HHS Public Access
Author manuscript
Am J Prev Med. Author manuscript; available in PMC 2024 August 18.

Published in final edited form as:
Am J Prev Med. 2021 December ; 61(6): 821–830. doi:10.1016/j.amepre.2021.05.043.

Measurement of Adverse Childhood Experiences: It Matters

Dennis E. Reidy, PhD[1,2], **Phyllis H. Niolon, PhD**[3], **Lianne F. Estefan, PhD**[3], **Megan C. Kearns, PhD**[3], **Ashley S. D'Inverno, PhD**[3], **Craig D. Marker, PhD**[4], **Melissa T. Merrick, PhD**[5]

[1]School of Public Health, Georgia State University, Atlanta, Georgia

[2]Center for Research on Interpersonal Violence, Georgia State University, Atlanta, Georgia

[3]Division of Violence Prevention, Centers for Disease Control and Prevention, Atlanta, Georgia

[4]College of Health Professions, Mercer University, Atlanta, Georgia

[5]Prevent Child Abuse America, Chicago, Illinois

Abstract

Introduction: Alternative measurement approaches for adverse childhood experiences (i.e., count score versus individual adverse childhood experiences measured dichotomously versus individual adverse childhood experiences measured ordinally) can alter the association between adverse childhood experiences and adverse outcomes. This could significantly impact the interpretation of adverse childhood experiences research.

Methods: Data were collected in 2018 (analyzed in 2020) via Amazon's Mechanical Turk and from people incarcerated in 4 correctional facilities (N=1,451). Included adverse childhood experience questions measured the following: physical, emotional, and sexual abuse; physical and emotional neglect; household mental illness, substance use, domestic violence, and incarceration; and exposure to community violence before age 18 years. A total of 19 measured outcomes spanned 4 domains of functioning: general functioning, substance use, psychopathology, and criminal behavior.

Results: Regression models using the count score explained the least amount of variance in outcomes, whereas multivariable regression models assessing adverse childhood experiences on a continuum explained the most variance. In many instances, the explained variance increased by 2–5 times across the predictive models. When comparing regression coefficients for multivariable regression models that measured adverse childhood experiences as binary versus ordinal, there were notable differences in the effect sizes and in which adverse childhood experiences

Address correspondence to: Dennis E. Reidy, PhD, School of Public Health, Georgia State University, Atlanta GA 30341. dreidy@gsu.edu.

CREDIT AUTHOR STATEMENT
Dennis E. Reidy: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Writing - Original Draft, Writing - Review & Editing. Phyllis H. Niolon: Conceptualization, Funding acquisition, Investigation, Methodology, Writing - Original Draft, Writing - Review & Editing. Liane F. Estefan: Conceptualization, Writing - Original Draft, Writing - Review & Editing. Megan C. Kearns: Conceptualization, Project administration, Writing - Original Draft. Ashley S. D'Inverno: Conceptualization, Visualization, Writing - Review & Editing. Craig D. Marker: Formal analysis, Writing - Review & Editing. Melissa T. Merrick: Writing - Review & Editing.

SUPPLEMENTAL MATERIAL
Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2021.05.043.

predicted outcomes. Disparities in results were most pronounced among high-risk populations that experience a disproportionate amount of adverse childhood experiences.

Conclusions: Alternative methods of measuring adverse childhood experiences can influence understanding of their true impact. These findings suggest that the deleterious effects of imprecise measurement methods may be most pronounced in the populations most at risk of adverse childhood experiences. For the sake of prevention, the measurement of adverse childhood experiences must evolve.

INTRODUCTION

Adverse childhood experiences (ACEs) can radically and permanently disrupt a child's potential for well-being, health, and prosperity. ACEs comprise a broad range of potentially traumatic experiences occurring within the first 18 years of life[1] and contribute substantial burden to public health.[2] The burden of ACEs is disproportionately distributed and has particular salience among different populations and in different contexts (e.g., low-income communities).[2–4] ACEs are related to a host of adverse social, behavioral, economic, psychological, and physical health outcomes across the lifespan.[2,5] Moreover, evidence demonstrates a clear dose–response pattern between the number of ACEs and the likelihood and severity of adverse outcomes.[2,6–8]

Most research on ACEs has examined their impact using a simple count score (i.e., ACE score). Whether using the original ACE scale from the seminal Centers for Disease Control and Prevention–Kaiser study[6] or 1 of the approximately 20 modified versions,[9] researchers have summed binary responses to individual ACE questions to demonstrate associations with health outcomes. Some have argued that there is value in the simplicity of the ACE count score. For example, it has been used as an advocacy tool to bring attention to childhood adversities[10] and prioritize upstream prevention efforts.[4] However, there are many limitations in this measurement approach. For one, it does not highlight differences in the proportion of youth exposed to the distinct ACEs.[11] Additionally, the count score equates all ACEs. The count score method assumes that living with someone who was depressed or experiencing parental separation/divorce, for instance, will have equivalent impact as being the direct victim of physical or sexual abuse. However, different forms of adversity do have differential impact.[8,12–14] Moreover, it assumes a single mechanism through which ACEs lead to a specific outcome and precludes any test of how ACEs might operate in tandem or opposition to produce outcomes.[14] For example, in some situations, parental divorce may protect the child from maltreatment, witnessing violence between parents, living with someone with mental illness, or someone who is abusing drugs.[15] Likewise, it cannot illuminate potential cascade effects among ACEs (e.g., depressed mothers are more likely to perpetrate abuse and/or neglect[16]). It also assumes that these mediating processes are the same across various domains of outcomes (e.g., economic, social, physical health, psychiatric, behavioral). These limitations are problematic because this information is critical to informing the development and focus of prevention strategies. Thus, some have called for more research on which ACEs are related to specific outcomes.[17]

