universities, hospitals, and other research facilities with requisite neuroimaging technology (ABCD, 2023). ABCD utilizes a sampling strategy that emulates a multi-stage probability sample of youth, recruiting children from a probability sample of schools around sites; these sites were not randomly sampled, however (Garavan et al., 2018). School recruitment, following contact of local administrations, took the form of disseminated recruitment materials to all students, whose parents could then follow up for screening and, if eligible, enrollment (Garavan et al., 2018). Recruitment was highly inclusive, with limited exclusion criteria for children including lack of English proficiency, inability to complete an MRI at baseline, and severe neurological, medical or other personal limitations that inhibit a child's ability to comply with the protocol (Garavan et al., 2018; Palmer et al., 2022). Table 1 describes the unweighted demographic characteristics of children in the baseline data. The sample was majority male (52.2%), white (51.3%), and had a household income of 75,000 or higher (51.6%).

Table 1
[a]Sample demographics of baseline ABCD participants, aged 9–10, N = 11,876.

	N	Unweighted (%, 95% CI)
Overall	11876	100.0
Sex		
Female	5680	47.8 (46.9, 48.7)
Male	6196	52.2 (51.3, 53.1)
Race/Ethnicity		
Asian	253	2.1 (1.8, 2.4)
Black	1765	14.9 (14.2, 15.5)
Hispanic/Latino	2411	20.3 (19.6, 21.0)
Multiracial/Other	1164	9.8 (9.3, 10.4)
White	6094	51.3 (50.4, 52.2)
Income (Past 12 Months)		
Up to $11,999	838	7.1 (6.6, 7.5)
$12,000 to $15,999	273	2.3 (2.0, 2.6)
$16,000 to $24,999	524	4.4 (4.1, 4.8)
$25,000 to $34,999	654	5.5 (5.1, 5.9)
$35,000 to $49,999	934	7.9 (7.4, 8.4)
$50,000 to $74,999	1499	12.6 (12.0, 13.2)
$75,000 to $99,999	1572	13.2 (12.6, 13.9)
$100,000 to $199,999	3314	27.9 (27.1, 28.7)
$200,000+	1250	10.5 (10.0, 11.1)
Experiencing Poverty		
Yes	1682	14.2 (13.5, 14.8)
No	8981	75.6 (74.8, 76.4)

[a] For variables with missing data, missingness ranged from 1.6% (race/ethnicity) to 10.2% (experiencing poverty).

Psychopathology symptoms were measured with the Child Behavior Checklist (CBCL) (Achenbach and Edelbrock, 1991), a validated instrument for children. The CBCL is a 113-item instrument based on parent report of child behavior. For these analyses, we used the CBCL to examine twenty dimensions of mental health: ADHD Problems, Aggressive Problems, Anxiety Problems, being Anxious/Depressed, Attention Problems, Conduct Problems, Depressive Problems, Externalizing Problems, Internalizing Problems, Obsessive-Compulsive Problems, Oppositional-Defiant Problems, Rule-Breaking Behavior, Sluggish Cognitive Tempo Problems, Social Problems, Somatic Complaints, Somatic Problems, Stress Problems, Thought Problems, Total Problems, and being Withdrawn/Depressed. We used recommended cut-scores to stratify data into non-significant symptoms, sub-threshold symptoms, and clinical symptoms (with non-significant symptoms at a score <65, sub-threshold symptoms at a score from 65 to 69, and clinical symptoms at a score of 70+. These thresholds were lower for internalizing, externalizing, and total problems, with non-significant symptoms at a score <60, sub-threshold symptoms at a score from 60 to 63, and clinical symptoms at scores of 64+) (Achenbach, 2001; Achenbach and Edelbrock, 1991). We examined the prevalence of children with clinical or sub-threshold symptoms across all 20 CBCL domains.

2.1. Analytic approach

To estimate state-level differences in the prevalence of clinical or sub-threshold symptoms across each CBCL domain, we used a multi-step approach. Here we explain the logic of the approach overall, and the analytic details of its implementation.

