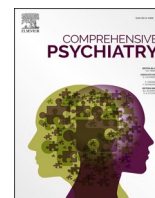




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## Digital engagement profiles and binge eating symptoms in adolescents: A person-centred, longitudinal analysis<sup>☆</sup>

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## ABSTRACT

**Background:** Binge eating symptoms emerge in early adolescence and are clinically meaningful below diagnostic thresholds. Digital media engagement may be relevant, yet most studies rely on aggregate screen time and rarely separate patterns of use from addiction-like features. This study tested whether screen use profiles and social media addiction risk were associated with binge eating symptom indicators in a large longitudinal cohort.

**Methods:** Data were drawn from the Adolescent Brain Cognitive Development (ABCD) Study at Time 3 (T3;  $n = 10,465$ ; ages 10–13 years) and Time 5 (T5;  $n = 9257$ ; ages 12–16 years). Latent profile analysis of six screen modalities derived screen use profiles. Social media addiction risk was classified using the Social Media Addiction Questionnaire. Four binge eating symptom indicators were assessed at each wave using item-level data from the Kiddie Schedule for Affective Disorders and Schizophrenia. Binomial logistic regression models tested associations, adjusting for sex, family conflict, and school environment.

**Results:** Two profiles were supported: High Screen Usage (44.5%) and Low Screen Usage (55.5%). At T3, High Screen Usage and higher social media addiction risk were each associated with higher odds of all symptom indicators after adjustment. At T5, High Screen Usage remained associated with binge-related distress, binge eating behaviour, and recurrent binge eating, while social media addiction risk differentiated all four symptoms. Family conflict showed the strongest associations, whereas a more positive school environment was associated with lower odds of symptoms.

**Conclusions:** Higher overall screen engagement and addiction-like social media use were independently associated with binge eating symptoms across early to mid-adolescence. Social media addiction risk showed more consistent symptom differentiation than screen use profiles, suggesting engagement quality may be more clinically informative than duration.

**Abbreviations:** ABCD, Adolescent Brain Cognitive Development Study; AIC, Akaike Information Criterion; AWE, Approximate Weight of Evidence; BED, Binge-Eating Disorder; BIC, Bayesian Information Criterion; CI, Confidence Interval; CLC, Classification Likelihood Criterion; CVUP, Class-Varying Unrestricted Parameterisation; DSM-5, Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition; FES, Family Environment Scale; h, Entropy (classification precision index); IRT, Item Response Theory; KIC, Kullback Information Criterion; K-SADS-PL, Kiddie Schedule for Affective Disorders and Schizophrenia – Present and Lifetime Version; OR, Odds Ratio; RQ, Research Question; SCRTV, Total Television-Related Screen Use (combined TV modalities into one variable); SD, Standard Deviation; SMAQ, Social Media Addiction Questionnaire; SRPF, School Risk and Protective Factors; STQ, Screen Time Questionnaire; T3, Time 3 (study wave/assessment); T5, Time 5 (study wave/assessment); US, United States; S1, Characteristics of binge eating (e.g., eating too fast); S2, Binge-eating-related distress; S3, Engagement in binge eating behaviour; S4, Recurrent binge eating ( $\geq 1$  episode/week for 3 months).

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## 1. Introduction

Binge eating and loss-of-control eating are clinically meaningful presentations during adolescence, often emerging before full diagnostic criteria can be reliably assessed [1,2]. These behaviours may also function as early markers of eating-disorder risk and, for some individuals, precede the later emergence of full-syndrome pathology [2]. Binge eating disorder (BED) is characterised in the DSM-5-TR by recurrent binge eating episodes (consumption of an objectively large amount of food in a discrete period of time) accompanied by marked distress and associated features (e.g., eating rapidly, eating when not hungry), occurring at least once per week for three months, in the absence of regular compensatory behaviours [3].

Community data indicate a median age of onset of approximately 12.6 years for binge eating episodes in nationally representative samples [4], yet BED has traditionally been characterised as a disorder of late adolescence and adulthood [3]. Converging evidence challenges this framing. A narrative review estimated the point prevalence of BED at one to 5% among community youths aged 10–24 years [1], binge eating has been reported at a lifetime prevalence of approximately 2% in children as young as six [5], and loss-of-control eating assessed at age 10 prospectively predicts incident BED four years later [2]. Taken together, these findings suggest that the developmental window for clinically meaningful binge eating risk begins well before the diagnostic threshold is typically applied.

Digital media engagement is one plausible and prevalent candidate. Three pathways connect it to binge eating specifically. Exposure to idealised body content on social media drives social comparison, generating body dissatisfaction and negative affect, both well-established triggers for loss-of-control eating [6,7]. Screens are also frequently used as a way of escaping or managing emotional distress, a pattern that parallels the emotional regulation function binge eating often serves [8,9]. Finally, impulsivity is a well-established risk and maintenance factor for binge eating [9], and addiction-like digital use has been independently linked to poorer impulse control and heightened food cravings, pointing to a shared vulnerability [9]. Together, these pathways provide a coherent basis for examining digital media engagement as a specific risk factor for binge eating rather than disordered eating broadly.

Growing empirical evidence supports this positioning. A pre-registered systematic review and meta-analysis of 32,295 participants found that problematic internet use was significantly associated with eating disorder psychopathology, body dissatisfaction, and dietary restraint across multiple independent samples, with effects small but consistent and likely to accumulate across the extended engagement periods characteristic of adolescence [10]. At the modality level, social media use has been associated with disordered eating attitudes and behaviours in adolescents across multiple independent cohorts [7], and a meta-analysis examining specific digital modalities found that both television and social media contributed independently to disordered eating in young people, with individual patterns of use functioning as a key moderating factor [11]. Cross-sectional evidence from a sample of 653 adolescents demonstrated that high social networking use was associated with nearly double the odds of disordered eating (OR = 1.88), and that addiction-like social networking behaviour was associated with OR = 2.04, a larger effect than time spent alone, suggesting that the quality of engagement matters beyond volume [12]. Experimental evidence similarly indicates that the combination of high social media use with exposure to weight-loss content was associated with significantly more binge eating days than either factor alone, demonstrating that content type and volume interact in shaping eating-related risk [8].

However, two limitations constrain the current evidence base. First, most existing studies rely on aggregate screen time (i.e., total daily hours collapsed across activities) as the primary exposure metric [13,14]. This approach obscures meaningful heterogeneity at the modality level and cannot distinguish adolescents whose engagement is broadly elevated

across multiple screen activities from those whose use is concentrated in specific domains.