A second problem with the common measurement of ACEs is that most measures have typically assessed ACEs as binary experiences (i.e., exposed versus unexposed). Even when measures of ACEs ask about frequency, they typically collapse responses into dichotomized outcomes.[4] The practice of assessing the mere presence or absence of an ACE obscures the impact of frequency, intensity, or chronicity of that particular ACE.[18] For example, the original Centers for Disease Control and Prevention–Kaiser ACE study asked respondents whether they had been emotionally or physically abused and neglected *often or very often* but asked if they had *ever* been sexually abused. This is problematic because it assumes that infrequent physical or emotional abuse does not have an adverse impact. It likewise equates 1 instance of sexual touching with repeated violent rape victimizations. Yet, overwhelming evidence avers that frequency and chronicity of these forms of victimization does matter.[13,14,19–21] The examination of ACEs as binary, whether separately or combined into a count score, limits the ability to understand the context in which ACEs occur and the differential impact these contextual factors may have on subsequent outcomes.[22]

Fortunately, there is growing consensus about the need to increase the precision of ACE measurement and to consider the best way to measure different ACEs.[3,10] This study begins to fill this gap. The purpose of this study is to explore how altering measurement schemes can impact the interpretation of research on ACEs. In doing so, predictive models using the traditional ACE count score versus models that account for the differential ACEs (i.e., multiple regression) are compared. Additionally, measurement models where individual ACEs are measured as dichotomous versus a model where ACEs are conceptualized as occurring on a continuum are compared. These comparisons are made across a host of outcomes falling into 4 domains: general functioning, substance use, psychopathology, and violent crime. The intent of these analyses is not to make inferences about associations among specific ACEs and specific outcomes that are generalizable to the population, nor is it to develop clinical or diagnostic measures. Rather, the purpose is to illustrate how these seemingly simple variations in measurement can alter analytic results and interpretation, thereby impacting generalizations to the broader population. To do so, a large convenience sample of adults in the U.S. is utilized.

METHODS

Study Sample

The sample (N=1,451) was recruited from Amazon's crowdsourcing platform Mechanical Turk (*n*=1,286)[23,24] and 4 prisons (*n*=165). Individuals were recruited from prisons to oversample for ACEs and criminal behaviors that have low base rates in general population samples.[25] Recruitment was restricted to individuals residing in the U.S. Demographic data are presented in Table 1. All materials and procedures were approved for this study by the IRB of the American Institutes for Research and by the Office of Management and Budgets. Additional details about procedures are provided in the Appendix (available online).

Measures

Adverse childhood experiences.—ACE items from prior research were modified to have ordinal response scales.[3,6] A total of 13 items were measured on a 5-point scale, ranging from 0 (*never*) to 4 (*very often*), and an additional 4 items included the response options *no* (coded 0) and *yes* (coded 1). Exact survey items and response options are listed in the Appendix (available online).

General functioning.: Participants reported their highest level of school completed among 6 ordinal options: 8th grade or less; some high school, but did not graduate; high school graduate or GED; some college or 2-year degree; 4-year college graduate; and more than 4-year college degree. Participants were asked: What is the longest you have held a job? Response options included: less than 6 months, 6–11 months, 1–2 years, 3–5 years, 6–10 years, and 10 or more years.

Psychopathology.: Items assessing psychopathology were adapted from previous research.[26] Participants were asked: *Has a doctor, therapist, or other health professional ever told you that you have any of the following conditions?* They were provided 2 response options: *no* (coded 0) and *yes* (coded 1). Specific diagnoses included post-traumatic stress disorder (PTSD), anxiety, depression, oppositional defiant disorder/conduct disorder, and borderline personality disorder.

Substance use.: A modified version of the National Institute on Drug Abuse–Modified Alcohol, Smoking, and Substance Involvement Screening Test[27] was used to assess current substance abuse. Participants were asked to report use in number of days during a typical month for cannabis products (e.g., marijuana), cocaine, illicit opioids, amphetamines, and prescription pain medicine. Participants also reported number of days during a typical month that they drink alcohol until intoxicated. Response options ranged from 0 (*never*) to4 (*very often*).

Violent crime.: Participants were provided with 8 response options to assess how many times they had been arrested for various offenses (ranging from *0 times* to *40+ times*). Specific arrest outcomes included the following: (1) total number of arrests, (2) arrests for sexual violence (SV), and (3) arrests for violence against a dating partner or spouse. Participants also self-reported the number of violent assaults they had committed in their lifetime. Respondents indicated the number of times they had (1) attacked someone with a weapon, (2) attacked and injured someone so badly they needed medical care, and (3) forced or attempted to force someone to have sex when they did not want to or could not consent. Response options ranged from 0 (*never*) to5 (*9+ times*).