2.2. Weighting and projection logic

To understand how the weighting process generates state-specific variation and projected estimates, we have provided additional information in Supplemental Tables 1–3. Supplemental Tables 1 and 2 show the unweighted prevalences of CBCL outcomes by sex, race/ethnicity, poverty, and family income, factors that vary across states. There were lower reported levels of clinical and sub-threshold symptoms among children who were female, Asian, or from a higher-income family. For example, of the 20 outcomes assessed at the clinical symptom cut off, 16 were highest in prevalence among those participants in the lowest income category (<$12,000 per year in family income). All clinical, and all but one sub-threshold, symptom outcomes were higher for children experiencing poverty.

Then, in Supplemental Table 3, we provide distributions of demographic characteristics by US state. States vary across demographic dimensions (Supplemental Table 3) that are associated with psychopathology symptoms in children (Supplemental Tables 1–2), in turn shaping projected estimates of state-level symptom prevalence. For instance, because clinical symptoms are highest among children with the lowest household income, we would expect a higher prevalence of psychopathology symptoms in states where a higher proportion of residents have low household incomes.

We used a raking procedure to develop sample weights using this state to state variation in socio-demographic factors. We adjusted state child psychopathology symptom prevalence estimates based on the proportion of each state with certain demographic factors associated with higher or lower symptom prevalence. For state-level estimates, we incorporated income, race/ethnicity, sex, and poverty, factors that vary both between states and within a state's population. The decision to utilize a raking approach is standard in large-scale data collection efforts, including in the ABCD study itself. Indeed, ABCD's national weights employed raking techniques raked to demographics comparable to the ones used for this analysis (Heeringa and Berglund, 2019). Additionally, raking has been employed across a number of population-based studies to generate representative national estimates (e.g., the Behavioral Risk Factor Surveillance System, the National Alcohol Survey, and the National Comorbidity Survey Replication Adolescent Supplement) (Kessler et al., 2009; Pierannunzi et al., 2012; Zuwallack et al., 2022).

2.3. State-specific weights

We developed state-specific sampling weights for the 17 states in which ABCD data collection occurred. In order to balance recency and population specificity, we used 2019 census data on 9 and 10-year-olds for sex and race/ethnicity (United States Census Bureau, 2020), and 2021 census data on past-year income among households with children (American Community Survey, 2021). State-level poverty was assessed using 2018 state-level census statistics for rates among children ages 5–17 (U.S. Census Bureau, 2018). We used raking procedures in R to develop and implement state-specific weights based on the composition of each state in terms of sex, race/ethnicity, poverty and household income, using respondents with non-missing data on all demographic measures (N = 10,482). Raking procedures used the rake() function from the survey package (Lumley, 2020).

2.4. Statistical analysis

After the weighting and projection procedures, we estimated the prevalence of all 20 CBCL domains by state in the US. With these estimated prevalences, we examined the rank of US states from highest prevalence to lowest prevalence for each CBCL domain, and estimated the prevalence ratio between the prevalence in the state with the lowest and highest prevalence to estimate how different US states may be with regard to the prevalence of child psychopathology symptoms. We also averaged the ranks across all symptom domains to attain an overall metric of symptom prevalence.

3. Results

There was substantial variation in the prevalence of psychopathology symptoms among children across US states based on raked weighted estimates. Overall, prevalence of clinical symptoms was highest for broad symptom domains, with the projected prevalence of clinical internalizing problems ranging from 11.0% (95% CI: 9.8%, 12.2%; Oklahoma) to 7.9% (95% CI: 6.9%, 9.0%; Maryland) across states, and the projected prevalence of clinical externalizing problems ranging from 6.9% (95% CI: 6.1%, 7.8%; South Carolina) to 4.5% (95% CI: 3.7%, 5.4%; California). While state-level prevalence ranges were lower for more specific symptom domains, estimates were always above 1% regardless of state and outcome (e.g., a range of 1.9% [95% CI: 1.4%, 2.3%; Oklahoma] to 1.4% [95% CI: 1.1%, 1.6%; Connecticut] for clinical social problems, the least frequent outcome). Interactive maps projecting each outcome's prevalence by state and level of symptoms (clinical, sub-threshold, or any) can be found here: https://tinyurl.com/ABCDFigures.

