Adolescent screen use trajectories and daily psychosocial functioning in emerging adulthood: a multi-timeframe design

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Data availability

Data are available on reasonable request and on signature of a data sharing agreement from author

D.R.

Declaration of competing interest

The authors declare that they have no conflicts of interests.

Abstract

Adolescent screen use is highly heterogeneous, varying across dimensions such as activity type, time spent, purpose, and content exposure, with patterns that may persist or shift over time. However, little is known about how such heterogeneity relates to later psychosocial functioning in everyday life. This study addressed this gap by examining longitudinal trajectories of screen time and media content engagement across adolescence and their associations with day-to-day psychosocial functioning in emerging adulthood. Data were drawn from the Zurich Project on Social Development from Childhood to Adulthood (z-proso) and its add-on study, Decades-to-Minutes (D2M), which employed ecological momentary assessment (EMA). Parallel latent class growth analysis modelled trajectories of three screen activities (ages 11,13,15,17) and three types of media content exposure (ages 13,15,17,20) in z-proso (n=1521). Daily psychosocial functioning was assessed in the D2M sample at ages 21 (n=255) and 27 (n=451), and associations with adolescent screen-use trajectories were examined using dynamic structural equation modelling (DSEM). Results showed that youth in the *high TV/DVD and chatting/surfing, moderate-content* group exhibited higher mean levels and variability of daily aggression and aggressive reactivity. The *high-use, high-content* group displayed greater daily cannabis use, aggressive reactivity, and provocation inertia. The *moderate-use, escalating-content* group showed higher stress variability, aggression inertia, aggressive reactivity, and cannabis use. The *low-use, low-content* group consistently displayed the most adaptive daily functioning. These findings underscore the importance of jointly considering adolescent screen time and media content patterns, given the distinct relations of different joint trajectories to (mal-)adaptive dimensions of psychosocial functioning into adulthood.

Keywords: screen time; media content; adolescence; trajectories; daily psychosocial functioning

1. Introduction

Growing research suggests that the associations between screen use, especially when measured as total screen time, and youth mental health are inconsistent and highly dependent on individual, contextual, and content-related factors (Odgers et al., 2020; Sanders et al., 2024; Tang et al., 2021). However, less is known about how screen use (e.g., high screen time and engagement with potentially harmful media content) relates to longer-term daily psychosocial functioning, especially in the course of real-life. This represents an important gap, as screen use could have limited effects on serious mental health symptoms or disorders, yet still be meaningfully related to day-to-day functioning and experiences such as emotions, stress, aggression, and emotional and behavioural regulation. Moreover, examining screen use through repeated measures (e.g., longitudinal trajectories) rather than at a single time point can shed light on its potential cumulative or habitual effects. To address this gap, the current study examines longitudinal trajectories of both screen time and media screen content exposure and links them to daily psychosocial functioning in emerging adulthood, captured through ecological momentary assessment (EMA).

Adolescence is a developmental period marked by heightened engagement with digital technologies, raising concerns about the potential for problematic behaviours such as excessive screen time and digital addiction (Odgers et al., 2020; Odgers & Jensen, 2020). Screen use during this period is highly heterogeneous, for example, varying across devices and activities (e.g., TV/DVDs, gaming, social media, computers, mobile phones), purpose (e.g., communication, entertainment), content exposure (e.g., violent material), and the frequency and intensity of engagement. Group-based trajectory modelling has been employed to capture this heterogeneity by identifying distinct longitudinal patterns of screen use (e.g., defined by screen time) across time (Coyne et al., 2018; Coyne & Stockdale, 2021; Paquin et al., 2024; Wang et al., 2024; Zhu et al., 2023). This method provides a more nuanced characterization of persistent (e.g., consistently high) or shifting (e.g., increasing or decreasing) patterns of engagement, while also enabling the examination of cumulative effects, that is, the developmental consequences associated with sustained or escalating use across adolescence. For example, research suggests that certain screen-use trajectories, such as consistently high use, increasing use across adolescence, or elevated use beginning in early adolescence, are associated with negative developmental outcomes, such as depressive symptoms, anxiety, suicidality, aggression, psychotic experiences, and substance use (Coyne et al., 2018; Paquin et al., 2024; Wang et al., 2024; Zhu et al., 2023).

Though some studies have examined screen use trajectories in adolescence, often focusing on total screen time (Shao et al., 2023; Wang et al., 2024; Zhang et al., 2025), research on trajectories that capture specific types of screen use or more nuanced aspects, such as exposure to potentially harmful content (see Coyne & Stockdale, 2021; Krahé et al., 2012, on violent content trajectories in adolescence), remains relatively scarce compared to the large body of cross-sectional or longitudinal work on overall effects of screen use. This study thus investigates the joint trajectories of time spent on various screen activities (e.g., internet surfing/chatting, computer gaming) during adolescence, alongside their exposure to or engagement with different domains of potentially harmful and age-restricted digital content (e.g., pornography, violence-related material).