Statistical Analysis

Analysis was conducted in 2 stages. First, a series of 3 ordinary least square regression models was computed for each outcome variable. Model 1 regressed outcomes on the continuous ACE count score as the sole predictor of variance. The count score was derived by dichotomizing each of the ACE items (0=never experienced ACE versus 1=experienced ACE rarely to very often), summing the number of ACEs endorsed (range=0–17). In Model 2, multiple regressions were computed wherein an individual outcome was simultaneously regressed on the 17 binary ACEs as predictors. In Model 3, outcomes were regressed on the 17 ordinal ACE predictors (i.e., 0=never–4=very often). Adjusted R^2 (R^2_{adj}) values are reported as the measure of explained variance in outcomes to account for potential overfitting of regression models.[28–30] R^2_{adj} is a measure of shrinkage and more accurately reflects the population values of R^2 that would be detected if new samples were repeatedly drawn from the population and fit the same model.[29] As such, it is a more accurate estimate of the true population explained variance. R^2_{adj} modifies the traditional R^2 by applying a penalty for each additional predictor added to the model and only increases if the new term improves the model more than would be expected by chance. If the predictor improves the model by less than expected by chance, R^2_{adj} will decrease. Consequently, it is possible to obtain negative values of R^2_{adj} in models where few predictors are significantly associated with the outcome. In these instances, the value of R^2_{adj} is reported as 0.

In Stage 2, individual effect sizes (i.e., standardized regression coefficients) were computed to compare the binary and ordinal ACE predictors. Because of space constraints, only results for 1 outcome from each domain are presented: job length, PTSD, opioids, and SV arrests. Regressions were computed using maximum likelihood estimation in Mplus, version 8.4. Maximum likelihood produces parameter estimates that are robust to violations of normality.[31] Bootstrapping analysis with 10,000 replications was conducted to account for instability in SEs. Given the low prevalence for some measured outcomes (e.g., SV arrests), 0-inflated Poisson and 2-part random effects models were also conducted.[32,33] These models had equivalent results to regression models, so only the regressions are reported.

Of note, some of the response scales are binary in nature. However, traditional linear regression methods are reported to maintain consistency of metric in the measures: generalized linear regressions do not provide R^2_{adj} or regression coefficients that are readily interpretable. Fortunately, the estimates from linear regressions are robust to violations of normality because of large sample sizes, the use of R^2_{adj}, maximum likelihood estimation, and bootstrapping procedures.[29,31,34]

RESULTS

Table 2 shows the R^2_{adj} estimates for the regression models comparing the count score (Model 1), binary multiple regression (Model 2), and ordinal multiple regressions (Model 3). A pattern emerged wherein the amount of variance in the outcome explained by ACEs generally increased with each successive model. For many of the outcomes, the amount of explained variance increased by 2–5 times. Findings may be more pronounced when looking at certain subsets of at-risk individuals. Table 3 shows the results conducted among only the racial/ethnic minority participants (who are at higher risk for experiencing more ACEs[2]). Here again, the amount of explained variance tended to significantly increase with the successive predictive models. Results comparing models for White participants, Mechanical Turk participants, and correctional participants separately can be found in the Appendix (available online). Across all subgroup analyses, results demonstrated a consistent pattern of increased explained variance as ACE measurement became more fine grained.

Next, the standardized regression coefficients with the binary ACE predictors and ordinal ACE predictors to predict job stability, PTSD, illicit opioid use, and arrests for SV among the racial/ethnic minority subsample were computed. As can be seen in Table 4, using the binary assessment of ACEs can lead to different interpretations as to which individual ACEs contribute to outcomes. For example, in looking at SV arrests, ACE Items 2 (emotional abuse) and 3 (physical abuse) were nonsignificant and nil when measured as binary. However, these both became significant and moderately large when measured on the ordinal scale. Alternatively, living with someone who attempted suicide (Item 16) and feeling unloved (Item 7) were significantly related to the outcome of PTSD when measured as binary. When ACEs were measured dimensionally, these predictors were no longer significant, suggesting an illusory association when measured dichotomously.[35]

DISCUSSION

The goal of this research is to illustrate how variations in measurement of ACEs influence analytic results and, consequently, interpretation. Results highlight the importance of the way ACEs are measured in understanding their impact on health, behavior, and quality of life outcomes. In almost all instances, measuring ACEs individually, rather than as a sum score, substantially improved the amount of variance explained in the overall outcome, especially when the individual ACE variables were measured on an ordinal rather than a dichotomous scale. Measuring ACEs individually has the added benefit of being able to examine the unique contributions of each ACE to the explained variance in the outcome. However, this analysis makes clear that whether ACEs are measured as binary (experienced/did not experience) versus on an ordinal scale indicating frequency/chronicity alters interpretation of how these variables contribute to the outcomes. These patterns were observed across both men and women, incarcerated and general population participants, and White and racial/ethnic minority participants. These results underscore suggestions that measuring ACEs distinctly, rather than as a count score, will help to better understand the influence of ACEs on subsequent outcomes and suggest that better measurement of ACEs might help identify which ACEs are most critical to certain outcomes when designing prevention strategies.

Although there is growing recognition across disciplines and among the public of the need to prevent childhood adversity, these data suggest that the urgency with which such prevention efforts need to be prioritized is drastically underestimated. In a systematic review and meta-analysis of ACEs across Europe and North America, ACEs had population attributable fractions (population attributable fraction is the proportion of disease or death in a population that would be prevented if exposure to a risk factor [e.g., ACEs] was prevented) rangingfrom 30% to 40% for depression, anxiety, and illicit drug use.[36] Surveillance data from 25 U.S. states indicated population attributable fractions of 5% and 15% for education and unemployment, 13% and 15% for heart disease and stroke, 24% and 33% for being a heavy drinker and current smoker, and 44% for depression.[2] However, results of the varying measurement models presented here suggest that the traditional ACE count score may significantly underestimate the amount of attributable variance in many outcomes. This measurement difference may be most critical in the highest-risk populations. For instance, among racial/ethnic minority male individuals in this sample, the ACE count score predicted 3% of the variance in monthly frequency of intoxication; however, this number jumped to 19% when accounting for the individual effect of each ACE and their frequency in the multiple ordinal predictor model. Educational attainment increased from 2% to 11%

explained variance, illicit opioid use increased from 11% to 35% explained variance, and perpetrating assault with a weapon increased from 11% to 60% explained variance. Thus, it is possible that the population attributable fractions for ACEs on the various health outcomes could be even higher than estimated in the overall population. Public health communication strategies that effectively articulate the magnitude of ACEs to policymakers, practitioners, and lay audiences may facilitate needed resources, policies, and laws that mobilize prevention efforts targeting systemic and structural causes of ACEs (e.g., poverty, racism).