State patterns are summarized in Table 2, which shows maxima and minima for the proportion with clinical symptoms of each CBCL outcome, as well as the prevalence ratio between them to articulate the level of heterogeneity in prevalence across states. The prevalence ratio between the maximum and minimum of symptom prevalence ranged from 1.26 (Attention Problems) to 1.91 (Conduct Problems). This indicates that for outcomes with more heterogeneity, the proportion of children with clinical symptoms could hypothetically nearly double between states based on demographic composition alone. Table 3 shows similar findings for sub-threshold symptoms, where the range of prevalence ratios is slightly weaker (1.15 [Internalizing Problems] to 1.64 [Rule-Breaking Behavior]). It is worth noting the consistency of states exhibiting maxima and minima across domains, such as Oklahoma consistently exhibiting the highest projected symptoms for most outcomes, and states like California and Maryland consistently exhibiting low prevalences. Oklahoma had the highest prevalence of clinical symptoms for 14 of 20 outcomes, and the highest prevalence of sub-threshold symptoms for 14 of 20 outcomes.

Additionally, Fig. 1 provides a visualization of child psychopathology symptom prevalence rankings by state across all states and outcomes, averaging them to an overall ranking. These rankings further identify consistent patterns of the areas experiencing high or low symptoms, as states carried similar rankings across domains. Based on average rankings, symptoms were typically highest in Oklahoma and Missouri and lowest in Connecticut, Maryland, and Virginia.

Based on domain-specific maxima and overall rankings, the states in this sample with the highest psychiatric symptoms were Oklahoma, South Carolina, Vermont, and Missouri. Across various domains, there was a particularly consistent, strong signal from Oklahoma, likely due to a unique demography (e.g., a high prevalence of poverty and a unique racial composition). Symptoms were typically lowest in California, Connecticut, Maryland, and Virginia (all of which have a higher prevalence of residents at the highest income brackets).

4. Discussion

US states vary widely in the expected prevalence of child psychopathology symptoms, and these patterns can help shape both future research and mental health care. States within the ABCD sample that may warrant particular attention to increasing access to youth mental health services include Oklahoma, South Carolina, Vermont, and Missouri. State-level variation in demographic composition influences the magnitude of mental health symptom prevalence, with projected prevalence of many psychopathology symptoms nearly doubling between states based on demographic composition alone. State variation in psychiatric symptom prevalence among children underscores the importance of the social environment and drivers of sociodemographic risk. Further, these results provide support that ABCD data can derive useful information for state-level investigations even though the data are not nationally representative.

We used a novel strategy to leverage population-based data from 17 states to estimate state-level prevalence across the country. It is thus reassuring, then, that our findings align with other research examining

Table 2
Maxima and minima of clinical[a] mental health symptom prevalence by state/district in projected analysis of ABCD sample participants.

Outcome	Maximum Projected Prevalence	State/Area with Projected Maximum	Minimum Projected Prevalence	State/Area with Projected Minimum	Projected Prevalence Ratio
	Prevalence (95% C.I.)		Prevalence (95% C.I.)		
Conduct Problems	0.032 (0.027, 0.037)	South Carolina	0.017 (0.013, 0.020)	California	1.905
Rule-Breaking Behavior	0.027 (0.021, 0.032)	South Carolina	0.016 (0.012, 0.019)	California	1.699
Thought Problems	0.050 (0.040, 0.059)	Vermont	0.032 (0.026, 0.038)	Maryland	1.544
Externalizing Problems	0.069 (0.061, 0.078)	South Carolina	0.045 (0.037, 0.054)	California	1.528
Aggressive Problems	0.026 (0.022, 0.030)	South Carolina	0.017 (0.013, 0.022)	California	1.511
Withdrawn/Depressed	0.031 (0.026, 0.036)	Oklahoma	0.021 (0.017, 0.024)	Maryland	1.495
ADHD Problems	0.032 (0.026, 0.038)	Oklahoma	0.022 (0.017, 0.027)	California	1.488
Depressive Symptoms	0.034 (0.028, 0.040)	Oklahoma	0.023 (0.018, 0.028)	Maryland	1.469
Stress Problems	0.033 (0.026, 0.041)	Oklahoma	0.023 (0.017, 0.028)	Maryland	1.461
Internalizing Problems	0.110 (0.098, 0.122)	Oklahoma	0.079 (0.069, 0.090)	Maryland	1.386
Somatic Problems	0.041 (0.036, 0.047)	Oklahoma	0.030 (0.026, 0.034)	Maryland	1.380
Anxious/Depressed	0.031 (0.023, 0.038)	Oklahoma	0.022 (0.017, 0.028)	Maryland	1.377
Total Problems	0.081 (0.070, 0.092)	Oklahoma	0.059 (0.052, 0.066)	Maryland	1.376
Anxiety Problems	0.035 (0.029, 0.042)	Oklahoma	0.026 (0.020, 0.031)	Maryland	1.368
Social Problems	0.019 (0.014, 0.023)	Oklahoma	0.014 (0.011, 0.016)	Connecticut	1.367
Sluggish Cognitive Tempo Problems	0.027 (0.022, 0.031)	Oklahoma	0.020 (0.016, 0.023)	Maryland	1.351
Obsessive-Compulsive Problems	0.046 (0.037, 0.054)	Oklahoma	0.034 (0.029, 0.039)	Maryland	1.336
Somatic Complaints	0.030 (0.024, 0.036)	Oklahoma	0.022 (0.018, 0.027)	Maryland	1.334
Oppositional-Defiant Problems	0.037 (0.031, 0.043)	Vermont	0.028 (0.024, 0.033)	California	1.314
Attention Problems	0.031 (0.025, 0.037)	Oklahoma	0.025 (0.020, 0.029)	Maryland	1.262