It is also important to examine whether adolescent screen-use trajectories carry meaningful developmental implications, especially as potential earlier indicators of later outcomes such as daily psychosocial functioning. Day-to-day psychosocial functioning reflects how individuals experience and regulate emotions, thoughts, and behaviours in real-life contexts (e.g., emotional reactivity to stressors) and may function as (early) markers and/or manifestations of regulatory difficulties and mental health symptoms, given their links to broader outcomes, such as depression, anxiety, suicidality, ADHD, and aggression (Murray et al., 2021; Murray et al., 2021; Sedano-Capdevila et al., 2021; Zhu et al., 2024). Daily psychosocial functioning can be captured effectively using EMA, which involves (near) real-time assessments of individuals' emotions, behaviours, and other experiences in naturalistic environments (Shiffman et al., 2008). Moreover, indices derived from EMA enable researchers to examine dynamic regulatory processes, including (a) inertia/carryover (persistence of states from one moment to the next), (b) variability (fluctuations over time), and (c) reactivity (e.g., emotions and behaviours as responses to internal states or external contexts). A further aim of this study is therefore to explore whether adolescent screen-use trajectories are associated with multiple indicators of daily psychosocial functioning in emerging adulthood, including mean levels, inertia, and variability of negative emotions, stress, interpersonal provocation, substance use, and aggression, as well as emotional and behavioural reactivity.

Several theoretical perspectives support investigating the association between screen use trajectories and daily psychosocial functioning, such as emotional and behavioural regulation. From a developmental perspective, persistent high screen use may reflect and potentially deepen vulnerabilities in self-regulation that extend into adulthood, leading to difficulties in managing emotions and behaviour in daily life (John et al., 2023; Xiao et al., 2025). Displacement theory suggests that screen time can displace activities that promote mental and physical health, such as face-to-face social interactions and sleep, which are important for developing and applying adaptive regulation strategies. Frequent exposure to violent or emotionally charged media may also activate aggressive thoughts, model maladaptive behaviours, and heighten negative emotions or perceived stress (Bender et al., 2018), consistent with Bandura's social learning theory (Bandura et al., 1961), which posits that individuals can learn and reproduce behaviours (e.g., aggression) through observing others and emphasizes the importance of imitation, modelling, and reinforcement in the learning process. Social comparison theory highlights another mechanism: social media often amplifies tendencies to compare oneself to others, leading to feelings of inadequacy, negative emotions, and regulation issues (Festinger, 1954; McComb et al., 2023). Other shared risk factors, such as sleep disturbances, may contribute to both elevated screen use and difficulties in emotional and behavioural regulation (e.g., Carter et al., 2016; Palmer et al., 2018). Based on these perspectives, screen use trajectories could act as earlier markers for issues in psychosocial functioning in later stages of development, as well as potentially contributing to these outcomes via various mechanisms.

1.1. The current study

Drawing on these theoretical perspectives, the study integrates long-term trajectory data with intensive, moment-to-moment assessments to investigate whether adolescent screen-use patterns predict daily psychosocial functioning in emerging adulthood. Specifically, leveraging the available data, it examines whether joint developmental trajectories, capturing time spent on different screen activities (including computer gaming, internet surfing/chatting, and TV/DVD viewing) from ages 11 to 17 and frequency of exposure to or engagement with specific content types (including pornography, horror, and violence-related material) from ages 13 to 20, are associated with daily functioning (including negative emotion, stress, aggression, provocation, substance use, and emotional and behavioural regulation) at ages 21 and 27. The integration of longitudinal and EMA methods provides a multi-timescale perspective by linking long-term patterns (meso/macro timescale) with moment-to-moment or day-to-day processes (micro timescale), offering a more nuanced understanding of how screen use relates to psychosocial development in real-world contexts. These insights are essential for identifying youth at heightened risk of daily emotional or behavioural dysregulation and for informing the design of prevention and intervention strategies that promote healthier media use and improve daily functioning. They also help clarify whether long-term screen-use patterns (potentially capturing subgroups characterized by earlier initiation of higher use, persistent high use, or escalating use over time), as well as long-term patterns of exposure to or engagement with potentially harmful content (e.g., violence-related material), are related to outcomes in ways that warrant greater concern. This is particularly relevant given that most previous studies, which neither modelled long-term screen use with repeated measures nor jointly considered screen time and media content engagement, have typically reported only small-to-moderate associations with broad psychosocial outcomes

(Mallawaarachchi et al., 2024; Mougharbel & Goldfield, 2020; Przybylski et al., 2020).

