



Excessive digital devices use as an intermediate variable between heterogeneous adverse childhood experiences and psychopathology in US adolescents: a latent class cross-sectional analysis

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Abstract

Background Adverse childhood experiences (ACEs) represent a significant public health concern in the US. While research has established links between ACEs and psychopathology, the behavioral mechanisms intermediating this relationship in adolescents remain limited, particularly regarding digital device usage behaviors in the technological era.

Objective I examined the intermediate role of excessive digital device use (EDDU) in the relationship between heterogeneous ACEs and psychopathology in a nationally representative sample of US adolescents.

Methods Data from the 2021–2023 National Survey of Children’s Health included 50,285 adolescents ($M_{age}=14.47\pm 1.7$, 49% girls, weighted $N=23,930,493$). Latent class analysis identified ACE patterns. Logistic regression models and the Karlson-Holm-Breen method assessed associations between ACE classes, EDDU, and disorders, controlling for sociodemographic factors and accounting for complex survey design.

Results Four distinct ACE classes emerged: Low ACE Exposure (LAE), Economic and Family Hardship (EFH), Community and Discrimination Stress (CDS), and Pervasive ACEs Exposure (PAE). Compared to LAE, PAE showed the strongest association with EDDU ($OR=2.28$, 95% CI [1.89,2.74]) and with depression ($OR=7.72$, 95% CI [6.28,9.48]) and anxiety ($OR=5.36$, 95% CI [4.43,6.47]). EDDU significantly intermediated the relationship between ACE classes and all three disorders, showing stronger effects for internalizing disorders than for ADHD.

Conclusions ACE patterns show heterogeneous associations with adolescent EDDU and psychopathology in this cross-sectional analysis. Statistical relationships between ACEs, EDDU, and mental health problems suggest potential behavioral pathways that warrant longitudinal investigation. While causal relationships cannot be established, these findings highlight digital device use as a potentially relevant factor when supporting adolescents with adverse childhood experiences.

Keywords Adverse childhood experiences · Adolescents · Excessive digital device use · Psychopathology · Intermediate variable · Latent class analysis

Introduction

In the United States, adverse childhood experiences (ACEs) have emerged as a significant public health concern. According to the Centers for Disease Control and Prevention (CDC), approximately 64% of adults report experiencing at least one ACE, while 17.3% report four or

more ACEs [1]. Since the seminal CDC-Kaiser ACE Study [2], substantial empirical evidence has confirmed associations between childhood adversity and multiple health conditions in adulthood, including cardiovascular disease, chronic pulmonary disease, depression, and substance abuse [3, 4]. However, research on the adverse consequences of ACEs and their mechanisms has predominantly focused on adulthood health outcomes, with a shift toward adolescents occurring only recently [5, 6]. Studies indicate that the impacts of ACEs on adolescents are equally severe and extensive, affecting multiple developmental domains, including cognition, emotional regulation, and behavioral control [7, 8, 9].

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Regrettably, our understanding of the underlying mechanisms connecting ACEs and psychopathology among adolescents remains limited, particularly regarding intermediate pathways of adolescent behavior within the digital era. Adolescence represents a critical, sensitive period for neurodevelopment and socialization, making it a crucial stage for understanding the mechanisms of ACE impacts and exploring effective intervention opportunities [6, 10]. From a methodological perspective, current scholarship continues to conceptualize ACE as a single homogeneous risk index *vis-à-vis* more nuanced approaches that would acknowledge the heterogeneity among different types of adversity [11]. Additionally, the majority of research on adolescent ACEs still relies on convenience samples, which constrains the generalizability and applicability of findings [5]. To address these gaps, I examined the potential intermediate role of excessive digital device use (EDDU) between specific ACE types and three forms of psychopathology in a nationally representative sample of US adolescents.

Adverse childhood experiences and excessive digital device use

With the rapid spread of the internet, digital devices have become a central component of modern life, particularly for *Gen Z* adolescents, who have been known as “digital natives” [12]. While appropriate use of digital devices offers positive value for learning, social connection, and information access, excessive digital device use (EDDU) — defined as usage that exceeds normal duration — can potentially negatively affect adolescents’ physical and mental health [13, 14].

ACEs may serve as crucial clues to EDDU. Stress coping theory suggests that adolescents who experience adversity may be more inclined to utilize media as a strategy for regulating negative emotions or escaping reality [15]. This phenomenon has been conceptualized as the “self-medication hypothesis,” whereby individuals may employ digital devices to alleviate psychological distress or satisfy unmet psychological needs. For instance, adolescents experiencing domestic violence may temporarily escape family stressors by immersing themselves in virtual environments [16]. Similarly, the social compensation hypothesis further elaborates that adolescents facing social difficulties may turn to online environments to seek social connection and acceptance [17]. For adolescents who have experienced discrimination, social media may provide a social environment with a perceived lower risk [18]. These theoretical frameworks have received partial empirical support. Kim et al. [19] found that emotion regulation difficulties partially mediate the relationship between ACEs and EDDU. Additionally, a recent British large-scale longitudinal study demonstrated

that ACEs predict increased social media use and gaming behaviors during adolescence [20]. However, another longitudinal study from China revealed substantial heterogeneity in the relationship between child maltreatment and EDDU, with only the emotional abuse subtype being positive [21].

Resolving these contradictions requires examining the heterogeneity of ACEs. ACE represents a broad concept, with different types potentially influencing adolescent development through distinct mechanisms, resulting in differentiated health outcomes [22, 23, 24]. Traditionally, ACEs have been approached through a cumulative risk model, calculating the total number of different ACE types [2]. This method assumes equivalent weighting and similar impact mechanisms across all ACE types, failing to capture the complexity and specificity of adverse experiences. The Dimensions of Adversity and Psychopathology (DMAP) model attempts to provide a more nuanced framework by distinguishing between threat-based and deprivation-based experiences, positing that different ACE categories influence various health domains through distinct neurodevelopmental mechanisms [25, 26]. However, this approach faces conceptual and measurement challenges, such as the high co-occurrence among ACE types that complicates precise categorization [24]. In survey contexts, the DMAP model functions more effectively as a theoretical framework rather than an operational guide.

To address these challenges, I employ latent class analysis (LCA), using the DMAP model as a conceptual guide rather than a strict classification scheme. This data-driven approach identifies natural co-occurrence patterns of ACEs based on empirical relationships, providing a more precise conceptualization than traditional cumulative scoring or arbitrary categorization. Rather than forcing ACEs into predetermined theoretical dimensions, this approach allows complex patterns to emerge from the data while still being informed by theoretical perspectives. Based on previous research, I anticipate the emergence of distinct patterns that may partially reflect aspects of threat and deprivation dimensions while likely showing more complex co-occurrence patterns that transcend simple dichotomies. Several studies have already used LCA for typological analysis of ACEs [27, 28]. Wang et al. [29] reviewed LCA applications in ACEs research and found that most studies reveal a high/multiple ACEs group, with community violence groups also appearing frequently. They further note that current research often lacks theoretical guidance, insufficient attention to regional specificities, and relies on non-representative samples. I will address these gaps in this study.