Second, time-based indicators do not capture qualitative differences in the nature of engagement. In particular, the addiction-like features (salience, mood modification, tolerance, withdrawal, conflict, and relapse) that characterise a subset of users and are consistently associated with poorer mental health outcomes [15,16]. The distinction between high usage and high-risk usage has direct implications for identifying which adolescents are most vulnerable. To the best of the authors' knowledge, no prior study has simultaneously examined multi-modal screen use profiles derived from a person-centred approach and social media addiction risk as dual predictors of binge eating symptom indicators in a longitudinal adolescent cohort.

### 1.1. Contextual factors: family, school, and the cyberdevelopmental framework

Understanding the relationship between digital media use and binge eating in adolescence requires situating digital behaviour within its broader developmental context. Adolescents do not enter digital spaces as a blank slate; offline environments, particularly the family and school contexts, shape and are shaped by online experiences in interconnected ways [16]. The Cyberdevelopmental Framework [16] offers a useful theoretical scaffold here, proposing that adolescents' digital trajectories and associated health outcomes reflect the interaction between individual characteristics, the nature of digital engagement, and the broader offline developmental context. The present study draws on this framework to examine family and school environments as contextual covariates alongside digital engagement indicators.

Family conflict is a well-established correlate of both binge eating and problematic screen use in young people. Family relational strain has been consistently associated with loss-of-control eating and binge eating symptoms in youth, partly via depressive symptomatology [17], consistent with the interpersonal model of binge eating [18]. Family conflict also predicts greater adolescent screen use, potentially via escape- and avoidance-based coping [19]. The school environment is similarly implicated: support school contexts (e.g., school connectedness/safety) has been associated with lower binge eating and related behaviours [20,21], and may be associated with more structured patterns of discretionary time, including screen use [22]. Both contextual factors are therefore plausible confounders of the primary associations of interest and are included as a priori covariates in the present study.

### 1.2. The present study

Despite growing evidence linking digital media use to binge eating symptoms in adolescents, several gaps remain. Most existing studies rely on aggregate screen time rather than examining modality-specific patterns or addiction-like dimensions of engagement, limiting their ability to identify which patterns of use carry the greatest risk. Existing research has typically treated adolescent screen users as a homogeneous group, obscuring meaningful individual differences in engagement. Yet, where person-centred methods have been applied, between two and five distinct profiles of digital engagement emerge in young people [23–27]. Younger adolescents, a key developmental window for the emergence of binge eating symptoms, remain underrepresented in longitudinal work [28]. Finally, few studies have simultaneously examined screen use profiles, social media addiction risk, and binge eating symptom indicators within a prospective design that adjusts for contextual covariates.

The present study addresses these gaps using data from the Adolescent Brain Cognitive Development (ABCD) Study, a large, longitudinal, population-based cohort of United States (US) children followed from early to mid-adolescence. Although engagement is assessed via the Screen Time Questionnaire, the present study moves beyond aggregate screen time through two methodological decisions: the application of

latent profile analysis (LPA) to identify modality-specific patterns of engagement across six digital activities, and the inclusion of the Social Media Addiction Questionnaire to capture the compulsive, preoccupied quality of engagement rather than duration alone. LPA is a person-centred statistical method that identifies subgroups of individuals who share similar patterns across a set of indicators, enabling the detection of meaningful differences in the nature and intensity of engagement that variable-centred approaches obscure [29,30]. LPA-derived screen use profiles are then examined alongside social media addiction risk as dual predictors of binge eating symptom endorsement at two longitudinal timepoints, specifically, Time 3 (T3; ages 10–13 years) and Time 5 (T5; ages 12–16 years), while adjusting for sex, family conflict, and school environment.

The study addresses the following research questions:

**RQ1:** What is the optimal number and nature of screen use profiles among adolescents, based on patterns of engagement across digital modalities?

**RQ2:** What proportion of adolescents are classified into each screen use profile, and how do profiles differ in levels of engagement across indicators?

**RQ3:** Do screen use profile membership and social media addiction risk differentiate adolescents on binge eating symptom indicators at T3, after adjusting for sex, family conflict, and school environment?

**RQ4:** Do screen use profile membership and social media addiction risk differentiate adolescents on binge eating symptom indicators at T5, after adjusting for sex, family conflict, and school environment?

By examining distinct patterns of digital engagement alongside an addiction-specific social media measure and binge eating symptom indicators derived from a validated clinical interview, this study contributes to a more nuanced understanding of the digital correlates of disordered eating in early-to-mid adolescence. Findings carry direct relevance for clinicians, educators, and policymakers seeking to identify and support adolescents at risk.

## 2. Methods

### 2.1. Participants

Participants were drawn from the ABCD study, a large, longitudinal cohort study designed to examine brain, behavioural, and health development in US children. The ABCD study recruited participants using epidemiologically informed school-based sampling strategies to enhance national representativeness. Baseline recruitment occurred when children were aged 8–10 years (mean = 11.3;  $SD = .62$ ), with annual follow-up assessments thereafter.

The present study utilised data from T3 (age range between 10 to 13 years; mean 12.07 ( $SD = .67$ ); mean weight was 108.38 (in pound;  $SD = 32.66$ )) and T5 (age range between 12 to 16 years; mean 14.17 ( $SD = .71$ ); mean weight was 136.55 (in pound;  $SD = 39.41$ )) of the ABCD Study (Release 6.0). At T3, 10,973 participants had available screen use data. Sociodemographic characteristics of the analytic T3 sample are presented in Table 1. Detailed information regarding ABCD recruitment procedures and measurement protocols is available in the ABCD data documentation [31].

After excluding cases with missing screen use information and implausible extreme values, the final LPA sample comprised 10,491 participants. Of these, 10,465 participants had complete data for the T3 regression analyses. At T5, 9,739 participants completed follow-up assessments, representing 7.2% attrition from the T3 LPA sample. After applying complete-case inclusion criteria for covariates and outcome variables, the final T5 regression sample comprised 9,257 participants.

As the present study utilised an existing longitudinal cohort, sample size was determined by the ABCD Study design rather than prospective

recruitment. For the rarest outcome at T3 (recurrent binge eating; 1.5%,  $n = 156$ ), the fully adjusted logistic regression models included seven parameters, yielding approximately 22 events per parameter. This exceeds recommended thresholds (10–20 events per parameter) for stable logistic regression estimation. However, the High Risk social media subgroup comprised 100 participants and included seven outcome events; accordingly, contrasts involving this subgroup are interpreted cautiously. Further details regarding power considerations are provided in the Supplementary file (see Appendix A).