We hypothesised that unfavourable adolescent screen-use trajectories (e.g., persistent high use or increasing use over time) would predict more negative daily-life functioning in emerging adulthood, including higher negative emotions, stress, aggression and provocation, and substance use, as well as emotional and behavioural dysregulation (operationalized as negative emotional or aggressive reactivity to interpersonal provocation), relative to low screen-use trajectories. We also hypothesised that trajectory groups characterized by higher or increasing engagement with violent content (potentially including subgroups with greater computer gaming activity, given the prevalence of violent content in many games, and that some studies suggest video game violence may be especially harmful due to its immersive nature relative to TV/DVDs) would be linked to heightened aggression and poorer behavioural regulation. Given inconsistent prior findings and limited research on horror content in relation to psychological outcomes, we make no specific hypotheses regarding pornography or horror content (Svedin et al., 2023; Willoughby et al., 2018).

2. Methods

2.1. Participants

Data were drawn from the Zurich Project on Social Development from Childhood to Adulthood (z-proso; Ribeaud et al., 2022; Shanahan et al., 2024) and one of its add-on-data collections, the Decades-to-Minutes (D2M) study. z-proso is a longitudinal cohort study following a representative sample of children in the city of Zurich, Switzerland. The study began in 2004 when participants entered public school (age 7) and included follow-ups at ages 8, 9, 10, 11, 12, 13, 15, 17, 20, and 24. A stratified sampling procedure was used, with schools as the sampling unit and stratification by size and location, with the aim of ensuring representation across socioeconomic backgrounds. The target sample was 1,675 children, of whom 1,521 provided screen-use data during at least one wave (ages 11–20) and were included in the trajectory analysis.

The D2M study, embedded within the z-proso study, employed an EMA design with four daily assessments over two consecutive weeks, conducted in two bursts to capture daily experiences at distinct developmental stages of emerging adulthood. In burst 1 (winter 2018), 255 participants (aged 21;38.4% male, 61.6% female) completed at least one valid EMA survey on the key measures. In burst 2 (winter 2024), data were obtained from 451 participants (aged 27; 41.9% male, 58.1% female) who completed at least one valid EMA survey. For burst 2, surveys completed in implausibly short or long times, potentially reflecting careless responding (e.g., Jaso et al., 2022), were excluded. For burst 1, no such exclusions were applied, consistent with prior publications based on these data, which analyzed the full set of EMA surveys (e.g., Murray et al., 2023). For both bursts, participants were recruited during the z-proso main data collection waves and represent convenience subsamples of z-proso. The difference in sample size between the two bursts reflects differences in available resources for data collection (e.g., participant compensation) while ensuring sufficient power to detect meaningful effects. After providing informed consent, they downloaded an EMA application (*LifeDataCorp LLC*) to their smartphones. The app sent four quasi-random notifications per day between 10:00 a.m. and 10:00 p.m., each linking to a short survey. Incentives were response-based, with participants receiving up to 50 CHF for achieving >70% compliance over the two-week period.

Ethical approval was obtained from the Ethics Committee from the Faculty of Arts and Social Sciences of the University of Zurich. Informed consent was obtained from parents or from the youth themselves.

2.2. Measures

2.2.1. Screen use survey measures

Screen use was assessed using two types of measures: screen time and screen content.

Screen time was measured at ages 11, 13, 15, and 17 using three self-report items assessing the average daily time spent on different media activities (watching TV/DVDs, playing computer games, and surfing/chatting on the Internet). Participants reported their screen time separately for a normal school day and for a weekend day (e.g., "How many hours do you spend chatting and surfing on the Internet on a normal school day?") on a 5-point scale ranging from *never* to *more than 3 h/day*. Weekday and weekend reports for each activity were averaged to create three composite scores, one for each media activity.

Screen content was measured at ages 13, 15, 17, and 20 using eight items adapted from a prior measure (Mößle et al., 2007). Although screen content was also measured at age 24, this time point was excluded from the present analyses to maintain the temporal ordering of variables, as the outcome measures were assessed at ages 21 and 27. Items captured exposure to or engagement with violent and age-restricted media content across three domains: horror content (watching horror movies suitable for ages 18+), pornographic content (watching porn movies suitable for ages 18+), and violent content (viewing violent content on the internet or on a cell phone, watching thriller or action movies 18+, filming violence on a cell phone, sharing violent content via a cell phone, and playing 18+ action-packed computer/video games containing intense and/or realistic depictions of violence, e.g., first-person shooters). Responses were recorded on a 7-point scale from *never* to *daily*, and composite scores were calculated separately for each content domain.

2.2.2. EMA measures

All EMA measures examined here were completed through self-report, referenced experiences within the last 30 minutes, and were administered using the same items at both burst 1 and burst 2.

Negative affect was measured using an adapted version of the expanded Positive Affect Negative Affect Schedule (PANAS-X) (Watson & Clark, 1999). Participants responded to seven items: *I felt… afraid; scared; hostile; guilty; ashamed; upset; and distressed*, using a 5-point scale from *very slightly or not at all* to *extremely*.