Adverse childhood experiences and psychopathology: intermediate role of excessive digital device use

Adolescence represents a high-incidence period for psychopathology, also serving as a critical window when many mental disorders first emerge. Approximately 50% of lifetime mental illnesses show symptoms before age 14 [30]. The developmental tasks and neurobiological changes during this period make adolescents particularly vulnerable to mental health challenges [6, 10]. Existing research suggests that ACEs are significant antecedents of adolescent psychopathology [6, 31]. From a biological perspective, early adversity may affect mental health by altering stress response systems and neurodevelopmental trajectories [24]. ACEs are associated with hypothalamic-pituitary-adrenal (HPA) axis dysfunction, enhanced inflammatory responses, and structural and functional changes in key brain regions (such as the prefrontal cortex and amygdala) [32, 33]. From a psychosocial perspective, ACEs may impact psychological adaptation by damaging attachment security, emotion regulation capacity, and cognitive development [34, 35]. These effects may be particularly significant during adolescence, as enhanced neuroplasticity and key socio-emotional developmental tasks during this period create both vulnerability to early adversity effects and potential recovery opportunities [33]. However, current research primarily focuses on biological and psychological variables, with less exploration of modifiable behavioral intermediate pathways.

EDDU may serve as a critical intermediate mechanism linking ACEs with adolescent psychological problems. The contact hypothesis suggests that online social interaction cannot fully satisfy socioemotional needs due to its lack of rich nonverbal cues and depth compared to face-to-face interactions [36]. Over-reliance on virtual socialization may restrict social skill development and increase social anxiety and loneliness [37, 38]. The cognitive-attention framework suggests associations between digital device use patterns and attentional processes, though the directionality remains unclear in current research [39]. While several studies have found correlations between media multitasking and attention measures, the evidence is mixed regarding causality [40]. These cognitive effects significantly overlap with attention deficit hyperactivity disorder (ADHD) symptoms, potentially explaining the association between screen time and attention problems [41]. Excessive screen time may also affect mental health through displacement mechanisms, replacing core activities that promote healthy development, such as sleep, physical activity, face-to-face socialization, and learning [15, 42]. This can trigger cascading effects: sleep deprivation increases emotional regulation difficulties and cognitive function decline, while reduced physical

activity affects brain plasticity and emotional regulation capacity [15]. These theories have received empirical support [43, 44], with Twenge et al. [45] noting that increased digital device screen time among adolescents correlates with depressive symptoms and suicide-related outcomes. More convincingly, Kushlev et al. [46] conducted a randomized field experiment showing that limiting mobile phone notifications for one week significantly reduced inattention and hyperactivity symptoms, suggesting the causal effects of digital interruptions on attentional processes.

Drawing on the theories above, I hypothesize that EDDU constitutes a key intermediate factor connecting ACEs with psychological problems. Different ACEs may influence screen use behaviors through distinct pathways, producing differentiated effects on various mental health domains. In this study, I assess anxiety, depression, and ADHD — three common and interrelated adolescent psychological disorders—as health outcomes. These three disorders represent the most prevalent mental health challenges during adolescence and can reflect the potential impacts of ACEs and excessive screen time on adolescent psychological well-being [47].

The present study

In this study, I propose a conceptual model to explore the complex relationships among ACEs, excessive digital device use, and adolescent mental/behavioral disorders in American adolescents (see conceptual diagram Fig. 1).

I propose the following research hypotheses:

H1 *Categorization of ACEs will reveal distinct patterns of adversity exposure that may partially align with conceptual dimensions such as threat and deprivation while likely showing more complex co-occurrence patterns.*

H2 *ACE classes will be significantly positively associated with adolescent EDDU, with different types of ACEs showing differentiated impact patterns.*

H3 *ACE classes will be significantly positively associated with adolescent psychopathology, with different types of ACEs showing differentiated impact patterns.*

H4 *EDDU will be significantly positively associated with adolescent psychopathology.*

H5 *EDDU will partially intermediate the relationship between ACEs and adolescent mental disorders. This indirect effect will vary by ACE type and specific disorder.*

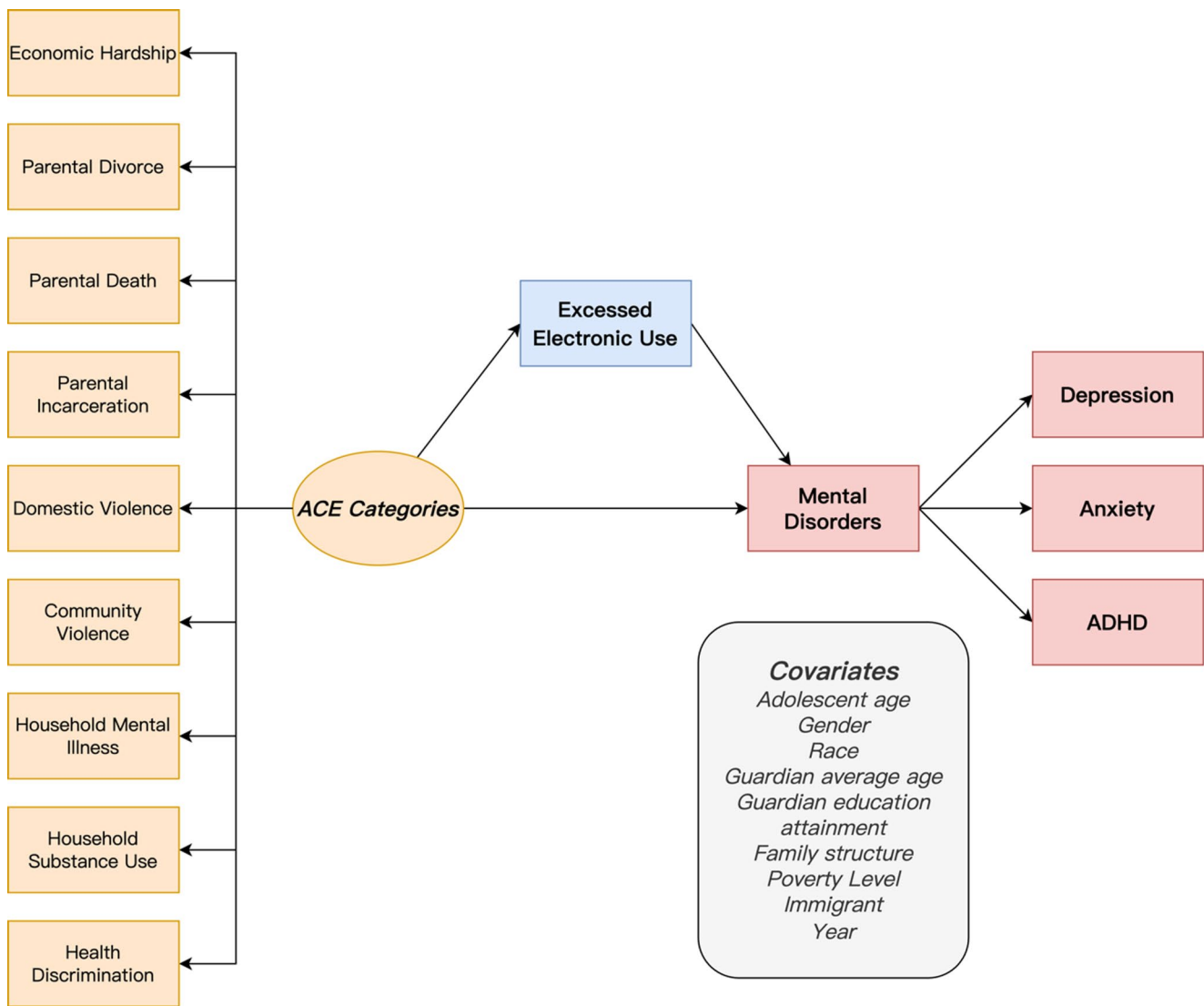


Fig. 1 Conceptual framework: ACE classes as antecedents of EDDU and mental health disorders

Methods

Data

The data come from the National Survey of Children's Health (NSCH) [48]. I use data from 2021 to 2023 (three years), integrating them into a repeated cross-sectional dataset. The NSCH is a nationally representative survey funded by the US Health Resources and Services Administration, designed to collect comprehensive information about the health, development, and well-being of US children and adolescents. The NSCH employs a complex sampling design to ensure national representativeness, covering families from diverse racial/ethnic and socioeconomic backgrounds. The survey collects information on children's health through parent/guardian reports. According to official

NSCH methodology reports [49], the survey achieved overall weighted response rates from 35.8 to 40.3%. The NSCH divides the surveyed population into three age groups—0–5 years, 6–11 years, and 12–17 years. I focused on the 12–17 year-old adolescent sample. This age range experiences critical neurodevelopmental and social transitions, represents the most active and independent stage of media use, and faces significant mental health risks, making it particularly suitable for exploring this study's core questions.