Beyond just understanding the magnitude of the over-all impact on one's functioning, ACE measurement has implications for how prevention strategies are developed and resources for tertiary responses are allocated. Realistically, even the most comprehensive of prevention efforts cannot address all forms of adverse experiences for all children. Often, prevention efforts must be triaged, implementing only those strategies that target the most critical risk factors. This requires understanding which ACEs may be the most adversely impactful and for which populations. These results suggest that the measurement scheme can alter interpretations of which ACEs are most critical in leading to adverse outcomes. For example, from analyses on these data, SV prevention experts could be led to believe that experiencing physical abuse is not relevant when using a binary ACE measurement model. Yet, when measured on the ordinal scale to capture the frequency of occurrence, physical abuse was the most impactful ACE in predicting SV arrests in these data (Table 4). Conversely, the binary ACE measurement model would suggest that, in this study, living with someone who attempted suicide or went to prison and experiencing injurious physical abuse were related to the frequency of opioid use as an adult. However, when the frequency of ACEs was measured in an ordinal nature, none of these ACEs were related to opioid use, suggesting that measuring them as though they are dichotomous can lead to illusory associations. Normally, dichotomizing phenomena that are naturally dimensional can reduce variance, thereby reducing effect sizes and power to detect a significant association. However, statisticians have highlighted how such a practice can have the exact opposite effect in certain circumstances, wherein the sample correlation is increased and is now significant because of dichotomization.[35,37]

Limitations

Several limitations must be noted. These data are cross-sectional, they rely on retrospective self-reported sensitive information, they do not represent the entire spectrum of adversities or critical dimensions (e.g., age at onset), and the sample is a convenience sample. Thus, these statistical findings should not be used as evidence of the true magnitude of ACEs' impact in the overall population, nor should they be used to argue which ACEs are most influential for various adverse outcomes. Moreover, there are numerous other structural and developmental variables (e.g., poverty, social support) that would need to be considered a priori before resolving such questions. The goal of this research was not to resolve such questions, but to explore how different models of measurement can lead to differences in knowledge about the contribution of ACEs to a variety of outcomes.

CONCLUSIONS

Despite limitations, this research contributes to the knowledge base about ACE measurement. Results demonstrate potentially drastic differences in the interpretation of the association between ACEs and outcomes based on the chosen measurement model. The results demonstrate clearly that the way ACEs are measured has substantial implications for this field of research and that a great deal more attention needs to be paid to the best way to measure ACEs to clearly understand their vast impacts and consequences. It seems evident that ACE measurement must evolve.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

ACKNOWLEDGMENTS

The findings and conclusions in this report are those of the author(s) and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

This work was funded by the Centers for Disease Control and Prevention through Contract #200–2015-F-88061.

No financial disclosures were reported by the authors of this paper.

REFERENCES

1. Jones CM, Merrick MT, Houry DE. Identifying and preventing adverse childhood experiences: implications for clinical practice. JAMA. 2020;323(1):25–26. 10.1001/jama.2019.18499. [PubMed: 31689343]
2. Merrick MT, Ford DC, Ports KA, et al. Vital signs: estimated proportion of adult health problems attributable to adverse childhood experiences and implications for prevention-25 States, 2015–2017. MMWR Morb Mortal Wkly Rep. 2019;68(44):999–1005. 10.15585/mmwr.mm6844e1. [PubMed: 31697656]
3. Cronholm PF, Forke CM, Wade R, et al. Adverse childhood experiences: expanding the concept of adversity. Am J Prev Med. 2015;49 (3):354–361. 10.1016/j.amepre.2015.02.001. [PubMed: 26296440]
4. Ports KA, Ford DC, Merrick MT, Guinn AS. ACEs: definitions, measurement, and prevalence. In: Asmundson GJG, Afifi TO, eds. Adverse Childhood Experiences: Using Evidence to Advance Research, Practice, Policy, and Prevention. Cambridge, MA: Academic Press, 2020:17–34. 10.1016/b978-0-12-816065-7.00002-1.
5. Gilbert LK, Breiding MJ, Merrick MT, et al. Childhood adversity and adult chronic disease: an update from ten states and the District of Columbia, 2010. Am J Prev Med. 2015;48(3):345–349. 10.1016/j.amepre.2014.09.006. [PubMed: 25300735]
6. Felitti VJ, Anda RF, Nordenberg D, et al. Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults. The Adverse Childhood Experiences (ACE) Study. Am J Prev Med. 1998;14(4):245–258. 10.1016/s0749-3797(98)00017-8. [PubMed: 9635069]
7. Brown DW, Anda RF, Tiemeier H, et al. Adverse childhood experiences and the risk of premature mortality. Am J Prev Med. 2009;37 (5):389–396. 10.1016/j.amepre.2009.06.021. [PubMed: 19840693]
8. Merrick MT, Ports KA, Ford DC, Afifi TO, Gershoff ET, Grogan-Kaylor A. Unpacking the impact of adverse childhood experiences on adult mental health. Child Abuse Negl. 2017;69:10–19. 10.1016/j.chiabu.2017.03.016. [PubMed: 28419887]