### 2.2. Measures

#### 2.2.1. *Kidde schedule for affective disorders and schizophrenia: Present and lifetime version (KSADS-PL): Individual questions for children (eating disorders)*

The KSADS-5 [32] is a semi-structured, computerized interview designed to assess symptoms of psychiatric disorders in children and adolescents in accordance with DSM-5 criteria. Within the ABCD Study, the KSADS-5 eating disorder module captures the presence, frequency, and associated features of disordered eating behaviours, including binge eating and related distress. In Release 6.0 of the ABCD dataset [33], formal algorithm-derived eating disorder diagnoses were removed due to concerns regarding underestimation of prevalence, and researchers are advised to derive symptom-based indicators from the underlying item-level data rather than relying on diagnostic flags. Accordingly, the present study operationalised BED-related outcomes using individual symptom endorsements rather than a clinician-confirmed diagnostic variable.

Participants were asked, “In the past two weeks, how often have you had eating binges when you lost control of your eating and ate way more than you needed because you were unable to stop yourself from eating?” Responses were recorded on a Likert scale ranging from 0 to 4, with responses indicating any symptom presence (scores  $\geq 1$ ) were coded as endorsing binge eating behaviour. Additional binary KSADS items were used to derive indicators reflecting core DSM-5 BED features (see

**Table 1**  
Baseline Characteristics of the Analytic Sample (T3;  $n = 10,491$ ).

Descriptive	<i>n</i>	%
<i>Sex</i>		
Male	5507	52.5
Female	4984	47.5
<i>Race/Ethnicity</i>		
White (incl. Western/Eastern European)	6196	59.1
Hispanic/Latino	1468	14
African American (incl. Afro-Caribbean)	1333	12.7
Asian (East, South, Southeast)	369	3.5
American Indian/Alaska Native	67	0.6
Native Hawaiian/Pacific Islander	19	0.2
Multiracial/Multiethnic	302	2.9
<i>Other Ethnicity</i>		
Not Reported	49	0.5
660	6.3	
<i>Caregiver Education</i>		
Up to high school (no diploma)	444	4.3
High school diploma/GED	903	8.7
Some college	3239	31.1
Bachelor's degree	2246	21.6
Graduate/professional degree	3587	34.4
<i>Household Income (USD)</i>		
< 25,000	1082	11.3
25,000–50,000	1187	12.4
50,000–75,000	1260	13.1
75,000–100,000	1329	13.8
100,000–200,000	3321	34.6
> 200,000	1429	14.9

*Note.* Percentages are based on available data for each variable. Minor variation in total *n* reflects variable-level missingness. Caregivers reported youth race (check-all-that-apply) and Hispanic/Latino ethnicity using standard US demographic questions; categories shown are harmonised for reporting.

Table 2), including characteristics of binge eating (S1), distress related to binge eating (S2), engagement in binge eating behaviours (S3), and recurrent binge eating occurring at least once per week for three months (S4). Each outcome was coded dichotomously (0 = absent, 1 = present) and analysed as a binary indicator in regression models at T3 and T5.

### 2.2.2. Screen Time Questionnaire (STQ; Youth)

The STQ was developed for the ABCD study to assess adolescents' screen use across various activities, including television, video streaming, gaming, texting, social media, and video chatting. Participants reported weekday and weekend use in categories ranging from less than 30 minutes to four or more hours (e.g. "Visit social networking sites like Facebook, Twitter, Instagram, etc.?" ) For the present study, weekday and weekend responses were aggregated into broader variables (e.g., all television-related use combined into a 'SCRTV' variable; see Supplementary Table S1). Additionally, participants were asked "Do you have at least one social media account?" to gather social media usage. The STQ has demonstrated good reliability in assessing screen use patterns and their associations with mental health outcomes [34–37].

**Table 2**  
KSADS-5 BED Behaviour and Prevalence at T3 and T5.

Symptom	Question	Abbreviation	T3 n (%)	T5 n (%)
Characteristics of binge eating	Note below all the things that are true when you binge eat: I eat much more rapidly than normal. I eat a lot even though I am not hungry. I eat alone because I am embarrassed. I feel disgusted or guilty after binge eating. I feel depressed after binge eating. I feel like I have no control when I binge eat.	S1	225 (2.1%)	392 (3.7%)
Distress related to binge eating	How much discomfort or distress does binge eating cause you? <sup>a</sup>	S2	292 (2.8%)	424 (4.0%)
Engaging in binge eating behaviours	In the past two weeks, how often have you had eating binges, when you lost control of your eating and ate way more than you needed, because you were unable to stop yourself from eating?	S3	745 (7.1%)	663 (6.3%)
Recurrent binge eating ( $\geq 1 \times$ /week for 3 months)	On average, did you binge eat at least once a week for at least three months?	S4	156 (1.5%)	285 (2.7%)

*Note.* Percentages reflect the proportion of participants endorsing each symptom at each timepoint. Outcomes represent symptom presence rather than formal DSM-5 diagnoses of binge eating disorder. BED was based on the following criteria: binge eating present, frequency of binge-eating at least once a week for at least 3 months (or 12 weeks), at least three characteristics of binge-eating, distress associated with binge-eating present, no current compensatory behaviour and does not meet criteria for current diagnosis of bulimia nervosa or anorexia nervosa. Binge-eating behaviour was based on the binge-eating behaviour question. Any binge-eating behaviour (frequency of one or more in the past two weeks) was coded as an affirmative for binge-eating behaviour. <sup>a</sup> Participants were asked to select a response ranging from 0 to 10. The Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS-5) assessment used a response of 3 or higher as the cutoff to indicate having distress with binge eating.

### 2.2.3. School risk and protective factors (SRPF)

School environment was assessed using the SRPF (School Environment subscale), administered as part of the ABCD youth-report interview protocol. This subscale is derived from the PhenX School Risk and Protective Factors protocol [38] and comprises six items assessing adolescents' perceptions of teacher support, fairness, recognition, and opportunities for participation in classroom decision-making (e.g., "In my school, students have lots of chances to help decide things like class activities and rules," "My teacher notices when I am doing a good job and lets me know about it"). Items are rated on a four-point Likert scale and averaged to form a composite score, with higher values indicating a more supportive and positive school environment. The School Environment subscale has previously demonstrated acceptable psychometric performance in large adolescent samples, with reported internal consistency estimates of approximately  $\alpha = 0.60$  [39].