After excluding individuals with missing outcome variables, I removed observations with more than 50% missing across the ten ACE variables. For the remaining observations, I conducted Little's MCAR test, which indicated that the data did not follow a Missing Completely At Random pattern ($\chi^2(105)=370.5, p<.001$). While the Missing At Random assumption cannot be directly tested, examination of missingness patterns about observed variables (see

S4) suggested that MAR was plausible, with missingness primarily associated with observed demographic characteristics rather than with the values of missing variables themselves. Furthermore, missing data rates were relatively low across variables (The highest missing rate is 0.78%). Therefore, for missing ACEs values, I employed Full Information Maximum Likelihood (FIML) when running the LCA. For other variables, I used the Missforest method for imputation [50], a machine learning-based approach with excellent performance. The final analytic sample consisted of 50,285 adolescent observations ($M_{age}=14.47\pm 1.7$, 49% girls). To generate population-representative estimates, I applied the NSCH-provided survey weights, which were constructed through a multi-stage process involving base weights, non-response adjustments, and post-stratification calibration to demographic benchmarks from the American Community Survey [49]. The sum of these weights (weighted $N=23,930,493$) represents the estimated national population of adolescents aged 12–17 during the study period.

Measures

Adverse childhood experiences

I assessed adolescent adversity using the nine-item NSCH-ACE scale. Adapted from the classic ACE questionnaire, this measure has demonstrated good reliability and validity [51, 52]. The NSCH-ACE evaluates: (1) Economic Hardship, (2) Parental Divorce, (3) Parental Death, (4) Parental Incarceration, (5) Domestic Violence, (6) Community Violence, (7) Household Mental Illness, (8) Household Substance Use, (9) Racial Discrimination and (10) Health Discrimination. The NSCH-ACE collects ACEs through guardian/parent reports, with guardians/parents being asked whether their child experienced these adversities. Except for Economic Hardship, all items are binary (No/Yes). I recoded the four Economic Hardship response options into a binary format (“never” and “rarely” as “no,” “somewhat often,” and “very often” as “yes”) to meet LCA requirements. LCA assumes categorical indicator variables and requires measurement on the same scale to facilitate the interpretation of conditional response probabilities and ensure model convergence [53]. While LCA can accommodate polytomous indicators, binary indicators often yield more stable solutions with fewer identification issues, particularly when working with complex survey data and when other indicators are already binary. In this study, Cronbach’s α of the NSCH-ACE is 0.72.

Excessive digital devices use

I measured adolescent EDDU with a single question. Guardians were asked about their child’s time using digital devices (including computers, phones, and television) on weekdays. Response options ranged from “Less than one hour” to “4 or more hours,” comprising five levels. Following standards from a recent CDC report [54], I coded “4 and more hours” as excessive digital device use (yes) and the remainder as no. In the study, 38% of the sample met the EDDU criteria.

Psychopathology

I measured three mental disorders: anxiety, depression, and ADHD. These three disorders represent the most common internalizing problems (anxiety, depression) and externalizing problems (ADHD) during adolescence. In the NSCH, these variables are based on parent-reported diagnoses by doctors or other healthcare providers. The specific question asked: “Has a doctor or other healthcare provider ever told you that your child has the following conditions: anxiety/depression/ADHD disorder?” If yes, respondents proceeded to the question: “Does this condition currently exist?” Those answering yes to both questions were coded as Yes; otherwise, they were no.

Covariates

I included a rich set of covariates including age, gender (boy/girl), race (White/Hispanic/Black/Asian/Multiple races/Other), average age of guardians, highest education degree among guardians (Less than high school~College degree or higher), family structure (Two parents/Single parent/Other family type), family income level (categorized as 0–99%, 100–199%, 200–399%, and $\geq 400\%$ of federal poverty level, see S1 for more details in definition), whether born in the US (No/Yes), and survey year.

For detailed definitions of the variables above, please refer to Supplementary Materials S1 and the descriptive statistics in S2.

Statistical methods

I began by conducting Latent Class Analysis (LCA), a person-centered finite mixture modeling approach that identifies unobserved subgroups within a population based on response patterns across observed indicators [53]. LCA is particularly appropriate for the present research question as it allows for the empirical identification of heterogeneous patterns of adversity exposure, moving beyond the limitations of cumulative risk scoring approaches that treat all ACEs as equivalent. This method can detect co-occurrence

patterns of different ACE types and classify individuals into mutually exclusive and exhaustive latent subgroups with similar adversity classes. I employed a systematic approach for number selection in LCA using multiple statistical and substantive criteria [55]. Indicators included information criteria—Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), and adjusted BIC (aBIC)—with lower values indicating better model parsimony and fit. Classification quality was assessed using entropy values, where values approaching 1 indicate clearer class differentiation. I also conducted nested model comparisons using the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) and Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT), where significant *p*-values indicate that a *k*-class model fits significantly better than a *k*-1 class model. Beyond these, I followed the recommended practice by considering substantive criteria, including theoretical interpretability, class prevalence, and distinctiveness of the identified patterns [53].

Following the AGRema guidelines [56, 57], I employed the mediation framework to examine associations among ACE classes (exposure), EDDU (intermediate variable), and adolescent psychopathology (outcome). Figure 1 illustrates this conceptual framework.

Several key assumptions warrant consideration. First, regarding temporal precedence, while the cross-sectional design cannot establish definitive temporal ordering, the nature of ACEs provides theoretical justification for assuming they preceded both EDDU and mental health outcomes, as these experiences often occur during childhood and were reported retrospectively. Second, concerning the no unmeasured confounding assumption, I included a comprehensive set of sociodemographic covariates to adjust for potential confounders of both ACE-EDDU and EDDU-mental health relationships. However, it must be acknowledged that unmeasured confounding remains a possibility in observational research. Third, regarding the consistency assumption, I employed validated measures of ACEs and mental health outcomes from the NSCH, with clear operationalization of excessive digital device use (≥ 4 h daily).

Despite these efforts to address key assumptions, the inherent limitations of cross-sectional design must be acknowledged. Causal inferences should be made cautiously, and the findings are best interpreted as statistical associations (or exploratory causal relationships) rather than definitive causal pathways. The observed relationships provide valuable insights into potential mechanisms, but longitudinal research is necessary to establish temporal ordering and causal relationships with greater confidence.

I conducted a series of models for intermediate analysis. First, I ran logistic models with ACE classes as independent variables and EDDU as the outcome variable to assess the

effects of different ACE classes on EDDU (indirect effect model). Next, I ran a set of logistic models with ACE classes and EDDU as independent variables and mental disorders as dependent variables (direct model) to estimate the direct effects of ACE classes. Finally, I ran models without EDDU based on the previous set to calculate the total effects of ACE classes (total effect model). I used the Karlson-Holm-Breen (KHB) method to assess the significance and magnitude of indirect effects, a technique suitable for intermediate analysis in nonlinear regression models [58]. I calculated indirect effects and standardized indirect effect proportions.