9. Holden GW, Gower T, Chmielewski M. Methodological considerations in ACEs research. In: Asmundson GJF, Afifi TO, eds. Adverse Childhood Experiences: Using Evidence to Advance Research, December 2021 Practice, Policy, and Prevention. Cambridge, MA: Academic Press, 2020:161–182. 10.1016/b978-0-12-816065-7.00009-4.
10. Finkelhor D, Shattuck A, Turner H, Hamby S. A revised inventory of adverse childhood experiences. Child Abuse Negl. 2015;48:13–21. 10.1016/j.chiabu.2015.07.011. [PubMed: 26259971]
11. Merrick MT, Ford DC, Ports KA, Guinn AS. Prevalence of adverse childhood experiences from the 2011–2014 Behavioral Risk Factor Surveillance System in 23 states [published correction appears in JAMA Pediatr. 2018;172(11):1104]. JAMA Pediatr.2018;172(11):1038–1044. 10.1001/jamapediatrics.2018.2537. [PubMed: 30242348]
12. Campbell JA, Walker RJ, Egede LE. Associations between adverse childhood experiences, high-risk behaviors, and morbidity in adulthood. Am J Prev Med. 2016;50(3):344–352. 10.1016/j.amepre.2015.07.022. [PubMed: 26474668]
13. Manly JT, Cicchetti D, Barnett D. The impact of subtype, frequency, chronicity, and severity of child maltreatment on social competence and behavior problems. Dev Psychopathol. 1994;6(1):121–143. 10.1017/S0954579400005915.
14. Jung H, Herrenkohl TI, Lee JO, Klika JB, Skinner ML. Effects of physical and emotional child abuse and its chronicity on crime into adulthood. Violence Vict. 2015;30(6):1004–1018. 10.1891/0886-6708.VV-D-14-00071. [PubMed: 26439922]
15. Dare PS, Mallett CA. Parental divorce: a protection from later delinquency for maltreated children. J Divorce Remarriage. 2009;50 (6):388–399. 10.1080/10502550902766498.
16. Turney K. Labored love: examining the link between maternal depression and parenting behaviors. Soc Sci Res. 2011;40(1):399–415. 10.1016/j.ssresearch.2010.09.009.
17. Mersky JP, Janczewski CE, Topitzes J. Rethinking the measurement of adversity: moving toward second-generation research on adverse childhood experiences. Child Maltreat. 2017;22(1):58–68. 10.1177/1077559516679513. [PubMed: 27920222]
18. Anda RF, Porter LE, Brown DW. Inside the adverse childhood experience score: strengths, limitations, and misapplications. Am J Prev Med. 2020;59(2):293–295. 10.1016/j.amepre.2020.01.009. [PubMed: 32222260]
19. English DJ, Graham JC, Litrownik AJ, Everson M, Bangdiwala SI. Defining maltreatment chronicity: are there differences in child outcomes? Child Abuse Negl. 2005;29(5):575–595. 10.1016/j.chiabu.2004.08.009. [PubMed: 15970326]
20. Kaysen D, Resick PA, Wise D. Living in danger: the impact of chronic traumatization and the traumatic context on posttraumatic stress disorder. Trauma Violence Abuse. 2003;4(3):247–264. 10.1177/1524838003004003004. [PubMed: 14697125]
21. Keller MB, Beardslee WR, Dorer DJ, Lavori PW, Samuelson H, Klerman GR. Impact of severity and chronicity of parental affective illness on adaptive functioning and psychopathology in children. Arch Gen Psychiatry. 1986;43(10):930–937. 10.1001/arch-psyc.1986.01800100020004. [PubMed: 3753160]
22. Ford DC, Merrick MT, Parks SE, et al. Examination of the factorial structure of adverse childhood experiences and recommendations for three subscale scores. Psychol Violence. 2014;4(4):432–444. 10.1037/a0037723. [PubMed: 26430532]
23. Buhrmester MD, Talaifar S, Gosling SD. An evaluation of Amazon's Mechanical Turk, its rapid rise, and its effective use. Perspect Psychol Sci. 2018;13(2):149–154. 10.1177/1745691617706516. [PubMed: 29928846]
24. Sheehan KB. Crowdsourcing research: data collection with Amazon's Mechanical Turk. Commun Monogr. 2018;85(1):140–156. 10.1080/03637751.2017.1342043.
25. Ross J, Waterhouse-Bradley B, Contractor AA, Armour C. Typologies of adverse childhood experiences and their relationship to incarceration in U.S. military veterans. Child Abuse Negl. 2018;79:74–84. 10.1016/j.chiabu.2018.01.023. [PubMed: 29426037]
26. Cuevas CA, Finkelhor D, Ormrod R, Turner H. Psychiatric diagnosis as a risk marker for victimization in a national sample of children. J Interpers Violence. 2009;24(4):636–652. 10.1177/0886260508317197. [PubMed: 18445831]

27. Oga EA, Mark K, Peters EN, VH Coleman-Cowger. Validation of the NIDA-modified ASSIST as a screening tool for prenatal drug use in an urban setting in the United States. J Addict Med. 2020;14(5):423–430. 10.1097/ADM.0000000000000614. [PubMed: 32032210]

28. Austin PC, Steyerberg EW. The number of subjects per variable required in linear regression analyses. J Clin Epidemiol. 2015;68 (6):627–636. 10.1016/j.jclinepi.2014.12.014. [PubMed: 25704724]

29. Babyak MA. What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. Psychosom Med. 2004;66(3):411–421. 10.1097/01.psy.0000127692.23278.a9. [PubMed: 15184705]

30. Freedland KE, Reese RL, Steinmeyer BC. Multivariable models in bio-behavioral research. Psychosom Med. 2009;71(2):205–216. 10.1097/PSY.0b013e3181906e57. [PubMed: 19218467]

31. Enders CK. Applied Missing Data Analysis. Methodology in the Social Sciences Series. New York, NY: Guilford Press; 2010.