Aggression was measured with the Aggression-ES-A (Murray et al., 2022), a 4-item abbreviated version of the Aggression-ES (Borah et al., 2021). Items assessed aggressive behaviours, such as losing one's temper and deliberately insulting someone. Responses were recorded on a 4-point Likert-type scale from *strongly disagree* to *strongly agree*. Previous psychometric analysis of burst 1 data from the current sample supported its factorial validity as well as within- and between-person level internal consistency (Murray et al., 2022).

Provocations were measured with 4 items (e.g., being insulted and someone trying to start an argument with the respondent), capturing momentary situations theorised to elicit aggression. Responses were recorded on the same 4-point Likert scale as the aggression measure. Previous research in this sample has shown that these items correlate with aggression at both the within- and between-person levels (Murray et al., 2022).

Stress was measured using an EMA-adapted, abbreviated version of the Perceived Stress Scale (PSS; Cohen et al., 1983; Murray et al., 2023). The four items assessed perceived stress, such as 'feeling a lack of control over the important things in one's life' and 'feeling nervous and stressed'. Responses were recorded on the same 5-point scale as the PANAS-X items, ranging from *very slightly or not at all* to *extremely*. Previous research in this sample (burst 1) has provided psychometric evidence for the factorial validity, internal consistency, and criterion validity of this EMA-adapted PSS at both the within- and between-person level (Murray et al., 2023).

Alcohol and cannabis use were measured by asking participants separately whether they had consumed alcohol or cannabis in the past 30 minutes (yes/no).

Composite scores were calculated for all multi-item measures.

2.3. Data analysis

This study was preregistered at https://doi.org/10.17605/OSF.IO/F4YSW, with minor deviations from the original plan. Initially, the plan was to apply a previously identified screen time trajectory model (Zhu et al., 2023) to examine its association with daily experiences. However, the dataset used in the earlier publication did not include EMA data. Because the data use agreement did not allow access to participant IDs, necessary for linking that previously subsetted screen-use dataset and the newly requested EMA data, we requested a new dataset that already included both screen use and EMA measures. The trajectories were thus re-estimated. In addition, content-related trajectories were incorporated to extend the analysis beyond measures focused solely on screen time.

Parallel-process latent class growth analyses (LCGAs) were conducted to model joint longitudinal patterns of time spent on TV/DVD viewing, computer gaming, and Internet chatting/surfing from ages 11 to 17, as well as exposure to or engagement with specific content types (horror, violent, and pornographic) from ages 13 to 20 in the full z-proso sample. Building on prior findings of screen time trajectories in this cohort (Zhu et al., 2023), both linear and quadratic growth parameters were estimated, and one- to eight-class solutions were evaluated. Model selection was based on a combination of statistical fit indices (BIC, AIC), a likelihood ratio test (LMR), classification quality (entropy), parsimony, and theoretical interpretability. Class membership from the final trajectory models in the z-proso sample was saved as a variable and merged with the D2M study dataset to enable subsequent analyses (first step of analysis). In the second step, this class membership variable was used as a categorical predictor (dummy-coded) of daily psychosocial functioning in emerging adulthood, which was examined using two-level dynamic structural equation modelling (DSEM; Asparouhov et al., 2018).

DSEM integrates multilevel modelling, time-series modelling, structural equation modelling (SEM), and time-varying effects modelling (TVEM), enabling the investigation of both within-person dynamics from EMA data and between-person differences, which can be linked to data from the longitudinal survey data. Within this framework, EMA data can be used to derive indicators that reflect dynamic emotional and behavioural regulation processes beyond overall means (e.g., overall stress, overall negative affect). Specifically, inertia was captured by autoregressive parameters, reflecting the extent to which a construct carried over from one moment to the next; variability was indexed by residual variances, capturing the degree of short-term fluctuations; and coupling strength between constructs was captured by cross-lagged parameters, such as emotional reactivity to prior provocation. These parameters are first estimated at the within-person level and then modelled as random effects at the between-person level, allowing the examination of individual differences and their associations with screen-use trajectory groups.

Univariate models were fitted for each EMA study variable (negative affect, stress, aggression, provocation), including an intercept, autoregressive slope, and residual variance at the within-person level. Substance use (alcohol and cannabis) was measured dichotomously (yes/no) and modelled with a probit link. This approach assumes a hypothetical underlying normally distributed latent variable, with a threshold that produces the observed binary response (0/1), such that relations over time and with other variables are modelled on this latent scale. For binary outcomes in probit DSEM, residual variances at the within-person level are constrained to 1 for identification; thus, only intercepts and autoregressive parameters are estimated for substance use (McNeish et al., 2024). Random effects at the between-person level were then added and retained if their variances yielded z-scores greater than 3 (Asparouhov & Muthén, 2022). Emotional and behavioural reactivity (i.e., regulation) were examined using coupling models that estimated lagged effects between provocation and negative affect and between provocation and aggression[1]. These models included intercepts, autoregressive effects, cross-lagged paths, and residual variances, with random effects added as appropriate.