### 2.2.4. Family environment scale (FES)

Family conflict was assessed using the Conflict subscale of the FES [39]. The FES is a multidimensional measure of family social climate designed to assess relational processes, personal growth, and system maintenance within the family environment. The Conflict subscale comprises nine dichotomous (true/false) items assessing the extent of openly expressed anger, criticism, and discord among family members (e.g., frequent arguments, loss of temper, and expression of negative emotions) [40]. Items are summed following appropriate reverse coding, with higher scores indicating greater levels of family conflict. In the ABCD study, this youth-report subscale mirrors the parent-report version and has been administered annually since baseline. The Conflict subscale has demonstrated acceptable reliability and strong external validity in adolescent samples [38]. In the present study, analyses were conducted using the composite family conflict score provided in the ABCD dataset.

### 2.2.5. Social media addiction questionnaire (SMAQ)

Problematic social media use was assessed at T3 using the SMAQ, a six-item self-report measure derived from the Bergen Social Media Addiction Scale [15]. The scale assesses core addiction-related experiences, including salience, mood modification, tolerance, withdrawal, conflict, and relapse. Items are rated on a five-point Likert scale reflecting frequency of experiences over the past year, with higher scores indicating greater addiction risk. Item responses were summed to generate a total score among participants who reported having at least one social media account. Internal consistency has demonstrated acceptable reliability and strong external validity in adolescent samples [41]. Prior research has supported the scale's reliability, unidimensional structure, and validity using item response theory (IRT) methods [15,42].

For analytic purposes, participants were classified into three groups. Adolescents who reported not having a social media account were categorised as non-users. Among users, SMAQ item responses were summed to generate a total score (range 6–30). Consistent with item response theory-derived cut-offs established in prior validation research [42], a raw score of  $\geq 26$  (corresponding to approximately +2 SD above the latent trait mean) was used to classify high-risk social media use. Users scoring below this threshold were classified as low risk. This three-level variable (non-user, low-risk user, high-risk user) was included as a primary predictor in regression analyses.

## 2.3. Procedure

The present longitudinal study used pre-existing data from the ABCD Study, a large, multisite, population-based cohort conducted in the U.S. Ethical approval for secondary data analysis was granted by the [removed for blinding] University Human Research Ethics Committee (HRE27145), and data access was approved by the National Institute of Mental Health (NIMH; 18,203).

**Table 3**  
Tidy LPA Model Solutions.

Model	Classes (n)	AIC	BIC	AWE	CLC	KIC
1	1	202,769.8	202,856.9	203,002	202,747.8	202,784.8
1	2	190,760.8	190,898.7	191,129.7	190,724.7	190,782.8
1	3	185,955.5	186,144.2	186,461.1	185,905.4	185,984.5
1	4	185,969	186,208.5	186,611.7	185,904.2	186,005
1	5	182,309.7	182,600.1	183,089	182,231.1	182,352.7
1	6	181,084.9	181,426	182,000.8	180,992.3	181,134.9
2	1	202,769.8	202,856.9	203,002	202,747.8	202,784.8
2	2	153,365.8	153,547.3	153,851.9	153,317.7	153,393.8
3	1	192,785.2	192,981.2	193,310.2	192,733.2	192,815.2
3	2	185,466.8	185,713.6	186,128.4	185,400.8	185,503.8
3	3	185,480.9	185,778.5	186,280.0	185,399.9	185,524.9
3	4	186,319.4	186,667.8	187,255.5	186,224.1	186,370.4
3	5	182,388.5	182,787.7	183,461	182,279.4	182,446.5
3	6	180,674.4	181,124.4	181,883.3	180,551.4	180,739.4
6	1	192,785.2	192,981.2	193,310.2	192,733.2	192,815.2
6	2	149,444	149,843.2	150,515.6	149,335.8	149,502

Note. An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests the best solution is Model 6 with 2 classes.

**Table 4**  
Standardised Screen Usage Scores and Baseline Scores Across Profiles.

Variables	High Screen Usage	Low Screen Usage
n	4673	5818
Online video (z)	0.414	-0.333
Video games (z)	0.503	-0.306
Streaming TV & movies (z)	0.38	-0.305
Texting (z)	0.525	-0.421
Video chat (z)	0.503	-0.404
Social media (z)	0.555	-0.446

Note. Z-scores reflect standardised engagement levels relative to the ABCD sample mean.

**Table 5**  
Final (Model 3) Odds Ratios for BED Symptoms at T3.

Symptom	Predictor	OR	95% CI	p
S1 Characteristics	High Screen Usage – Low Screen Usage	1.38	[1.02, 1.86]	0.034
	Low-risk SM – Non-User	1.50	[1.10, 2.04]	0.011
	High-risk SM – Non-User	4.42	[2.18, 8.98]	<0.001
S2 Distress	High Screen Usage – Low Screen Usage	1.59	[1.22, 2.06]	<0.001
	Low-risk SM – Non-User	1.35	[1.03, 1.77]	0.028
	High-risk SM – Non-User	3.13	[1.57, 6.24]	0.001
S3 Binge eating	High Screen Usage – Low Screen Usage	1.45	[1.23, 1.71]	<0.001
	Low-risk SM – Non-User	1.27	[1.07, 1.50]	0.006
	High-risk SM – Non-User	2.21	[1.28, 3.81]	0.004
S4 Recurrent binge	High Screen Usage – Low Screen Usage	2.55	[1.74, 3.74]	<0.001
	Low-risk SM – Non-User	1.40	[0.95, 2.04]	0.085
	High-risk SM – Non-User	3.29	[1.39, 7.76]	0.007

Note. All models adjust for sex, family conflict, and school environment. OR = odds ratio; SM = social media.