I also calculated average marginal effects (AMEs) for different ACE classes in indirect and total effect models and conducted between-group significance tests [59]. To more intuitively understand the effect sizes of various ACE classes on EDDU and disorders, I calculated 95% confidence intervals and 83.4% confidence intervals. The 95% CIs were used for significance assessment against null values. In comparison, 83.4% CIs were used for visual between-group comparisons, as non-overlapping 83.4% CIs correspond to statistically significant differences at the conventional $\alpha = 0.05$ level (see [60] and S5 for more details).

All analyses incorporated the complex sampling design of the NSCH to ensure unbiased population estimates and correct standard errors. Specifically, I applied survey weights to adjust for unequal selection probabilities, differential non-response, and post-stratification to population benchmarks (also see the manual of NSCH [49]). For LCA in Mplus, I used the *CLUSTER*, *STRATIFICATION*, and *WEIGHT* commands with the *TYPE = COMPLEX* option to properly account for the sampling design. In Stata, I employed the *svy* prefix command structure with appropriate subpopulation specifications to maintain the integrity of the variance estimation while focusing on the adolescent subsample. All *p*-values were two-tailed, with $p < .05$ considered statistically significant. LCA was completed in Mplus, while the remaining analyses were conducted in Stata 18.5.

Results

Latent class analysis

I first conducted LCA analyses, with results shown in Table 1. As the number of classes increased, all three information criteria indicators decreased. However, after $K=4$, these indicators began to converge without substantial further reductions (See the scree plot of AIC and aBIC in S3). Additionally, the VLMR test and LMR indicated that the 4-class solution was significantly superior to the 3-class solution ($p < 0.05$), while the 5-class solution did not significantly outperform the 4-class solution. Finally, the entropy

Table 1 Model fit indices for class 1 through 7 from the latent class analysis of NSCH-ACE

<i>K</i>	AIC	BIC	aBIC	Entropy	VLMR (<i>p</i>)	LMR (<i>p</i>)
1	315259.5	315347.7	315316.0	-	-	-
2	281581.5	281766.8	281700.1	0.834	0.0000	0.0000
3	279901.3	279113.7	279813.7	0.755	0.0000	0.0000
4	278556.5	278936.0	278799.4	0.787	0.0421	0.0322
5	278052.7	278529.3	278357.6	0.764	0.2879	0.2910
6	277700.7	278274.3	278067.8	0.768	0.7941	0.7946
7	277478.0	278148.7	277907.2	0.792	0.3884	0.3889

Note. The best-fitting model is indicated in bold. AIC, BIC, and aBIC values were used to evaluate model fit, with lower values indicating better fit. Entropy values closer to 1 suggest higher classification accuracy. The Vuong-Lo-Mendell-Rubin (VLMR) and Lo-Mendell-Rubin (LMR) likelihood ratio tests compare the fit of a *k*-class model to a (*k*–1)-class model; significant *p*-values (*p* < .05) indicate that the model with *k* classes provides a statistically superior fit relative to the model with one fewer class

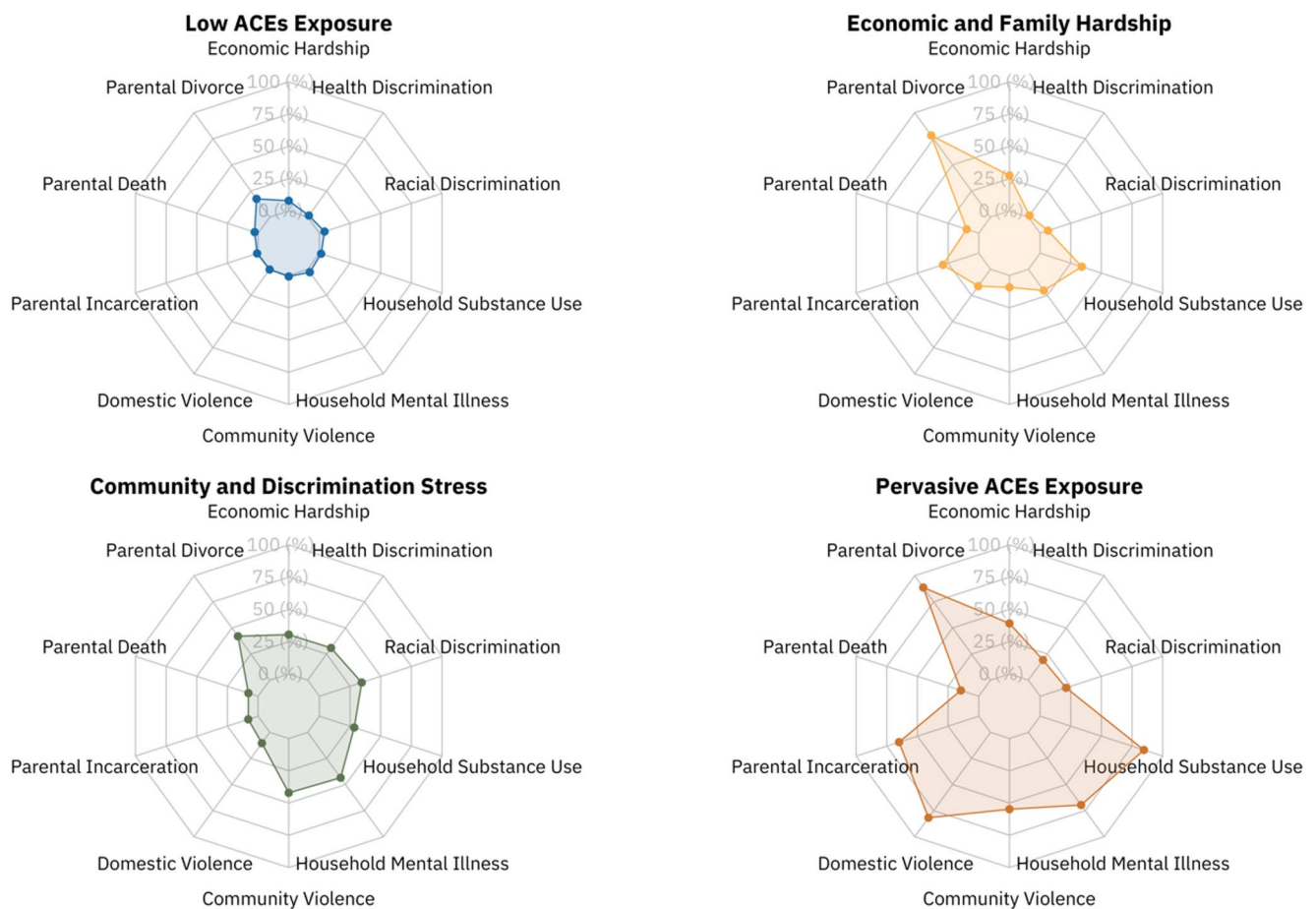


Fig. 2 Radar charts of ACE conditional probabilities by latent class. Note. Each radar chart displays the probability of endorsing each adverse childhood experience (ACE) indicator for the respective latent class (See S3 for table). The radial scale (0–100%) represents the conditional probability of each ACE within that class, with higher values

indicating greater likelihood. Four classes emerged from the latent class analysis: Low ACEs Exposure (LAE), Economic and Family Hardship (EFH), Community and Discrimination Stress (CDS), and Pervasive ACEs Exposure (PAE). These distinct patterns highlight the heterogeneity of ACEs among US adolescents

value demonstrated that the 4-class solution maintained relatively high classification quality (0.787). Therefore, I selected *K*=4 as the optimal solution.