Analyses were conducted separately for EMA data collected at ages 21 and 27, as only a partially overlapping subset of participants (approximately 140 individuals) contributed to both bursts. Screen use trajectories were entered as predictors of the retained random effects in the DSEM models by creating dummy variables, with each trajectory group used in turn as the reference category at the between-person level.

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[1] Concurrent effects in the coupling models (i.e., same-time effects between variables such as provocation and negative affect), preregistered as a sensitivity analysis, were not estimated because the models were already complex and prone to convergence issues; only the lagged effects (the primary analyses) were estimated.

All models were estimated in Mplus. Missing data for the longitudinal screen use data and EMA data were handled using full information maximum likelihood (FIML) and Bayesian estimation, respectively, both of which provide unbiased parameter estimates under the missing-at-random (MAR) assumption. For EMA data, the TINTERVAL command was used to align prompts to a predefined time schedule by inserting missing values for unobserved periods, ensuring a standardised time structure (Asparouhov & Muthén, 2020). Sex (assigned at birth) and parental socioeconomic status (SES; indexed by the International Socio-Economic Index of Occupational Status, ISEI) were included as covariates when estimating associations between trajectories and daily experiences.

3. Results

D2M participant demographic information is presented in Table S1 of the supplementary materials. Parallel-process LCGA results supported a four-class trajectory model as the best-fitting solution. This decision was based on lower AIC, BIC, and saBIC values compared with one- to three-class models, as well as the significant LMR test indicating that the four-class model fit better than the three-class solution. For models with more than four classes, the LMR test was not significant, indicating no additional improvement in fit. The four-class solution also showed good classification quality, with an entropy value of 0.88. Detailed results are presented in Table 1.

Class 1 (*high TV/DVD and chatting/surfing, moderate-content*; 18.9%) was characterized by relatively high levels of TV/DVD viewing in early adolescence, which first increased and then declined, alongside moderately high but decreasing computer gaming and consistently high, increasing frequency of chatting/surfing from ages 11 to 17. Members of this class also reported moderate engagement with violent content, moderate exposure to pornographic content, and moderately high but slightly declining exposure to horror content from ages 13 to 20.

Class 2 (*high-use, high-content*; 12.7%) generally showed the highest frequency of violent content engagement and horror and pornographic content exposure compared with the other three classes from ages 13 to 20, coupled with consistently high or moderately high time spent across all media activities (particularly computer gaming) from ages 11 to 17.

Class 3 (*moderate-use, escalating-content*; 24.6%) was characterized by relatively low to moderate time spent on chatting/surfing and TV viewing, with increasing and then very slightly declining time spent on gaming from ages 11 to 17. Engagement with violent content and exposure to pornographic content became more pronounced in later adolescence.

Finally, Class 4 (*low-use, low-content*; 43.8%) represented relatively low levels of time spent on gaming, chatting/surfing, and TV viewing, as well as relatively low frequency of violent content engagement and horror and pornographic content exposure across ages 11 to 20. Details of these four groups are presented in Figure 1.

The distribution of these groups was relatively comparable across the main z-proso sample and the D2M subsample: Class 1 comprised

13.7% and 20.0%, Class 2 7.8% and 8.2%, Class 3 21.2% and 23.1%, and Class 4 57.3% and 48.8% of participants in bursts 1 and 2, respectively. Notably, Class 1 accounted for a relatively higher proportion of participants in burst 1 compared with main z-proso sample. In both D2M bursts 1 and 2, Classes 1 and 4 were predominantly female, whereas Classes 2 and 3 were predominantly male. These distributions are reported in Table S2 of the supplementary materials.

In the two-level DSEM models for burst 1, the random effects for the intercepts, autoregressive slopes, and residual variances of the affect, stress, provocation, and aggression model were sufficiently large to justify their retention. The random effects for the autoregressive slopes of alcohol use and cannabis use were not large enough to warrant retention and were therefore constrained to zero at the between-person level. The same pattern of retained random effects was observed in the burst 2 data. No convergence issues emerged in the univariate EMA models, and the retained random effects were included as between-person outcomes of screen-use trajectories. For the coupling models between affect and provocation, the random effects for all intercepts, autoregressive slopes, cross-lagged slopes, and residual variances were sufficiently large to retain in both burst 1 and burst 2. For the coupling model between aggression and provocation, inclusion of the random effect for the lagged effect of aggression on provocation in burst 1 led to convergence issues, it was constrained to zero at the between-person level, while the remaining random effects were sufficiently large to retain. In the burst 2 data, the inclusion of random effects for residual variances also led to convergence issues, so these effects were constrained to zero, with the remaining random effects retained. To reduce model complexity, only the random effects of interest not captured in the univariate EMA models, specifically, the lagged effects of provocation on subsequent emotion and aggression, reflecting emotional and behavioural regulation, were modelled as outcomes of screen-use trajectory groups.