Adolescents self-reported their screen-based behaviours at T3 using the ABCD STQ, which assessed daily engagement across multiple digital activities (e.g., social media, video gaming, online videos). These indicators were used to derive screen use profiles via latent profile analysis. Social media addiction risk was assessed at T3 using the SMAQ, with participants classified as non-users, low-risk users, or high-risk

**Table 6**  
Final (Model 3) Odds Ratios for BED Symptoms at T5.

Symptom	Predictor	OR	95% CI	p
S1 Characteristics	High Screen Usage – Low Screen Usage	1.21	[0.94, 1.55]	0.140
	Low-risk SM – Non-User	1.26	[0.97, 1.63]	0.085
	High-risk SM – Non-User	2.48	[1.16, 5.32]	0.019
S2 Distress	High Screen Usage – Low Screen Usage	1.45	[1.16, 1.80]	0.001
	Low-risk SM – Non-User	1.52	[1.21, 1.92]	<0.001
	High-risk SM – Non-User	3.14	[1.61, 6.11]	<0.001
S3 Binge eating	High Screen Usage – Low Screen Usage	1.36	[1.14, 1.62]	<0.001
	Low-risk SM – Non-User	1.23	[1.03, 1.47]	0.025
	High-risk SM – Non-User	3.21	[1.85, 5.59]	<0.001
S4 Recurrent binge	High Screen Usage – Low Screen Usage	1.40	[1.07, 1.83]	0.013
	Low-risk SM – Non-User	1.55	[1.17, 2.06]	0.002
	High-risk SM – Non-User	3.96	[1.91, 8.23]	<0.001

Note. All models adjust for sex, family conflict, and school environment.

users.

BED symptoms were assessed at T3 and T5 using youth-report items from the clinician-administered KSADS. Four BED-related symptoms were examined at each time point: characteristics of binge eating (e.g., eating too fast), distress related to binge eating, engaging in binge eating behaviours, and engaging in binge eating at least once per week for three months. Symptoms were coded as present or absent in accordance with KSADS scoring conventions. Branching logic within the KSADS interview was used to skip non-applicable follow-up items, resulting in structurally missing data for participants who did not endorse initial screening items. Covariates included sex, FES (family conflict), and SRPF (school environment), assessed at corresponding time points. Identical analytic procedures were applied at T3 and T5 to allow comparison of associations across waves.

2.4. Statistical approach

To identify adolescent screen use profiles, LPA was performed using the tidyLPA package in R Language and Environment for Statistical Computing [43]. LPA is a statistical modelling technique that identifies

unobserved subgroups within datasets by grouping individuals based on shared characteristics [30]. Profiles were constructed based on screen use behaviours, with model fit assessed using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Approximate Weight of Evidence (AWE), Classification Likelihood Criterion (CLC), Kullback Information Criterion (KIC), and entropy (h) values. Lower AIC and BIC values and entropy scores above 0.80 indicated stronger model fit and classification accuracy. Detailed fit indices and models are provided in Supplementary Tables S2 and S3.

To address RQ3 and RQ4, hierarchical binomial logistic regression analyses were conducted to examine whether screen use profiles and social media addiction risk differentiated adolescents on BED symptoms at T3 and T5. Separate regression models were estimated for each BED symptom at each time point: (S1) characteristics of binge eating (e.g., eating too fast), (S2) distress related to binge eating, (S3) engaging in binge eating behaviours, and (S4) engaging in binge eating at least once per week for three months. All outcomes were treated as binary indicators.

For each symptom and time point, predictors were entered in three steps. Step 1 included covariates. Step 2 added screen use profile membership. Step 3 added social media addiction risk (non-user, low-risk user, high-risk user). This hierarchical approach allowed for evaluation of the incremental contribution of screen use profiles and social media addiction risk over and above demographic and contextual factors. Identical model structures were applied at T3 and T5 to enable direct comparison of associations across time. Model fit was evaluated using likelihood ratio tests and McFadden's pseudo- $R^2$ . Odds ratios (ORs) with 95% confidence intervals (CIs) are reported. Full model outputs are provided in the Supplementary Materials.

### 3. Results

#### 3.1. Missing and cleaning the data

Missing data handling and data cleaning were conducted separately for the screen use LPA at T3 and the logistic regression analyses at T3 and T5. At T3, the initial sample comprised 10,973 participants. Participants with missing screen use data were excluded prior to LPA estimation. Item-level missingness across screen use indicators was low (<5% for all variables), and no imputation was performed. Inspection of screen use distributions identified implausible values; participants reporting screen use above the 99th percentile on any indicator were excluded ( $n = 427$ ) to minimise the influence of extreme and likely erroneous values. The final LPA sample comprised 10,491 participants.

Logistic regression analyses were conducted using participants retained in the LPA sample and with available outcome data. At T3, missingness on covariates was minimal (family conflict:  $n = 13$ ; school environment:  $n = 15$ ). Social media addiction risk was derived from the SMAQ. Participants reporting no social media use were classified as non-users. For participants reporting social media use, SMAQ scores were computed when at least two items were completed, with missing items mean-replaced. Participants with insufficient SMAQ data ( $n = 3$ ) or missing responses to the social media use screening item ( $n = 6$ ) were excluded, resulting in a final T3 regression sample of 10,465 participants. At T5, 9739 participants completed assessments. This reflects a loss of 752 participants (7.2%) from the T3 LPA sample due to follow-up attrition. After applying the same inclusion criteria and removing cases with missing covariate or outcome data, the final T5 regression sample comprised 9257 participants. This represents an 11.5% reduction from the T3 regression sample. Missing data were handled using complete-case analyses at each stage.

#### 3.2. Number of screen use profiles

To address RQ1, fit indices were compared across several LPA models (see Table 3). The class-varying unrestricted parameterisation

(CVUP) with two profiles initially demonstrated strong fit based on AIC, BIC, AWE, CLC, and KIC indices [44]. The entropy score for the CVUP two-profile model was 0.90, which exceeds the recommended threshold of 0.76, associated with greater than 80% correct classification, and is also above the threshold of 0.64, which corresponds to an estimated 30% probability of false classification, indicating strong classification accuracy [45].

#### 3.3. Size of profiles

To address RQ2, descriptive statistics (i.e., frequencies) were applied to the two profiles to observe the sample percentage in each profile. The sample distribution was split between 44.5% for Profile 1 ( $n = 4673$ ) and 55.5% for Profile 2 ( $n = 5818$ ).

#### 3.4. Profiles across the indicators

To address RQ2, Table 4 presents the standardised means (z-scores) for the four profiles, highlighting their distinct patterns of screen use across various digital applications (see Fig. 1). Profile 1 demonstrated consistently higher standardised scores across all screen usage indicators, with values generally ranging between approximately 0.3 and 0.6 standard deviations above the sample mean (see Table 4). Accordingly, this group was characterised as the High Screen Usage profile. In contrast, Profile 2 exhibited a uniform pattern of below-average engagement across all screen usage indicators, with standardised scores consistently falling within approximately 0.3 to 0.45 standard deviations below the sample mean. As such, this group was characterised as the Low Screen Usage profile.