The conditional probability distributions for the optimal solution are illustrated in the radar chart in Fig. 2 (See S3 for a specific table). The blue class in the upper left represents

79% of the total sample, characterized by consistently low levels across all ACE indicators, representing adolescents with minimal adversity exposure. I labeled this class Low ACEs Exposure (LAE), which would serve as the reference group. The yellow class in the upper right comprises 11% of the sample, distinguished by high probabilities of economic

hardship and parental divorce, with slightly elevated risks of household substance abuse and mental illness, which I designated as Economic and Family Hardship (EFH). The green class in the lower left accounts for 4.8%, exhibiting unique sensitivity to racial discrimination, community violence, and health discrimination. I named this class Community and Discrimination Stress (CDS). The final class in the lower right represents the smallest proportion (4.6%), showing high probabilities across almost all ACE indicators, indicating multiple intersecting adversity experiences. This comprehensive ACE exposure pattern likely represents the most vulnerable adolescent group, simultaneously experiencing internal family dysfunction (high deprivation) and external environmental pressures (high threat), which I labeled Pervasive ACEs Exposure (PAE). These LCA results confirm my first hypothesis (H1).

Correlation analysis and descriptive statistics for ACE classes can be found in the S4 and S2. All classes except LAE show significant negative correlations with EDDU and all three disorders. EDDU demonstrates significant positive correlations with all disorders.

Regression analysis

Table 2 presents the regression analysis results. In the indirect effect model, I found that compared to the reference group (LAE), PAE showed the strongest association with EDDU (OR = 2.28, 95% CI [1.89, 2.74]). The coefficients for EFH and CDS were relatively similar. Further AME analysis indicates that PAE had the strongest AME (Fig. 3 (a), also see S5 for table), with 19.7% (95% CI [15.2%, 24.2%]) higher probability of EDDU compared to the reference group. Additionally, PAE's effect was significantly higher than EFH but did not differ significantly from CDS. This confirms H2.

In the three total effect models excluding EDDU, a gradient relationship among different ACE types was evident for all outcomes except ADHD. Specifically, PAE demonstrated the strongest associations with depression (OR = 7.72, 95% CI [6.28, 9.48]) and anxiety (OR = 5.36, 95% CI [4.43, 6.47]), followed by CDS and then EFH. For ADHD, however, CDS exhibited a higher coefficient than PAE (OR = 3.82, 95% CI [3.23, 4.52]). AME analysis revealed that for all three disorders (Fig. 3 (b)–(d)), both PAE and CDS had significantly higher AMEs than the EFH group. However, no significant differences existed between these two groups themselves. This confirms H3.

After including EDDU, the coefficients for ACE classes in all three direct effect models decreased to varying degrees, while coefficients for other covariates showed no significant changes. Furthermore, EDDU was significantly associated with all three mental disorders ($p < 0.05$), indicating that

EDDU intermediates the relationship between ACE classes and psychopathology.

Intermediate analysis

The results of the KHB analysis are presented in Table 3. All indirect effects were statistically significant ($p < 0.05$), with the proportion of indirect effects ranging from 2.64 to 9.69%. Vertically, the proportion of indirect effects for depression and anxiety was higher than for ADHD. Horizontally, differentiated intermediate patterns emerged across ACE classes, with the proportion of EDDU's indirect effects for the PAE group higher than others. In contrast, the other two groups showed minimal differences. These findings confirm H5.

Discussion

This study utilized a nationally representative sample of US adolescents to elucidate the complex relationship between adverse childhood experiences (ACEs) and adolescent mental disorders while systematically exploring—for the first time—the role of excessive digital device use (EDDU) as a potential intermediate mechanism. My findings extend the understanding of ACE heterogeneity and identify a behavioral intermediate pathway that helps explain how ACEs “permeate” daily behaviors and ultimately affect psychological well-being.

Heterogeneity of adverse childhood experiences

Through LCA, I identified four distinct classes of ACE exposure: Low ACEs Exposure (LAE), Economic and Family Hardship (EFH), Community and Discrimination Stress (CDS), and Pervasive ACEs Exposure (PAE). While these patterns provide some conceptual connection to the DMAP model's distinction between threat and deprivation [25, 26], it is important to acknowledge that the empirically derived classes reveal more complex co-occurrence patterns than a simple dichotomy would suggest. Many individual ACEs contain elements of both dimensions depending on their manifestation—for instance, parental incarceration may simultaneously represent family structural disruption (deprivation) and emotional distress or household instability (threat). The EFH class, while predominantly characterized by economic hardship and family structural challenges, also showed elevated rates of household substance use and mental illness, which can represent threat exposures. Similarly, the CDS class, though distinctive for community violence and discrimination experiences, also showed elevated economic hardship and parental divorce rates, reflecting

Table 2 Associations between ACE classes, excessive digital device use, and adolescent psychopathology

Characteristic	Indirect Effect Model	Depression	Depression (with EEU)	Anxiety	Anxiety (with EEU)	ADHD	ADHD (with EEU)
	OR [95% CI] ¹²						
ACE class							
Low ACEs Exposure	—	—	—	—	—	—	—
Economic and Family Hardship	1.83*** [1.62,2.07]	2.97*** [2.44,3.61]	2.74*** [2.25,3.33]	2.03*** [1.74,2.36]	1.90*** [1.64,2.21]	1.80*** [1.52,2.14]	1.75*** [1.47,2.08]
Community and Discrimination Stress	1.89*** [1.62,2.21]	6.26*** [5.22,7.51]	5.80*** [4.82,6.99]	4.93*** [4.18,5.82]	4.65*** [3.92,5.51]	3.82*** [3.23,4.52]	3.70*** [3.12,4.37]
Pervasive ACEs Exposure	2.28*** [1.89,2.74]	7.72*** [6.28,9.48]	7.00*** [5.70,8.60]	5.36*** [4.43,6.47]	4.96*** [4.09,6.01]	3.26*** [2.63,4.05]	3.13*** [2.51,3.90]
Adolescent age	1.11*** [1.08,1.13]	1.29*** [1.24,1.34]	1.27*** [1.22,1.32]	1.12*** [1.09,1.15]	1.11*** [1.08,1.14]	1.00 [0.97,1.03]	0.99 [0.96,1.02]
Gender							
Boy	—	—	—	—	—	—	—
Girl	0.90** [0.83,0.97]	2.07*** [1.82,2.34]	2.10*** [1.85,2.39]	1.83*** [1.67,2.00]	1.86*** [1.70,2.04]	0.51*** [0.46,0.56]	0.51*** [0.46,0.56]
Race							
White	—	—	—	—	—	—	—
Hispanic	1.30*** [1.17,1.44]	0.73*** [0.60,0.88]	0.70*** [0.58,0.85]	0.58*** [0.51,0.67]	0.56*** [0.49,0.65]	0.62*** [0.53,0.74]	0.62*** [0.52,0.73]
Black	1.45*** [1.27,1.64]	0.59*** [0.46,0.75]	0.56*** [0.44,0.71]	0.40*** [0.32,0.49]	0.38*** [0.31,0.46]	0.70*** [0.58,0.83]	0.68*** [0.57,0.82]
Asian	1.23** [1.05,1.43]	0.28*** [0.17,0.49]	0.28*** [0.16,0.47]	0.24*** [0.18,0.31]	0.23*** [0.17,0.30]	0.24*** [0.17,0.33]	0.23*** [0.16,0.33]
Multiracial	1.26*** [1.10,1.45]	1.04 [0.85,1.28]	1.01 [0.82,1.25]	0.84* [0.71,0.99]	0.82* [0.69,0.96]	0.96 [0.80,1.14]	0.94 [0.79,1.13]
Other	1.33 [0.94,1.87]	0.39*** [0.25,0.61]	0.37*** [0.24,0.59]	0.68 [0.45,1.03]	0.66 [0.44,1.00]	0.56* [0.36,0.88]	0.56* [0.35,0.88]
Guardian average age	1.01* [1.00,1.01]	0.99 [0.99,1.00]	0.99 [0.98,1.00]	1.00 [0.99,1.00]	1.00 [0.99,1.00]	1.00 [1.00,1.01]	1.00 [1.0,1.01]
Guardian education attainment							
Less than high school	—	—	—	—	—	—	—
High school degree or GED	1.10 [0.89,1.36]	1.23 [0.79,1.91]	1.23 [0.79,1.92]	2.02*** [1.44,2.85]	2.02*** [1.44,2.84]	1.61** [1.17,2.21]	1.60** [1.16,2.20]
Some college or technical school	1.08 [0.87,1.33]	1.38 [0.88,2.17]	1.39 [0.88,2.20]	2.10*** [1.51,2.93]	2.11*** [1.51,2.94]	1.84*** [1.36,2.49]	1.83*** [1.35,2.48]
College degree or higher	1.00 [0.81,1.22]	1.39 [0.89,2.17]	1.42 [0.90,2.23]	2.55*** [1.83,3.55]	2.59*** [1.86,3.60]	1.90*** [1.41,2.56]	1.90*** [1.40,2.56]
Family structure							
Two parents	—	—	—	—	—	—	—
Single parent (mother or father)	0.93 [0.84,1.03]	1.10 [0.95,1.26]	1.10 [0.96,1.27]	1.04 [0.92,1.17]	1.04 [0.93,1.17]	1.13 [0.99,1.30]	1.14 [0.99,1.30]
Other family type	0.81 [0.65,1.01]	1.19 [0.90,1.58]	1.24 [0.93,1.64]	1.06 [0.81,1.39]	1.08 [0.82,1.43]	1.20 [0.94,1.53]	1.21 [0.95,1.55]
Poverty Level							
0–99% of poverty level	—	—	—	—	—	—	—
100–199% of poverty level	1.13 [0.98,1.31]	1.05 [0.85,1.30]	1.04 [0.83,1.29]	0.92 [0.77,1.09]	0.91 [0.76,1.08]	0.90 [0.76,1.08]	0.90 [0.75,1.07]
200–399% of poverty level	1.11 [0.97,1.27]	0.86 [0.69,1.08]	0.85 [0.68,1.06]	0.80** [0.68,0.94]	0.79** [0.67,0.92]	0.74*** [0.63,0.88]	0.74*** [0.63,0.87]
400% or more of poverty level	1.08 [0.94,1.24]	0.78* [0.64,0.95]	0.77* [0.63,0.94]	0.87 [0.74,1.02]	0.86 [0.74,1.01]	0.81* [0.68,0.95]	0.80* [0.68,0.95]
Whether born in the U.S. [Yes]							