32. Gardner W, Mulvey EP, Shaw EC. Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. Psychol Bull. 1995;118(3):392–404. 10.1037/0033-2909.118.3.392. [PubMed: 7501743]

33. Olsen MK, Schafer JL. A two-part random-effects model for semicontinuous longitudinal data. J Am Stat Assoc. 2001;96(454):730–745. 10.1198/016214501753168389.

34. Gomila R. Logistic or linear? Estimating causal effects of experimental treatments on binary outcomes using regression analysis. J Exp Psychol Gen. 2021;150(4):700–709. 10.1037/xge0000920. [PubMed: 32969684]

35. MacCallum RC, Zhang S, Preacher KJ, Rucker DD. On the practice of dichotomization of quantitative variables. Psychol Methods. 2002;7 (1):19–40. 10.1037/1082-989x.7.1.19. [PubMed: 11928888]

36. Bellis MA, Hughes K, Ford K, Ramos Rodriguez G, Sethi D, Passmore J. Life course health consequences and associated annual costs of adverse childhood experiences across Europe and North America: a systematic review and meta-analysis. Lancet Public Health. 2019;4 (10):e517–e528. 10.1016/S2468-2667(19)30145-8. [PubMed: 31492648]

37. Maxwell SE, Delaney HD. Bivariate median splits and spurious statistical significance. Psychol Bull. 1993;113(1):181–190. 10.1037/0033-2909.113.1.181.

Table 1.

Demographics

Demographics	**Full sample (N=1,451), %**	**Mturk (*n*=1,286), %**	**Incarcerated (*n*=165), %**
Female	56.3	56.9	40.6
Male	42.1	41.4	39.4
Gender minority	1.7	1.7	0.6
Did not report	—	—	19.4
Hispanic	9.0	9.4	5.7
Black/African American	12.0	10.1	26.9
Asian	6.6	7.4	0
American Indian/ Alaska Native	2.2	2.3	1.9
Native Hawaiian/ Pacific Islander	0.4	0.5	0
White	83.1	84.1	75.0
≥2 races	10.1	12.0	6.5
Age range, years	18–76	18–76	18–61
Mean age, years (SD)	34.3 (10.7)	34.0 (10.8)	36.4 (9.3)
Median age, years	32	31	35
Median education	Some college or 2-year degree	4-year college graduate	High school graduate or GED
Modal education	Some college or 2-year degree	Some college or 2-year degree	High school graduate or GED
Median income, $	NA	35,000−49,999	NA

Note: Hispanic category includes all races. Racial categories add up to be >100% because respondents could endorse multiple races. Mturk, Amazon Mechanical Turk; NA, not applicable.

Table 2.

Model Estimates of Explained Variance for Full Sample

Outcome variables	Full sample (N=1,451)			Males (n=602)			Females (n=811)		
	R^2_{adj}Model 1	R^2_{adj}Model 2	R^2_{adj}Model 3	R^2_{adj}Model 1	R^2_{adj}Model 2	R^2_{adj}Model 3	R^2_{adj}Model 1	R^2_{adj}Model 2	R^2_{adj}Model 3
Education	0.04	0.07	0.08	0.05	0.09	0.10	0.03	0.05	0.06
Job length	0.01	0.02	0.03	0.01	0.03	0.04	0.01	0.01	0.03
PTSD	0.14	0.18	0.18	0.19	0.24	0.26	0.11	0.14	0.14
Anxiety	0.09	0.13	0.13	0.09	0.13	0.13	0.07	0.11	0.10
Depression	0.11	0.17	0.17	0.11	0.14	0.15	0.10	0.16	0.16
ODD/CD	0.07	0.11	0.14	0.11	0.16	0.16	0.04	0.06	0.14
Borderline	0.09	0.11	0.14	0.12	0.15	0.21	0.07	0.08	0.11
Intoxication	0.02	0.04	0.04	0.01	0.05	0.05	0.02	0.04	0.03
Cannabis	0.05	0.07	0.07	0.03	0.09	0.07	0.07	0.09	0.08
Cocaine	0.07	0.11	0.14	0.08	0.15	0.20	0.05	0.10	0.13
Illicit opioids	0.06	0.09	0.11	0.07	0.12	0.20	0.05	0.07	0.10
Pain medicine	0.05	0.08	0.07	0.07	0.11	0.13	0.04	0.06	0.15
Amphetamines	0.05	0.08	0.11	0.08	0.12	0.19	0.04	0.07	0.08
Arrests	0.07	0.15	0.18	0.07	0.15	0.21	0.07	0.16	0.16
IPV arrests	0.08	0.13	0.21	0.11	0.17	0.29	0.07	0.11	0.16
SV arrests	0.04	0.08	0.18	0.05	0.07	0.19	0.04	0.08	0.20
Rape	0.05	0.12	0.17	0.11	0.18	0.26	0.03	0.09	0.12
Assault injury	0.08	0.16	0.24	0.12	0.22	0.30	0.08	0.13	0.16
Assault with weapon	0.07	0.16	0.27	0.11	0.21	0.38	0.06	0.10	0.14