#### 3.5. Binge eating disorder symptoms, screen use profiles, and social media addiction risk at T3

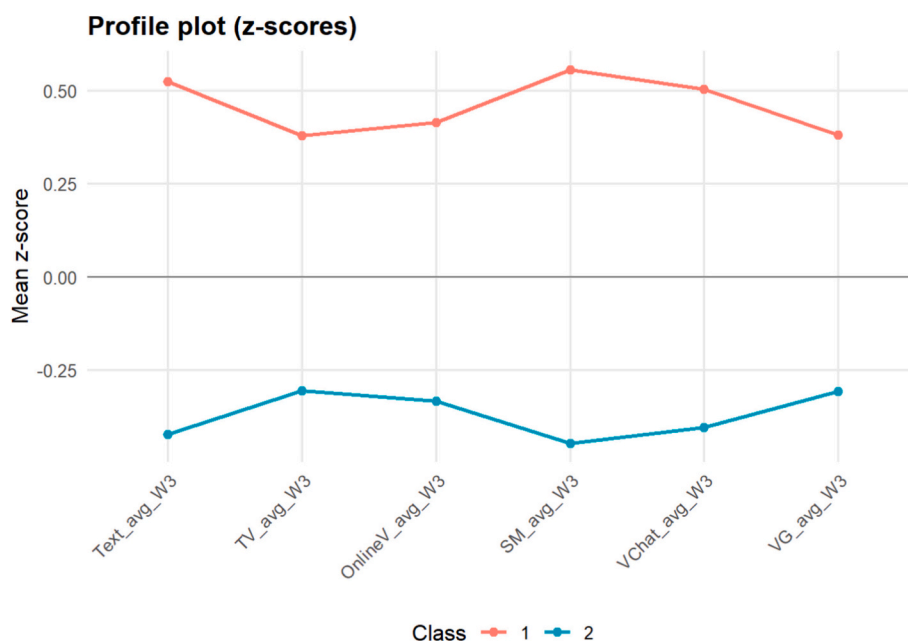
To address RQ3, hierarchical binomial logistic regressions were conducted to examine whether screen use profiles and social media addiction risk differentiated adolescents on four BED symptoms at T3, including characteristics of binge eating (S1), distress related to binge eating (S2), engaging in binge eating behaviours (S3), and engaging in binge eating at least once per week for three months (S4). All models controlled for sex, family conflict, and school environment. Full Model 1 and Model 2 results are provided in the Supplementary Materials and summarised in Table 5 (see Appendix B).

Across symptoms, higher family conflict was consistently associated with increased odds of symptom endorsement, whereas a more positive school environment was generally protective (see Appendix B in the Supplementary File). The addition of screen use profile (Step 2) and social media addiction risk (Step 3) significantly improved model fit across all four symptoms (all  $\Delta\chi^2$   $ps < 0.05$ ).

##### 3.5.1. Step 3 predictors across BED symptoms at T3

In the final step (Table 5), adolescents in the high screen use profile showed elevated odds of endorsing all BED symptoms relative to those in the low-use profile, with effects strongest for recurrent binge eating (S4). Social media addiction risk further differentiated symptom endorsement, with high-risk users consistently exhibiting the highest odds across symptoms. Low-risk users also showed elevated odds relative to non-users for most symptoms, though effects were smaller and less consistent.

Importantly, the strength of digital associations varied across BED symptoms. High screen use was least strongly associated with characteristics of binge eating (S1) and most strongly associated with behavioural outcomes, particularly engaging in binge eating behaviours (S3) and recurrent binge eating (S4). In contrast, social media addiction risk showed a graded pattern across symptoms, with the largest increases in odds observed for binge-eating-related distress (S2) and recurrent binge eating (S4).



**Fig. 1.** Standardised Screen Use Profiles at T3 Across Digital Applications Note. Values represent standardised means (z-scores) for each screen use indicator relative to the sample at T3. The High Screen Usage profile (Profile 1) demonstrated consistently above-average engagement across all indicators, whereas the Low Screen Usage profile (profile 2) demonstrated consistently below-average engagement. Indicators include texting, television/movies, online video, social media, video chat, and video games.

### 3.6. Binge eating disorder symptoms, screen use profiles, and social media addiction risk at T5

To examine whether associations observed at T3 persisted over time, hierarchical binomial logistic regressions were repeated at T5 using the same model structure and covariates. Across symptoms, family conflict remained positively associated with symptom endorsement, whereas school environment remained negatively associated with symptom endorsement. Compared with T3, female adolescents showed higher odds of endorsement across all four BED symptoms at T5. Associations between digital risk factors and BED symptoms differed across outcomes.

#### 3.6.1. Step 3 predictors across BED symptoms at T5

As shown in Table 6, high screen use (Profile 1) was associated with increased odds of distress related to binge eating (S2), engaging in binge eating behaviours (S3), and engaging in binge eating at least once per week for three months (S4), but was not associated with characteristics of binge eating (S1). Compared to non-users, high-risk social media users were associated with increased odds of all four BED symptoms. Higher odds of users at a low-risk of social media addiction compared to non-users were observed across BED symptoms, except for S1.

## 4. Discussion

The present study examined whether adolescents could be meaningfully differentiated by patterns of screen engagement across digital modalities, and whether screen use profile membership and social media addiction risk were associated with BED symptom indicators at two timepoints (i.e., T3 and T5). A person-centred latent profile approach supported a two-profile solution, distinguishing a High Screen Usage group (44.5%) and a Low Screen Usage group (55.5%) characterised by consistently higher versus lower engagement across online video, video games, streaming, texting, video chat, and social media.

In hierarchical models adjusting for sex, family conflict, and school environment, both High Screen Usage (vs Low) and social media addiction risk (non-user, low-risk, high-risk) differentiated endorsement of BED symptoms at T3, and associations were largely evident at T5.

Symptom patterns were not uniform. Specifically, at T5, High Screen Usage was not associated with the “characteristics of binge eating” (S1) indicator (eating too fast), whereas associations persisted for binge-eating-related distress (S2), binge eating behaviour (S3), and recurrent binge eating (S4); by contrast, social media addiction risk continued to differentiate all four outcomes. Across both waves, higher family conflict and a more positive school environment consistently differentiated symptom endorsement in the adjusted models, situating digital factors within a broader psychosocial context.