[a] Clinical: Score of 70+ for most domains, 64+ for internalizing, externalizing, and total problems.

Table 3
Maxima and minima of sub-threshold[a] mental health symptom prevalence by state/district in projected analysis of ABCD sample participants.

Outcome	Maximum Projected Prevalence	State/Area with Maximum	Minimum Projected Prevalence	State/Area with Minimum	Projected Prevalence Ratio
	Prevalence (95% C.I.)		Prevalence (95% C.I.)		
Rule-Breaking Behavior	0.023 (0.017, 0.029)	South Carolina	0.014 (0.011, 0.017)	California	1.636
Conduct Problems	0.042 (0.036, 0.048)	South Carolina	0.028 (0.021, 0.035)	California	1.495
Aggressive Problems	0.041 (0.034, 0.047)	Oklahoma	0.028 (0.023, 0.034)	California	1.440
Attention Problems	0.051 (0.045, 0.057)	Oklahoma	0.037 (0.031, 0.042)	California	1.386
Obsessive-Compulsive Problems	0.030 (0.023, 0.038)	Oklahoma	0.022 (0.018, 0.027)	Maryland	1.381
ADHD Problems	0.039 (0.032, 0.047)	Oklahoma	0.029 (0.021, 0.036)	California	1.379
Stress Problems	0.044 (0.039, 0.049)	Oklahoma	0.032 (0.027, 0.037)	Maryland	1.370
Somatic Complaints	0.058 (0.051, 0.064)	Oklahoma	0.042 (0.037, 0.048)	Maryland	1.362
Thought Problems	0.039 (0.031, 0.047)	Oklahoma	0.029 (0.023, 0.035)	California	1.361
Social Problems	0.024 (0.021, 0.027)	Oklahoma	0.018 (0.015, 0.021)	California	1.353
Sluggish Cognitive Tempo Problems	0.031 (0.027, 0.035)	Oklahoma	0.023 (0.017, 0.030)	California	1.334
Externalizing Problems	0.047 (0.041, 0.054)	Oklahoma	0.036 (0.031, 0.040)	California	1.322
Withdrawn/Depressed	0.049 (0.044, 0.054)	Oklahoma	0.038 (0.032, 0.043)	Maryland	1.295
Depressive Symptoms	0.044 (0.038, 0.051)	Oklahoma	0.035 (0.027, 0.042)	Maryland	1.281
Anxiety Problems	0.049 (0.042, 0.056)	Oklahoma	0.039 (0.033, 0.044)	Maryland	1.267
Total Problems	0.054 (0.048, 0.060)	Oklahoma	0.044 (0.038, 0.050)	Maryland	1.230
Anxious/Depressed	0.053 (0.047, 0.059)	Vermont	0.043 (0.038, 0.048)	Maryland	1.227
Somatic Problems	0.082 (0.073, 0.090)	Vermont	0.067 (0.058, 0.075)	California	1.221
Oppositional-Defiant Problems	0.024 (0.020, 0.029)	South Carolina	0.021 (0.019, 0.023)	Minnesota	1.157
Internalizing Problems	0.072 (0.064, 0.080)	Vermont	0.063 (0.055, 0.071)	Maryland	1.145