Results showed that, after adjusting for sex and parental SES, screen-use trajectories from ages 11 to 20 were significantly associated with daily negative emotion, stress, provocation, cannabis use, aggression, and aggressive reactivity at ages 21 and/or 27. Specifically, Class 4 (*low-use, low-content*) reported significantly lower mean levels of daily negative emotion at age 27 compared with Class 3 (*moderate-use, escalating-content*; b=-0.171, 95% CI =-0.354 to -0.007). Class 4 also showed significantly lower variability in daily perceived stress at age 21 compared with Class 3 (b=-0.262, 95% CI=-0.499 to -0.037). Consistently, Class 3 exhibited greater variability in stress relative to Class 4 (b=0.212, 95% CI=0.035 to 0.390).

For provocation, participants in Class 1 (*high TV/DVD and chatting/surfing, moderate -content*; b=-0.328, 95% CI=-0.636 to -0.031) and Class 3 (b=-0.408, 95% CI=-0.692 to -0.106) exhibited lower inertia of daily provocation at age 21, indicating provocation was less likely to persist from one time point to the next, compared with those in Class 2 (*high-use, high-content*). Parallel to this, participants in Class 2 showed greater inertia of age 21 daily provocation than those in Class 1 (b=0.266, 95% CI=0.012 to 0.460), Class 3 (b=0.274, 95% CI=0.060 to 0.443), and Class 4 (b=0.224, 95% CI=0.004 to 0.421).

For cannabis use, youth in Class 4 reported significantly lower daily cannabis use at age 21, compared with those in Class 1 (b=-0.279, 95% CI=-0.499 to -0.019), Class 2 (b=-0.448, 95% CI=-0.767 to -0.121), and Class 3 (b=-0.314, 95% CI=-0.589 to -0.029). A similar pattern was observed at age 27: Class 4 reported significantly lower cannabis use than Class 1 (b=-0.222, 95% CI=-0.406 to -0.031), Class 2 (b=-0.416, 95% CI=-0.677 to -0.164), and Class 3 (b=-0.327, 95% CI=-0.551 to -0.103). Consistently, participants in Class 2 (b=0.197, 95% CI=0.055 to 0.345) and Class 3 (b=0.219, 95% CI=0.018 to 0.405) reported significantly higher cannabis use compared with those in Class 4.

Regarding aggression, Class 4 showed lower inertia of daily aggression at age 21 compared with Class 3 (b=-0.344, 95% CI=-0.699 to -0.064). Consistently, Class 3 exhibited higher inertia of aggression (b=0.294, 95% CI=0.039 to 0.519) than Class 4. At age 27, youth in Class 4 reported significantly lower mean levels of daily aggression compared with Class 1 (b=-0.207, 95% CI=-0.338 to -0.083) and Class 3 (b=-0.182, 95% CI=-0.334 to -0.031). They also showed significantly lower variability in aggression compared with Class 1 (b=-0.196, 95% CI=-0.328 to -0.081) and Class 3 (b=-0.157, 95% CI=-0.317 to -0.025). Consistently, Class 1 displayed significantly higher overall mean levels (b=0.124, 95% CI=0.014 to 0.230) and greater variability (b=0.132, 95% CI=0.038 to 0.235) in aggression at age 27 compared with Class 4.

For aggressive reactivity to provocation, Class 4 showed significantly lower reactivity compared with Class 1 (b=-0.300, 95% CI=-0.519 to -0.071) at age 21, and compared with Class 3 (b=-0.262, 95% CI=-0.446 to -0.070) at age 27. Consistently, Class 1 displayed stronger reactivity than Class 4 at age 21 (b=0.218, 95% CI=0.040 to 0.374), and Class 3 showed greater reactivity than Class 4 at age 27 (b=0.215, 95% CI=0.054 to 0.368). Class 3 also exhibited lower reactivity at age 21 compared with Class 2 (b=-0.313, 95% CI=-0.563 to -0.033), consistent with the reverse comparison indicating stronger reactivity in Class 2 relative to Class 3 (b=0.190, 95% CI=0.010 to 0.353).

A small number of coupling models of screen-use trajectories with emotional and aggressive reactivity encountered convergence or non–positive definite issues; details on these models, along with the results from the remaining models, are provided in Tables S3-S9 of the supplementary materials.

4. Discussion

The current study combined longitudinal and EMA data to examine screen-use trajectories across ages 11 to 20 and their associations with daily psychosocial functioning at ages 21 and 27. This approach provides new insight into how screen-use patterns across adolescence are related to functioning in the flow of everyday life in emerging adulthood, extending prior research not only methodologically, by incorporating

EMA to enhance ecological validity, but also substantively, by shifting focus from predominantly studied mental health outcomes assessed through retrospective surveys to daily psychosocial functioning. Four distinct trajectories were identified, which differed in their associations with daily functioning: unfavourable trajectories (e.g., *high-use, high-content*) were linked to greater negative emotion, perceived stress, provocation, aggression, aggressive reactivity, and/or cannabis-use dynamics, whereas the *low-use, low-content* trajectory was associated with significantly lower levels of these outcomes.