Note: Model 1, ACE count score as sole predictor of outcomes; Model 2, multiple regression with binary ACE predictors; Model 3, multiple regression with ordinal ACE predictors. Education, highest level of school completed; Job length, longest job held; Borderline, borderline personality disorder; Intoxication, number of days in a typical month drank until intoxicated; Cannabis, number of days in a typical month used cannabis products; Cocaine, number of days in a typical month used cocaine; Illicit opioids, number of days in a typical month used illicit opioids; Pain medicine, number of days in a typical month used pain medicine; Amphetamines, number of days in a typical month used amphetamines; Arrests, number of times ever arrested; IPV arrests, number of times ever arrested for violence against a dating partner or spouse; SV arrests, number of times ever arrested for sexual assault; Rape, number of times forced or tried to force someone to have sex against their will; Assault injury, number of times ever attacked someone causing injury; Assault with weapon, number of times ever attacked someone with a weapon.

ACE, adverse childhood experience; IPV, intimate partner violence; ODD/CD, oppositional defiant disorder/conduct disorder; PTSD, post-traumatic stress disorder; R^2adj, adjusted R^2; SV, sexual violence.

Table 3.

Model Estimates of Explained Variance for Racial/Ethnic Minority Participants

	All minorities (n=389)			Males (n=183)			Females (n=200)		
Outcome variables	R^2_{adj}**Model 1**	R^2_{adj}**Model 2**	R^2_{adj}**Model 3**	R^2_{adj}**Model 1**	R^2_{adj}**Model 2**	R^2_{adj}**Model 3**	R^2_{adj}**Model 1**	R^2_{adj}**Model 2**	R^2_{adj}**Model 3**
Education	0.01	0.07	0.08	0.02	0.10	0.11	0.01	0.02	0.00
Job length	0.00	0.03	0.04	0.00	0.00	0.00	0.00	0.06	0.06
PTSD	0.15	0.20	0.20	0.22	0.28	0.37	0.10	0.19	0.17
Anxiety	0.08	0.11	0.12	0.08	0.12	0.15	0.07	0.05	0.09
Depression	0.13	0.17	0.18	0.13	0.17	0.19	0.11	0.15	0.12
ODD/CD	0.12	0.15	0.27	0.11	0.10	0.21	0.13	0.14	0.40
Borderline	0.16	0.20	0.26	0.22	0.31	0.50	0.12	0.14	0.16
Intoxication	0.03	0.05	0.10	0.03	0.10	0.19	0.04	0.04	0.03
Cannabis	0.06	0.09	0.12	0.05	0.22	0.22	0.08	0.07	0.07
Cocaine	0.10	0.18	0.26	0.16	0.29	0.44	0.06	0.06	0.11
Illicit opioids	0.11	0.18	0.28	0.11	0.21	0.35	0.13	0.19	0.31
Pain medicine	0.05	0.08	0.12	0.07	0.10	0.25	0.04	0.05	0.01
Amphetamines	0.10	0.16	0.29	0.18	0.27	0.54	0.04	0.05	0.10
Arrests	0.10	0.22	0.29	0.08	0.26	0.38	0.21	0.26	0.29
IPV arrests	0.11	0.21	0.30	0.12	0.25	0.38	0.14	0.17	0.26
SV arrests	0.06	0.08	0.23	0.02	0.00	0.06	0.09	0.10	0.36
Rape	0.06	0.09	0.18	0.09	0.08	0.21	0.04	0.07	0.22
Assault injury	0.09	0.22	0.37	0.13	0.33	0.50	0.14	0.17	0.28
Assault with weapon	0.08	0.18	0.43	0.11	0.25	0.60	0.10	0.21	0.31

Note: Minority status includes participants that identify as partially Caucasian and also a racial/ethnic minority. Model 1, ACE count score as sole predictor of outcomes; Model 2, multiple regression with binary ACE predictors; Model 3, multiple regression with ordinal ACE predictors. Education, highest level of school completed; Job length, longest job held; Borderline, borderline personality disorder; Intoxication, number of days in a typical month drank until intoxicated; Cannabis, number of days in a typical month used cannabis products; Cocaine, number of days in a typical month used cocaine; Illicit opioids, number of days in a typical month used illicit opioids; Pain medicine, number of days in a typical month used pain medicine; Amphetamines, number of days in a typical month used amphetamines; Arrests, number of times ever arrested; IPV arrests, number of times ever arrested for violence against a dating partner or spouse; SV arrests, number of times ever arrested for sexual assault; Rape, number of times forced or tried to force someone to have sex against their will; Assault injury, number of times ever attacked someone causing injury; Assault with weapon, number of times ever attacked someone with a weapon.

ACE, adverse childhood experience; IPV, intimate partner violence; ODD/CD, oppositional defiant disorder/conduct disorder; PTSD, post-traumatic stress disorder; R^2_{adj}, adjusted R^2; SV, sexual violence.

Table 4.