Table 2 (continued)

Characteristic	Indirect Effect Model	Depression	Depression (with EEU)	Anxiety	Anxiety (with EEU)	ADHD	ADHD (with EEU)
	OR [95% CI] ¹²						
No	—	—	—	—	—	—	—
Yes	1.17 [0.97,1.41]	0.83 [0.60,1.14]	0.80 [0.59,1.10]	0.89 [0.69,1.15]	0.88 [0.68,1.13]	0.70* [0.52,0.94]	0.70* [0.52,0.93]
<i>Year</i>	0.87*** [0.83,0.92]	0.99 [0.91,1.07]	1.00 [0.93,1.09]	1.06* [1.00,1.13]	1.08** [1.02,1.14]	0.99 [0.93,1.05]	0.99 [0.93,1.06]
Excessive digital device use							
No	—	—	—	—	—	—	—
Yes	—	—	1.78*** [1.56,2.04]	—	1.62*** [1.49,1.78]	—	1.26*** [1.14,1.40]

Note. Each column presents adjusted OR and 95% CI from logistic regression models. The “Indirect Effect Model” column shows results for excessive digital device use (EDDU) regressed on ACE classes and covariates. Columns under each disorder (“Depression,” “Anxiety,” “ADHD”) compare two models: one without EDDU (total effect) and one with EDDU (direct effect). Low ACEs Exposure serves as the reference group for ACE classes. All models control for age, gender, race, guardian age, guardian education attainment, family structure, poverty level, whether born in the US, and survey year. Confidence intervals are in brackets; All analyses account for the NSCH’s complex sampling design

*** $p < .001$, ** $p < .01$, * $p < .05$

deprivation elements. Rather than forcing these empirical patterns into rigid theoretical categories, these classes represent naturally occurring co-exposure patterns that transcend simple dichotomies while still showing distinctive characteristic features.

Wang et al.’s review indicates that current LCA analyses in ACE research often lack theoretical guidance and regional specificity [29]. My study addresses this gap by using the DMAP model as a conceptual framework, allowing empirical patterns to emerge from the data. The LCA captures region-specific adversity experiences within the US social context—particularly racial discrimination—which has frequently been overlooked in previous ACE classification research [52]. Given the historical and contemporary racial inequalities in the United States, the prominence of racial discrimination as a distinct childhood adversity within the CDS class warrants particular attention [61]. This finding emphasizes the importance of cultural and social contexts in conceptualizing and measuring ACEs, suggesting that effective ACE research and interventions must consider unique stressors within specific populations and environments without oversimplifying their complex interrelationships.

Excessive digital device use and psychopathology

My research reveals differentiated association patterns between various ACE classes and both EDDU and psychopathology (H2). Regarding EDDU, compared to LAE, PAE demonstrated the strongest association (AME = 19.7%), followed by CDS (AME = 15.8%) and EFH (AME = 10.3%). This finding can be interpreted through multiple theoretical

frameworks. Stress coping theory provides a foundational explanation, suggesting that adolescents facing adversity may employ digital media to regulate negative emotions [15]. Specifically, adolescents experiencing multiple adversities (such as those in PAE) likely face greater cumulative stress, potentially increasing their reliance on this strategy. The self-medication hypothesis further refines this mechanism, positing that individuals may use digital media to “self-medicate” psychological distress or fulfill unmet psychological needs [16]. For instance, adolescents exposed to domestic violence may escape family stressors by immersing themselves in virtual environments [16], while those facing persistent poverty might seek a sense of achievement and control through online gaming [62]. These findings align with previous studies [20, 63], though prior research typically employed cumulative scoring methods to calculate ACEs. My research further elucidates the differential associations of various ACE classes.

The non-significant difference between CDS and PAE regarding EDDU suggests that experiences of community violence and discrimination may mainly drive adolescents toward virtual environments. The social compensation hypothesis indicates that adolescents experiencing discrimination and community violence may feel unsafe or unaccepted in real-world social environments, thereby turning to online environments for social connection and validation [17, 61, 64]. This result corresponds with Urbanova et al. [64], who found that adolescents subjected to appearance-based discrimination reported higher levels of excessive internet use. My research extends this association to racial discrimination.