[a] Sub-threshold: Score of 65–69 for most domains, 60–63 for internalizing, externalizing, and total problems.

state-level patterns of child mental health. For instance, data from the 2016 National Survey of Children's Health on depression, anxiety, and ADHD among children found highest prevalences in similar geographic regions to the present study, including parts of the South and New England (Whitney and Peterson, 2019). However, the present study provides a more comprehensive range of outcomes, in a more recent time frame, suggesting that more thorough surveillance of this vulnerable demographic would be a beneficial data surveillance activity moving forward (Bitsko et al., 2022).

Projected state-level heterogeneity in psychopathology symptoms among children warrants a thorough examination of the ways in which mental health policy and treatment can be strengthened. Given the consistently higher symptoms among children from lower-income families, part of supporting a robust mental health infrastructure is ensuring care and coverage for lower-income families. Expanding Medicaid through the Affordable Care Act, for example, has been associated with significant improvements in children's mental health and reductions in socioeconomic disparities in mental health symptoms compared to states without this expansion (Cha et al., 2023; Weissman et al., 2023). However, expanding access may not be sufficient; the proportion of specialty mental health providers who accept Medicaid has declined in states that passed Medicaid expansion after the Affordable Care Act (Wen et al., 2019). Direct intervention to improve psychiatric outcomes among children through economic support has been shown throughout the literature, including in ABCD data (Weissman et al., 2023), and this approach may be particularly urgent given that

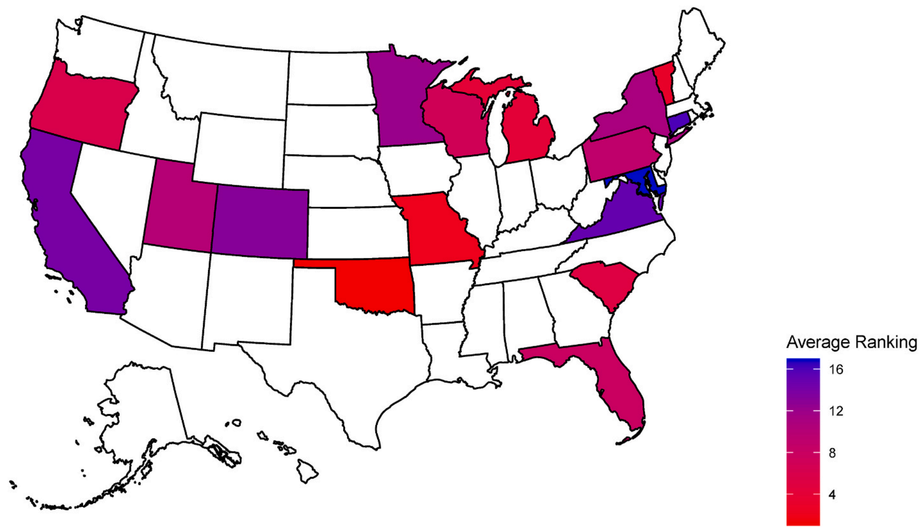

Fig. 1. Average ranking for state/district prevalence of projected clinical CBCL outcomes in the United States among 9/10-year-old participants in ABCD in 17 states.

half of US children with a clinically significant mental health disorder did not receive needed treatment (Whitney and Peterson, 2019). Reaffirming and restructuring systems of treatment and support to make mental healthcare more accessible for young people is a necessary step to addressing the increasing rates of mental health problems that leading health organizations have declared a national emergency (American Academy of Pediatrics).