This study identified four screen-use trajectories that differed in both time spent and content exposure, extending prior work on this sample (Zhu et al., 2023) by incorporating measures of exposure to potentially harmful and age-restricted digital content. The trajectories indicated that violent and pornographic content were closely aligned within each group, indicating a tendency for these behaviours to co-occur across adolescence. Time spent on computer gaming trajectories generally showed similar mean-level differences across the four identified groups when compared with violent and pornographic content engagement, and although the developmental trends diverged somewhat, they still point to partial convergence across these domains of media use. Notably, Class 1 (*high TV/DVD and chatting/surfing, moderate-content*) and Class 2 (*high-use, high-content*) showed higher use beginning in early adolescence, suggesting that interventions targeting these groups may need to be implemented earlier to be maximally effective.

More importantly, the current study found that the identified screen-use groups were associated with later daily psychosocial functioning, particularly in relation to provocation, cannabis use, and aggression. Specifically, individuals in the *high TV/DVD and chatting/surfing, moderate-content* group exhibited significantly stronger aggressive reactivity at age 21 and higher overall mean levels and greater variability in daily aggression at age 27, compared with those in the *low-use, low-content* group. These findings extend prior research, which has focused primarily on mean levels of maladaptive behaviour (e.g., Coyne & Stockdale, 2021), by showing that screen-use trajectories are also linked to aggressive reactivity to provocation and variability in daily aggression. Importantly, EMA allowed these dynamics to be captured in (near) real time within the flow of daily life. In this context, aggressive reactivity represents heightened aggressive responses when provoked (e.g., insults or arguments), and aggression variability represents short-term fluctuations in behaviour, both offering a window into behavioural dysregulation.

One possible explanation of these findings is that greater time spent on multiple screen activities and moderate-content exposure during adolescence may signal underlying vulnerabilities in self-regulation. Such associations may reflect either pre-existing vulnerabilities in self-regulation that contribute to greater screen use or a bidirectional process in which extensive screen engagement reduces opportunities for activities that promote regulatory skills (John et al., 2023), which may manifest as behavioural dysregulation in emerging adulthood. From a complementary perspective, the Compensatory Internet Use Theory (Kardefelt-Winther, 2014) suggests that individuals may engage in high levels of internet use as a coping strategy for psychosocial difficulties or unmet real-life needs, which may further be associated with negative outcomes such as behavioural dysregulation in daily life. Given that this group engaged in relatively higher levels of screen use from early adolescence, targeted interventions at an early stage may be particularly important for reducing high use and preventing later behavioural dysregulation. Prior research suggests that offering alternatives to screen use, such as creating opportunities for physical activity, can help reduce screen time (Barbosa Filho et al., 2019). Enhancing youths’ autonomous motivation has also been identified as a promising target for reducing recreational screen use (Babic et al., 2016).

The *high-use, high-content* group showed greater inertia of daily provocation at age 21 compared with the other three groups, as well as heightened aggressive reactivity at age 21 than the *moderate-use, escalating-content* group. These findings indicate that youth with higher levels of multiple screen use and greater exposure to or engagement with violent, horror, and pornographic content across adolescence may be more likely to remain in or re-enter provoking interpersonal contexts and to respond aggressively when provoked. These findings are consistent with Bandura’s social learning theory (Bandura, 1977), which suggests that repeated exposure to aggressive models may lead individuals to develop internalized behavioural models that increase the likelihood of aggressive responses. In addition, this group reported significantly higher daily cannabis use at age 27 compared with the *low-use, low-content* group; at age 21, the difference was not significant, but the *low-use, low-content* group reported significantly lower cannabis use than the *high-use, high-content* group.

Taken together, these findings may suggest that high screen use, particularly when combined with exposure to potentially harmful and age-restricted content, may be linked to difficulties disengaging from provoking interpersonal situations, heightened sensitivity to interpersonal triggers, and greater reliance on maladaptive regulation/coping strategies, such as aggression and substance use. The stronger aggressive reactivity observed in the *high-use, high-content* group relative to the *moderate-use, escalating-content* group may reflect the possibility that higher levels of screen use and earlier or accumulative exposure to harmful, age-restricted content could impede the normative development of self-regulatory capacities in adolescence, which are critical for adaptive behavioural functioning in adulthood. This highlights the need not only for prevention and interventions that target screen time but also for addressing risks tied to media content, with particular value in implementing these efforts earlier in development. Policy measures, such as age-verification requirements, for example, those introduced in the UK’s Online Safety Act (2023), represent one potential means of limiting access to harmful and age-restricted content and promoting healthier patterns of screen use.