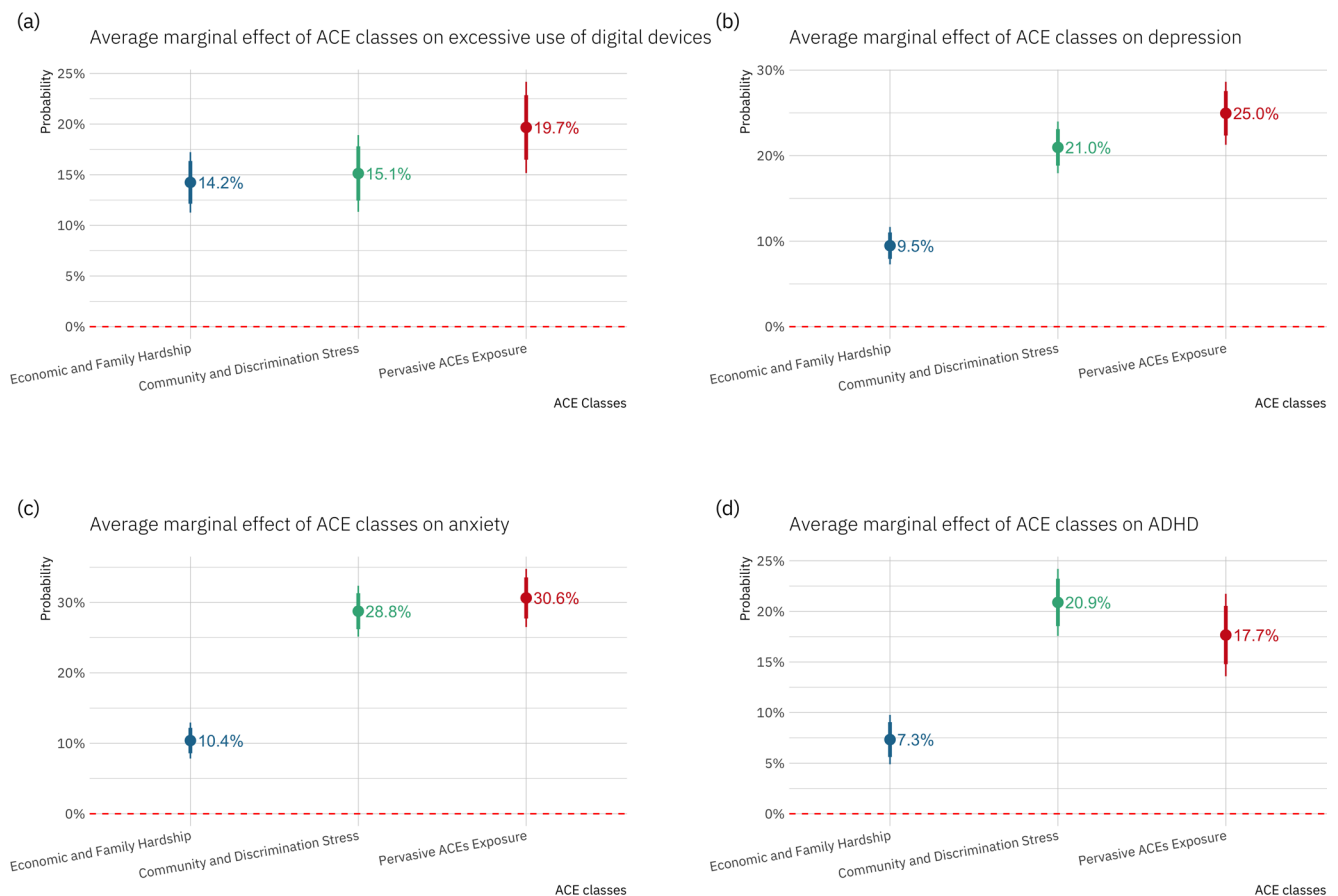


Fig. 3 Average marginal effects of ACE classes on EDDU and psychopathology. *Note.* Panels (a)–(d) illustrate the adjusted average marginal effects (AMEs) of each ACE class—Economic and Family Hardship (EFH), Community and Discrimination Stress (CDS), and Pervasive ACEs Exposure (PAE)—relative to the Low ACEs Exposure (LAE) reference group. Each point estimate is accompanied by two sets of confidence intervals: the thicker bars represent 83.4% CIs,

which facilitate between-group comparisons, and the thinner bars represent 95% CIs, used to assess statistical significance. Higher AMEs indicate greater predicted probability differences compared to LAE. Specifically, panel (a) shows the effects of excessive digital device use (EDDU), while panels (b), (c), and (d) present effects on depression, anxiety, and ADHD, respectively

Table 3 Indirect effects of excessive digital device use on the relationship between ACE classes and adolescent psychopathology

Mental problems	Economic and Family Hardship		Community and Discrimination Stress		Pervasive ACEs Exposure	
	Indirect effect	Proportion of indirect effect %	Indirect effect	Proportion of indirect effects %	Indirect effect	Proportion of indirect effects %
Depression	0.083*** [0.044, 0.121]	7.60%	0.088*** [0.049, 0.128]	4.79%	0.115*** [0.073, 0.156]	5.57%
Anxiety	0.069*** [0.036, 0.102]	9.69%	0.074*** [0.040, 0.107]	5.58%	0.096*** [0.060, 0.132]	5.62%
ADHD	0.033** [0.012, 0.054]	5.61%	0.035** [0.014, 0.057]	2.64%	0.046*** [0.020, 0.072]	3.87%

Note. Each column presents the indirect effects of excessive digital device use (EDDU) mediating the relationship between ACE classes and mental health outcomes (depression, anxiety, ADHD), estimated using the Karlson-Holm-Breen (KHB) method. For each outcome, the table displays the estimated indirect effect (with 95% confidence intervals in brackets) and the proportion of the total effect that is mediated (%). Low ACEs Exposure serves as the reference group for ACE classes. All models control for age, gender, race, guardian age, guardian education attainment, family structure, poverty level, whether born in the US, and survey year. All analyses account for the NSCH's complex sampling design

*** $p < .001$, ** $p < .01$, * $p < .05$

The relatively lower EDDU risk in the EFH group likely reflects differences in family dynamics and social contexts rather than economic resources alone. Despite experiencing similar or higher levels of economic hardship, adolescents in the CDS and PAE groups face additional stressors (e.g., community violence and discrimination) that may increase digital media use as a coping mechanism or escape. Additionally, family structure differences characterizing the EFH group might influence parental monitoring patterns. While single parenthood might suggest reduced supervision, it may also entail increased parentification of adolescents, potentially limiting leisure screen time due to increased household responsibilities [65]. Furthermore, the psychological impacts of discrimination and community violence (more prevalent in CDS and PAE) may specifically increase motivation for seeking online social connection and validation [17, 64], driving higher digital use in these groups compared to the EFH group, whose stressors are predominantly structural rather than social-environmental.

It seems there exists a gradient association between ACE classes and the three disorders, with PAE typically exhibiting the strongest associations, followed by CDS and EFH. This pattern is consistent with a cumulative impact of multiple adversities, where greater exposure to diverse ACEs is associated with increased risk for psychopathology [3]. While this gradient pattern could potentially reflect synergistic effects, where the impact of combined adversities exceeds the sum of their individual effects [22, 66], the current analysis cannot definitively distinguish between cumulative versus synergistic mechanisms. The greater psychopathology risk observed in the PAE group may simply reflect their exposure to a higher number of adversities rather than true interaction effects. Nevertheless, these findings highlight that adolescents facing multiple adversities across different domains show particularly elevated psychopathology risk, potentially reflecting the impact of stress across multiple biological systems, including stress response regulation, neuroplasticity, and development of adaptive coping abilities [3, 32, 33].

Notably, for ADHD, the CDS group demonstrated a comparable association strength to the PAE group. This finding is particularly meaningful considering that the PAE group experienced a substantially broader range of adversities than the CDS group. The fact that adolescents exposed primarily to community violence and discrimination showed attention difficulties similar to those with pervasive adversity exposure suggests that these specific types of adversity may have particularly strong impacts on attention systems, even in the absence of other family-level adversities. This pattern aligns with McLaughlin and Lambert's research on threat-based experiences affecting executive functioning [67]. From a neurobiological perspective, exposure to

community violence and discrimination may lead to adaptations in brain regions associated with threat detection while affecting prefrontal cortex functions responsible for attentional control [68], manifesting as symptoms that overlap with ADHD [69]. This finding underscores the importance of targeted intervention approaches for adolescents experiencing community-level stressors, as their impact on attention regulation may be disproportionately strong even when occurring without the constellation of multiple adversities seen in the PAE group.