Standardized Regression Coefficients Comparing Binary and Ordinal ACE Scales Among Racial/Ethnic Minority Participants (n=389)

	Job length		PTSD		Opioids		SV arrest	
ACEs questions	**Binary, β(*p*-value)**	**Ordinal, β(*p*-value)**	**Binary, β(*p*-value)**	**Ordinal, β(*p*-value)**	**Binary, β(*p*-value)**	**Ordinal, β(*p*-value)**	**Binary, β(*p*-value)**	**Ordinal, β(*p*-value)**
How often did a parent or other adult in the household swear at you, insult you, put you down, or humiliate you?	0.05 (0.50)	−0.06 (0.45)	0.05 (0.35)	0.04 (0.58)	−0.06 (0.20)	−0.09 (0.18)	−0.06 (0.31)	−0.13 (0.11)
How often did a parent or other adult in the household act in a way that made you afraid that you might be physically hurt?	−0.14 (0.05)	−0.15 (0.08)	−0.19 (<0.001)	−0.21 (0.05)	0.06 (0.12)	0.05 (0.62)	−0.03 (0.67)	−0.20 (0.03)
How often did a parent or other adult in the household push, slap, or throw something at you?	0.10 (0.20)	0.13 (0.20)	−0.03 (0.62)	0.01 (0.95)	0.01 (0.80)	0.10 (0.26)	0.06 (0.13)	0.28 (0.01)
How often did a parent or other adult in the household ever hit you so hard that you had marks (bruises or cuts) or were injured?	0.02 (0.77)	0.04 (0.67)	0.09 (0.14)	0.12 (0.20)	0.11 (0.01)	−0.02 (0.85)	−0.02 (0.77)	−0.03 (0.81)
As a child, how often did anyone ever force you to have sex or to do something sexual that you did not want to do?	−0.04 (0.47)	−0.09 (0.11)	0.17 (0.01)	0.21 (0.01)	0.01 (0.88)	0.02 (0.84)	0.12 (<0.001)	0.16 (0.02)
As a child, how often did you hear or see one of your parents or guardians being physically hurt (e.g., hit, slapped, punched, kicked, etc.) by their partner?	0.10 (0.12)	0.02 (0.78)	0.01 (0.85)	0.00 (0.97)	−0.01 (0.78)	−0.01 (0.92)	0.03 (0.35)	0.01 (0.86)
How often did you feel that no one in your family loved you or thought you were important or special?	−0.18 (0.01)	−0.11 (0.15)	0.12 (0.02)	0.08 (0.26)	0.03 (0.40)	0.01 (0.83)	−0.02 (0.51)	0.07 (0.21)
How often did you feel that you didn’t have enough to eat, had to wear dirty clothes, and had no one to protect you?	0.04 (0.54)	0.19 (0.02)	0.04 (0.55)	0.00 (0.99)	−0.07 (0.34)	0.04 (0.77)	0.01 (0.77)	−0.03 (0.68)
How often did you feel that your parents or guardians were too drunk or high to take care of you or take you to the doctor if you needed it?	−0.06 (0.46)	−0.05 (0.54)	0.03 (0.70)	0.01 (0.93)	0.07 (0.27)	0.11 (0.20)	0.14 (0.01)	0.23 (0.01)
How often did you see anyone shot or stabbed?	0.01 (0.93)	−0.08 (0.37)	0.10 (0.17)	0.03 (0.68)	0.30 (<0.001)	0.29 (<0.001)	0.10 (0.10)	0.10 (0.30)
How often did you see anyone beaten up or hurt really badly by someone else?	0.03 (0.61)	0.05 (0.50)	0.05 (0.35)	0.11 (0.14)	−0.03 (0.41)	−0.02 (0.81)	−0.02 (0.64)	−0.13 (0.05)
How often were you afraid to go outside because of gangs or drugs in your neighborhood?	−0.04 (0.56)	−0.14 (0.07)	0.12 (0.10)	0.04 (0.56)	−0.11 (0.09)	−0.27 (<0.001)	0.01 (0.73)	0.00 (0.98)
How often did you have to hide someplace because of gun violence in your neighborhood?	0.04 (0.50)	0.14 (0.05)	−0.02 (0.73)	0.08 (0.35)	0.11 (0.07)	0.31 (<0.001)	0.11 (<0.001)	0.24 (0.01)
Did you live with anyone who was a problem drinker or alcoholic or who regularly used drugs to get high?	0.09 (0.24)	0.09 (0.19)	0.11 (0.11)	0.13 (0.06)	−0.04 (0.36)	−0.05 (0.32)	−0.09 (0.03)	−0.09 (0.04)
Did you live with anyone who was depressed or mentally Ill?	0.18 (<0.001)	0.17 (0.01)	0.00 (0.99)	0.02 (0.68)	0.03 (0.46)	0.05 (0.32)	−0.01 (0.90)	0.01 (0.81)
Did you live with anyone who attempted suicide?	−0.15 (0.01)	−0.15 (<0.001)	0.14 (0.04)	0.12 (0.10)	0.16 (0.01)	0.09 (0.08)	0.11 (0.07)	0.05 (0.30)

ACEs questions	Job length		PTSD		Opioids		SV arrest	
	Binary, β(*p*-value)	Ordinal, β(*p*-value)	Binary, β(*p*-value)	Ordinal, β(*p*-value)	Binary, β(*p*-value)	Ordinal, β(*p*-value)	Binary, β(*p*-value)	Ordinal, β(*p*-value)
Did you live with anyone who ever went to prison?	−0.05 (0.46)	−0.07 (0.23)	−0.01 (0.85)	−0.05 (0.46)	0.12 (0.01)	0.04 (0.46)	0.04 (0.45)	−0.04 (0.41)

Note: Job length, longest job held; Opioids, number of days in a typical month used illicit opioids; SV arrests, number of times ever arrested for sexual assault.

ACE, adverse childhood experience; PTSD, post-traumatic stress disorder; SV, sexual violence.