Mental health services for children exhibit highly variable accessibility across demographics (e.g., higher rates of access among white children) and geography, with some states exhibiting more than twice as much utilization as others (e.g., 2016–2019 data showing 6.5% of all youth ages 3–17 in Nevada accessing treatment vs 15.6% in Montana) (Bitsko et al., 2022). These disparities likely reflect broader national variation in the provision of mental healthcare. For instance, based on 2014 data examining regional differences in availability of mental health providers, the West South Central Census Division (Texas, Oklahoma, Arkansas, and Louisiana) consistently fared worst (e.g., 69% of counties lacked a psychiatrist as opposed to just 6% of New England counties) (Andrilla et al., 2018). While similar work has not been conducted specific to child and adolescent mental health service providers, other research has identified patterns and disparities in care provision for this demographic, particularly with regard to who provides services and where. For instance, more than a third of adolescents accessing mental healthcare services only received them in an educational setting (e.g., a counselor or school psychologist) rather than inpatient, outpatient, or other medical services (e.g., a pediatrician), and this was higher for those from low-income backgrounds and racial/ethnic minority children (Ali et al., 2019). Fostering service availability in a variety of settings equitably requires further examination of the disparities that exist across geography, venue, and demography that exist in this domain, disparities that likely inform the psychiatric outcome disparities examined in this manuscript.

Based on the results of this study, future research would benefit from capturing more comprehensive data on demographic factors and ensuring that samples are geographically diverse and representative of specific target populations, a research aim that has been suggested elsewhere (Dotson and Duarte, 2020; Falk et al., 2013; Garcini et al., 2022). There is clear evidence that sex, race/ethnicity, poverty, and parental education can influence prevalence of psychiatric outcomes (Alegria et al., 2010; Chen et al., 2022; Hoffmann et al., 2022; McBain et al., 2022; Xiao and Lindsey, 2021), and future population-based samples and studies should consider the other demographics and clinical characteristics that may inform mental health, such as immigration status (Filion et al., 2018; Finno-Velasquez et al., 2016; Georgiades et al., 2018), religious background (Goforth et al., 2014; Hope et al., 2017; Wong et al., 2006), sexual orientation (Russell and Fish, 2016; Wilson and Cariola, 2020), gender identity (Jardas et al., 2023; Turban et al., 2021) and disability (Buckley et al., 2020; Cogswell et al., 2022). Thoughtful consideration and analysis of the populations being examined within neuropsychiatric research requires an understanding of the individuals and identities that comprise those populations. Ensuring representative, inclusive sampling and research is a fundamental part of rigorous science that is both equitable and accurate (Falk et al., 2013; Gard et al., 2023). Accuracy would also be strengthened by sampling from a larger number of geographic units. While the present analyses project symptom prevalence to the state-level, monitoring mental health at the level of county or even town (e.g. (Hoffmann et al., 2023),) could improve the ways in which we study and intervene on child and adolescent mental health. Having a robust infrastructure of neuropsychiatric surveillance at multiple levels of geography (e.g., state, county) can provide insight into greater targeting of resources and care, and a deeper understanding of potential factors underlying elevated symptoms.

This study has a number of strengths, but also limitations to consider. Study results are based on a large dataset, as well as the wide array of psychiatric outcomes featured in ABCD. Providing prevalence estimates by state and outcome adds important nuance often lacking from studies of child and adolescent psychiatric well-being in the United States. Similarly, aggregating rankings across outcomes allowed for useful patterns of geographic clustering to arise. However, limitations include CBCL outcomes being parent-reported, meaning results may not align with children's self-reported outcomes (though the CBCL does exhibit strong reliability and validity across a broad range of metrics) (Achenbach and Edelbrock, 1991; Ebesutani et al., 2010; Seligman et al., 2004). Additionally, our results only reflected weighting based on a subset of all possible pertinent factors, and raking methods for weighting do not account for all potential interactions among variables used in the weight estimates. Further research using alternative methods for weighting would be beneficial for validating the weighted estimates.

5. Conclusions

In summary, this study used projected estimates weighted to state-level demographies to examine potential heterogeneity in psychopathology symptoms among US children. Not only did this approach demonstrate substantial heterogeneity in symptom prevalence, but also identified potential regions for further examination, such as parts of the South and Vermont. Committing to the examination of differences in psychopathology symptom prevalence across US state geographies, as well as the influence of complex demographic factors, is a vital step toward more inclusive, accurate findings and improved mental health among children.

Declaration of generative AI

None.

CRediT authorship contribution statement

Katherine M. Keyes: Writing – original draft, Funding acquisition, Conceptualization. **Noah T. Kreski:** Writing – original draft, Formal analysis, Data curation, Conceptualization. **David Weissman:** Writing – review & editing, Data curation. **Katie A. McLaughlin:** Writing – review & editing, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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