Overall, the differentiated association patterns between ACE classes, digital device use, and psychopathology indicate that ACE effects may be pattern-specific, supporting the DMAP model. This insight has significant implications for developing more precise and effective screening tools and intervention strategies.

Intermediate role of excessive digital device use

Another core contribution of this study is the confirmation of EDDU as a partial intermediate variable between ACEs and mental health problems, providing an actionable behavioral pathway for understanding ACE impact mechanisms. All indirect effects reached statistical significance, supporting our fifth hypothesis. This finding extends beyond the biological and psychological intermediate mechanisms that traditional ACE research has primarily focused on [5]. Compared to neuroscience indicators, digital media use is more readily identifiable by parents, teachers, and health-care providers and more amenable to modification through behavioral interventions.

I identified two distinct patterns in the indirect effects. First, the proportion of EDDU's indirect effects was stronger for internalizing problems (depression and anxiety) than for externalizing issues (ADHD), a finding consistent with previous research documenting stronger associations between screen time and depressive symptoms [44, 45]. The virtual interaction displacement hypothesis posits that digital use may deprive adolescents of opportunities to practice and develop social skills by reducing face-to-face social interactions, thereby increasing the risk of social anxiety and loneliness. Given that adolescence represents a critical window for socioemotional development, such displacement effects may be particularly detrimental [6, 10]. The displacement mechanism theory suggests that EDDU may be a substitute for core activities that promote healthy development [15, 42]. These activities are crucial for developing emotional regulation capabilities and, when displaced by digital media use, may specifically impact emotional health. Screen use's interference with sleep (through blue light exposure, content-induced arousal, and reduced sleep duration) has been

established as a significant risk factor for depression and anxiety [70].

The second key pattern reveals that indirect effects vary by ACE class. The EFH group exhibited the highest indirect proportions, particularly for anxiety (9.69%) and depression (7.60%). This may reflect adolescents' specific vulnerabilities in environments characterized by economic hardship and family instability [71]. In contrast, the CDS group showed the lowest indirect proportion for ADHD (2.64%), suggesting that community violence and discrimination may primarily affect attention networks through direct neurobiological mechanisms. This aligns with research indicating that early threat exposure may directly alter prefrontal cortex development and attention network functioning [8, 68, 72]. In other words, for this group, EDDU may represent more of a concomitant phenomenon of ACE effects rather than a primary transmission mechanism. This nuanced distinction carries significant implications for intervention strategies, indicating that different types of ACEs may require distinct intervention priorities. The PAE group demonstrated moderate indirect proportions but the highest absolute indirect effect values (0.046 to 0.115), potentially reflecting how the broad developmental impact of multiple adversities is challenging to capture fully through a single intermediate mechanism.

My findings suggest the existence of a “risk spiral”: adolescents experiencing ACEs may be more susceptible to developing EDDU behaviors, which may, in turn, increase the risk of psychopathology by affecting cognitive development, social skills, and emotional regulation capabilities. This could lead to further dependence on digital media as a coping strategy, creating a negative feedback loop. This aligns with the perspective of the development cascade model [73].

Implications

In theoretical terms, my results support the concept of ACE heterogeneity, confirming that different types of ACEs may influence psychopathology through distinct pathways, consistent with the DMAP model's distinction between threat-based and deprivation-based adversities. Furthermore, identifying EDDU as a behavioral intermediate mechanism provides a novel perspective for understanding ACE influences.

For clinical practice, my research indicates that ACE screening should consider specific patterns of different ACE types rather than simple cumulative scoring. Digital media usage patterns may serve as early visible indicators of ACE impacts, warranting attention from clinicians, educators, and parents. However, interventions must carefully consider the functions that digital device use serves for adolescents

facing adversity. For youth experiencing community violence or family dysfunction, digital environments may represent essential, safe spaces for social connection, identity exploration, and emotional support that are unavailable in their physical environments. Any intervention approach must first assess the adaptive value of digital engagement before considering reduction strategies. Rather than focusing primarily on reducing usage time, interventions should optimize digital experiences and build media literacy while addressing the underlying adversities and ensuring access to safe alternatives. For instance, approaches for the CDS group should acknowledge the potential protective role of online communities for youth facing discrimination while promoting healthy engagement patterns. Similarly, interventions for adolescents in the EFH group should address family support and economic resources as primary targets, with digital use addressed contextually rather than as an isolated behavior.

Macro-level policies should prioritize addressing root issues such as economic inequality, community violence, and racial discrimination. Digital policies should focus on promoting digital literacy education, creating safer online environments, and encouraging healthy use without stigmatizing the adaptive digital engagement of vulnerable youth. Additionally, mental health service policies should increase accessibility for high-risk adolescents and ensure cultural sensitivity in service delivery while recognizing the complex role of technology in adolescents' coping and social development.

Limitations

I must caution readers about several limitations. First, the cross-sectional design fundamentally restricts causal inference, as the temporal ordering essential for establishing causal pathways cannot be definitively determined. Although ACEs conceptually precede current behaviors, bidirectional relationships between EDDU and psychopathology remain plausible. Second, this study relies on guardians' reports, possibly introducing reporting bias. Guardians might underestimate adversities or screen time experienced by their children or be reluctant to acknowledge specific sensitive issues. Third, the NSCH data lacks some key ACE types, such as physical abuse and sexual abuse. These severe forms of ACEs have particularly significant impacts on adolescent development, and their omission may lead to underestimation of certain risk types. Finally, while LCA offers advantages over cumulative scoring approaches, it also has limitations. This approach cannot account for the effects of developmental timing. The same adversity likely has different effects depending on the child's developmental stage, yet the current analysis treats adversities as static

events. Additionally, the identified latent classes reflect differences in the types and the number of ACEs experienced. The observed gradient pattern makes it difficult to disentangle whether observed associations stem from qualitative differences in adversity types or quantitative differences in overall adversity burden. This confounding of type and number remains a methodological challenge in understanding the specific mechanisms linking different ACE patterns to outcomes.

Conclusion

This study reveals the complex relationships among ACEs, EDDU, and adolescent psychopathology through analysis of a nationally representative sample of US adolescents. I identified four conceptually meaningful ACE exposure patterns, confirmed the differentiated impacts of various ACE types on adolescents, and systematically validated EDDU as an intermediate mechanism connecting ACEs with mental disorders for the first time. These findings enrich our understanding of ACE impact mechanisms and provide actionable behavioral pathways for intervention.

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Author contributions Zékai (Zachary) Lu: Writing - original draft, Writing - review & editing, Visualization, Conceptualization, Formal analysis, Software, Methodology, Resources.

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Data availability The data used in this study can be found at the Data Resource Center for Child & Adolescent Health: <https://www.childhealthdata.org/learn-about-the-nsch/NSCH>.

Declarations

Competing interests The authors declare no competing interests.

Conflicts of interest The author declare that there is no conflict of interest regarding the publication of this paper.

Ethical consideration This study involves the analysis of publicly available data from the National Survey of Children's Health (NSCH),

which can be accessed at the Data Resource Center for Child & Adolescent Health. Since the data are publicly available and do not contain any identifiable information, the research is exempt from ethical review according to the Tri-Council Policy Statement in Canada.

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