### 4.1. Screen use profiles of adolescents (RQ1–2)

Addressing RQ1–RQ2, the LPA supported a two-profile solution comprising a High Screen Usage group (44.5%) and a Low Screen Usage group (55.5%). The defining feature of this solution was that profiles were differentiated by overall intensity of screen engagement across modalities (online video, video games, streaming, texting, video chat, and social media), rather than by distinct modality-dominant patterns.

In practical terms, adolescents in the High Screen Usage profile reported consistently higher engagement across the full indicator set, whereas those in the Low Screen Usage profile reported consistently lower engagement across the same indicators, indicating that the primary source of between-person heterogeneity captured here was overall level of engagement across multiple screen activities. This pattern aligns with the broader person-centred screen use literature, in which the number of empirically derived groups varies across studies depending on the developmental period assessed, the indicators included, and whether models focus on cross-sectional patterns or longitudinal [46,47].

Within that broader range of findings, the present two-profile solution suggests that, in this cohort, adolescents were best differentiated by how much they engaged with screens across common activities, rather than by which single activity was most characteristic of their engagement. One plausible explanation is that adolescents often use screens for several purposes as part of everyday life, switching between entertainment, communication, and social media in ways that produce a coherent high-versus-low distinction when engagement is measured across activity categories [16]. This interpretation also aligns with wider

critiques in the screen time literature emphasising that global time-based metrics can summarise diverse online experiences into broad averages and may therefore be less sensitive to differences in what adolescents do online, why they engage, and the contexts under which engagement may be most relevant for psychosocial outcomes [13]. For the purposes of the present study, a high-versus-low distinction in overall engagement level is meaningful because it captures the broader intensity of screen exposure associated with BED symptom endorsement, rather than attributing risk to any single platform or activity.

#### 4.2. Screen use and BED symptoms at T3 (RQ3)

RQ3 examined whether screen engagement, operationalised via latent profile membership (High vs Low Usage), and social media addiction risk (Non-User, Low Risk, High Risk) each showed associations with four binary BED symptom indicators at T3 after adjusting for sex, family conflict, and school environment, and whether both digital variables contributed uniquely when modelled together.

The results suggested that higher screen engagement and greater social media addiction risk were each associated with higher concurrent odds of BED symptom endorsement, above and beyond sex, family conflict, and school environment. Consistent with Chu et al. [48], in which each additional hour of total screen time was associated with higher odds of binge eating and binge-related distress at two-year follow-up, the high-engagement profile was associated with higher symptom odds across all four indicators. The largest association was observed for recurrent weekly binge eating (S4); whether this reflects a meaningful pattern or is an artefact of the low base rate of this indicator (~1.5%), which raises the possibility of rare-event bias in logistic regression estimates, cannot be determined from this sample [49].

Social media addiction risk showed a graded pattern, with high-risk classification associated with substantially higher symptom odds than non-use across all indicators. The gradient is consistent with the possibility that problematic use captures features of compulsive or preoccupied engagement not indexed by time alone [48]; whether these features are specifically relevant to the distress and loss-of-control dimensions of binge eating, perhaps via shared difficulties in affect regulation, remains a plausible hypothesis rather than an established finding. This interpretation aligns with evidence that content type and quality of engagement, rather than duration per se, may be more relevant to eating-related outcomes [8]. Livet et al. [9] additionally reported longitudinal associations between social media exposure and eating-related symptoms, with reductions in self-esteem as a plausible within-person pathway. Low-risk associations were less consistent, particularly for binge-related distress and recurrent binge eating; this may reflect a threshold effect in which only more clinically salient patterns of use reliably differentiate these outcomes, though limited statistical power for rarer indicators is also a plausible explanation.

#### 4.3. Screen use and BED symptoms at T5 (RQ4)

RQ4 examined whether screen use profile membership and social media addiction risk differentiated BED symptom endorsement at T5, after adjusting for sex, family conflict, and school environment. Associations were broadly sustained across most symptoms, providing support for the T3 findings in a sample now aged 12–16 years. High screen engagement remained associated with binge-related distress (S2), binge eating behaviour (S3), and recurrent binge eating (S4), while social media addiction risk continued to differentiate all four symptoms. The notable exception was the characteristics of binge eating indicator (S1), for which the screen profile association did not persist to T5.

The absence of a significant association between screen profile membership and S1 at T5 is a post-hoc observation and should be interpreted cautiously. The T3 effect size for S1 was the smallest of the four indicators, and the T5 non-significant result may reflect statistical imprecision rather than a meaningful change. It is also possible that S1

(which captures general eating characteristics, such as eating too quickly) is more variable across development than the other indicators, though there is no direct evidence to support this from the present data and proposed as a hypothesis that requires further research. The sustained associations with the remaining indicators across both waves suggest that screen engagement level remained relevant to binge eating risk as adolescents moved into mid-adolescence, a period in which food autonomy and unsupervised screen time tend to increase [1].

For social media addiction risk, the high-risk pattern was consistent across both waves. These findings are supported by independent longitudinal evidence from Shi et al. [50], who found that social media addiction symptoms, but not time spent on social media, were associated with binge eating at follow-up, supporting the distinction between engagement quality and exposure volume. In the present study, social media addiction risk remained associated with BED symptom endorsement, indicating that risk classification differentiated symptoms among adolescents with comparable overall screen engagement. For low-risk users, the pattern differed by symptom and wave: the low-risk association with recurrent binge eating was not statistically reliable at T3 but was statistically reliable at T5, whereas the low-risk association with characteristics of binge eating was evident at T3 but not at T5; the practical meaning of this shift is uncertain and may reflect sampling variability and/or limited precision for smaller effects on less prevalent symptoms.

Together, these findings indicate that associations between problematic social media use and binge eating-related symptoms were observed at both assessment waves; however, because the predictors were operationalised at T3 and the study remains observational, the results should not be interpreted as establishing temporal ordering or longitudinal prediction.

#### 4.4. Covariate pattern: Family conflict, school environment, and sex across T3-T5

Across both timepoints, family conflict was the strongest differentiator of symptom endorsement. This is consistent with evidence that adolescents with BED tend to report family environments characterised by poor cohesion and high conflict [51], and with twin-sample findings associating greater family conflict with higher odds of loss-of-control eating in girls, mediated by depressive symptoms [17]. The interpersonal model of binge eating offers a plausible framework: social difficulties generate negative affect that precipitates loss-of-control eating [52], though the present design does not permit conclusions about direction or mediation. School environment was consistently protective across both waves, in line with evidence that school connectedness is a correlate of lower disordered eating risk in adolescents, including binge eating [18–20].

Sex showed a notably different pattern across timepoints. At T3, sex was only significantly associated with binge-related distress (S2); by T5, female adolescents showed higher odds of endorsement across all four symptoms. This broadening is consistent with developmental evidence that female predominance in binge eating symptoms becomes more pronounced across puberty, driven by hormonal changes and heightened sociocultural appearance pressures [53], a trajectory that maps onto the age range of the present sample (T3: 10–13 years; T5: 12–16 years).

Together, the covariate pattern situates digital engagement within a broader psychosocial context in which relational and institutional environments are at least as salient as screen use across adolescence. The magnitude of the family conflict effect in particular warrants care when interpreting digital variables in isolation: shared-liability accounts, in which underlying adversity or emotional dysregulation co-occurs with both higher screen engagement and symptom endorsement, cannot be excluded at either wave.

#### 4.5. Limitations and future research directions

Several limitations should be considered when interpreting these findings. Screen use profiles and social media addiction risk were derived exclusively from T3 data, meaning that associations with T3 BED symptom indicators are cross-sectional and the direction of effects cannot be established; adolescents experiencing binge-related distress may increase their screen engagement rather than vice versa, and the data cannot distinguish between these possibilities. Although the two-year gap between T3 predictors and T5 outcomes provides a more favourable temporal ordering, bidirectional accounts remain plausible at both waves, and the T5 models did not adjust for BED symptom endorsement at T3, so some of the T5 associations may reflect symptom continuity rather than the unique contribution of earlier digital engagement.

Furthermore, several important covariates were not assessed in the present study, including family history of eating pathology, anxiety, and personality traits, which may confound associations between digital engagement and BED symptoms. BED symptoms were based on youth-reported KSADS symptom endorsements rather than clinician-derived diagnoses, which limits direct comparability with clinical samples. Estimates involving the High Risk social media subgroup ( $n = 100$ ) should be interpreted with caution given the small subgroup size and correspondingly wide confidence intervals. In addition, some symptom indicators had low endorsement rates, which may reduce estimate precision and increase susceptibility to sparse-data bias in logistic regression.

Screen time was assessed via self-report, which may introduce recall bias and does not capture the content or quality of engagement, factors likely more proximal to eating-related outcomes than duration alone. Finally, the analytic sample is predominantly White and higher income, limiting generalisation to more diverse populations. These limitations notwithstanding, the large sample, longitudinal design, person-centred analytic approach, and consistent pattern of associations across multiple symptom indicators and timepoints strengthen confidence in the overall pattern of findings. Future work should prioritise sex-stratified analyses to examine whether associations between digital engagement profiles and BED symptoms differ by sex, given known sex differences in both social media use and eating pathology, and should incorporate objective screen use measurement, longitudinal tracking of digital engagement across multiple waves, and a broader set of psychological covariates, such as anxiety, personality, and family eating history, to better isolate the specific contribution of screen engagement to binge eating risk.

#### 4.6. Implications and conclusions

The findings carry implications across clinical, educational, and public health contexts. The graded association between social media addiction risk and BED symptom endorsement (i.e., present across all four indicators and at both timepoints) suggests that the nature of social media engagement, rather than duration alone, is relevant to binge eating risk in adolescence. This distinction has implications for clinical assessment. Specifically, when screening for eating-related concerns in young people, clinicians may find it more informative to enquire about compulsive or preoccupied patterns of use, rather than focusing solely on time spent. The consistent protective association of a positive school environment across both waves, independent of digital risk factors, points to school connectedness as a meaningful context for early prevention efforts. Similarly, the finding that family conflict was the strongest differentiator of BED symptom endorsement across both waves suggests that family relational dynamics warrant consideration within clinical formulations for adolescents presenting with binge eating symptoms.

At a population level, the identification of a High Screen Usage group comprising nearly half the analytic sample, with consistently elevated

odds across BED symptom indicators, is relevant to how digital engagement is positioned within public mental health frameworks for adolescents. The sustained associations from early to mid-adolescence indicate that risk associated with digital engagement is not confined to a narrow developmental window, and the broadening of sex differences between T3 and T5, with female adolescents showing elevated odds across all four BED symptoms by mid-adolescence, suggests that digital use patterns among girls during the pubertal transition may warrant particular attention.

Taken together, this study demonstrates that both the level and the nature of adolescent digital engagement are associated with BED symptoms across early and mid-adolescence, above and beyond established psychosocial risk factors. The consistent pattern across multiple symptom indicators and two timepoints provides an empirical basis for incorporating digital use assessment into clinical and preventive frameworks for adolescent binge eating, while the covariate pattern underscores that digital factors operate within, rather than independently of, broader relational contexts of family and school life.

#### Availability of data and materials

The data utilized in this research were obtained from the Adolescent Brain Cognitive Development (ABCD) Study, a publicly available dataset.

#### Ethical standards – animal rights

All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Ethical approval for the study was granted by RMIT University Human Research Ethics Committee (HRE27145), with data access approved by the National Institute of Mental Health (NIMH; 18,203).

#### Confirmation statement

The authors confirm that this paper has not been either previously published or submitted simultaneously for publication elsewhere.

#### Copyright

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#### Author note

This manuscript includes original work not previously published or presented and not under current review elsewhere. The data utilized in this research were obtained from the Adolescent Brain Cognitive Development (ABCD) Study, a publicly available dataset. Consequently, the authors did not have control over the selection of measures, or the sampling procedures employed. The authors declare no conflict of interest.

#### CRediT authorship contribution statement

**Taylor Brown:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vanessa Tanti:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Natasha Wilson:** Writing – review & editing, Writing – original draft, Formal analysis. **Mark D. Griffiths:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Dan Lubman:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization.

**Kaiden Hein:** Writing – review & editing, Writing – original draft, Formal analysis. **Vasileios Stavropoulos:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

### Informed consent

Informed consent was obtained from all individual participants included in the study.

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### Declaration of competing interest

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

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ABCD Consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in the analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD Consortium investigators. [docs.abcdstudy.org](https://docs.abcdstudy.org)

### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.comppsy.2026.152694>.

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