Youth in the *moderate-use, escalating-content* group, compared with those in the *low-use, low-content* group, showed greater variability in perceived stress and higher inertia of aggression at age 21, as well as higher aggressive reactivity and cannabis use at age 27. These findings indicate that screen use, particularly escalating engagement with pornographic and violent content during late adolescence, was associated with daily emotional and behavioural dysregulation. A possible mechanism is that harmful content exposure and/or engagement (e.g., violence) may reinforce aggressive behaviours/responses, promote substance use, and heighten stress variability, highlighting the critical role of media content in emotional and behavioural regulation. In addition, theories in the media literature, such as the Differential Susceptibility to Media Effects Model (Valkenburg & Peter, 2013), suggest that media effects are often transactional and conditional (shaped by factors such as dispositional and developmental susceptibilities), with youth selecting content aligned with existing tendencies (e.g., aggression) and repeated engagement maintaining or strengthening those patterns. Overall, these results further underscore the importance of prevention and intervention strategies that monitor and address escalating involvement with potentially harmful content in adolescence. Importantly, youth in this group may be especially responsive to such interventions, given their relatively moderate screen use and the comparatively late emergence of escalating exposure to harmful content.

Youth in the *low-use, low-content* group consistently showed the most adaptive daily functioning, including significantly lower variability in perceived stress at age 21 (vs. Class 3), inertia of provocation at age 21 (vs. Class 2), cannabis use at both ages 21 and 27 (vs. Classes 1, 2, and 3), inertia of aggression at age 21 (vs. Class 3), aggressive reactivity at age 21 (vs. Class 1) and age 27 (vs. Class 3), mean levels of negative emotion at age 27 (vs. Class 3), and mean levels and variability of aggression at age 27 (vs. Classes 1 and 3). More significant associations were detected when this group was used as the benchmark, whereas relatively fewer emerged in the reverse comparisons. This likely reflects both variation in effect sizes, since higher-use groups generally showed elevated negative daily functioning, but differences reached significance only on certain indicators, and greater statistical power, as the *low-use, low-content* group comprised about half of the D2M sample. These findings may highlight the protective role of maintaining low or modest levels of recreational screen use and limiting exposure to potentially harmful content in supporting better daily life functioning. It is also plausible that youth following this trajectory were already relatively well-adjusted in early adolescence, and that such early advantages increased the likelihood of maintaining low screen use and limited exposure to harmful content over time, thereby contributing to more adaptive outcomes in emerging adulthood. It should also be noted that, while our findings emphasise risks associated with higher screen time and harmful content use, recent evidence suggests that the effects of screen time are conditional; under certain circumstances (e.g., game console ownership), gaming can lead to improvements in well-being (Egami et al., 2024), underscoring the need for nuanced, context-sensitive guidance rather than a one-size-fits-all approach.

4.1. Limitations and Future Directions

The limitations of the current study should be acknowledged. First, screen-use data were collected through self-reports and traditional surveys. Future research could incorporate objective measures (e.g., accelerometer-based monitoring) and high-frequency methods such as EMA to provide more accurate and fine-grained documentation of screen-use activities. Second, D2M burst 1 and 2 were drawn from convenience subsamples of the z-proso study, and participation was likely affected by attrition in the main cohort. Future studies should apply EMA designs to full cohort samples to minimize potential selectivity and attrition bias. Third, the study relied on secondary data, which limited coverage of newer media forms; in particular, contemporary social media platforms and short-form video applications were not assessed. Future research should address this by capturing current patterns of youth screen engagement and their links to daily experiences. Finally, the study focused only on negative indicators of daily functioning. Including both positive and negative dimensions would provide a more comprehensive understanding of how screen use shapes everyday life.

5. Conclusions

The current study examined longitudinal patterns of screen use across the entire adolescent period and their associations with daily psychosocial functioning, measured using EMA, in both proximal (age 21) and more distal (age 27) emerging adulthood. By integrating long-term trajectories of both screen time and content exposure with fine-grained EMA assessments of dynamic regulatory processes in daily life, the study offers a multi-timescale perspective on how adolescent screen-use patterns are linked to everyday psychosocial functioning. Four distinct trajectories were identified, with particularly notable differences in daily provocation, cannabis use, and aggression dynamics. These findings underscore the importance of prevention and intervention efforts that are sensitive to both screen time and media content, with tailored strategies addressing different patterns of adolescent screen use to promote adaptive psychosocial functioning into adulthood.

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Table 1 Model fits for the 1–8 class models

Model	**LMR**	***p***	**AIC**	**BIC**	**saBIC**	**Entropy**
1-class	–	–	100338.399	100562.138	100428.715	N/A
2-class	6791.120	<0.001	93536.497	93861.452	93667.670	0.914
3-class	2186.455	<0.001	91372.336	91798.506	91544.367	0.914
4-class	**1545.308**	**<0.001**	**89853.929**	**90381.314**	**90066.817**	**0.884**
5-class	903.511	0.727	88981.927	89610.528	89235.672	0.878
6-class	740.678	0.231	88273.929	89003.745	88568.532	0.890
7-class	598.166	0.259	87709.467	88540.498	88044.926	0.879
8-class	558.123	0.221	87185.335	88117.581	87561.652	0.887

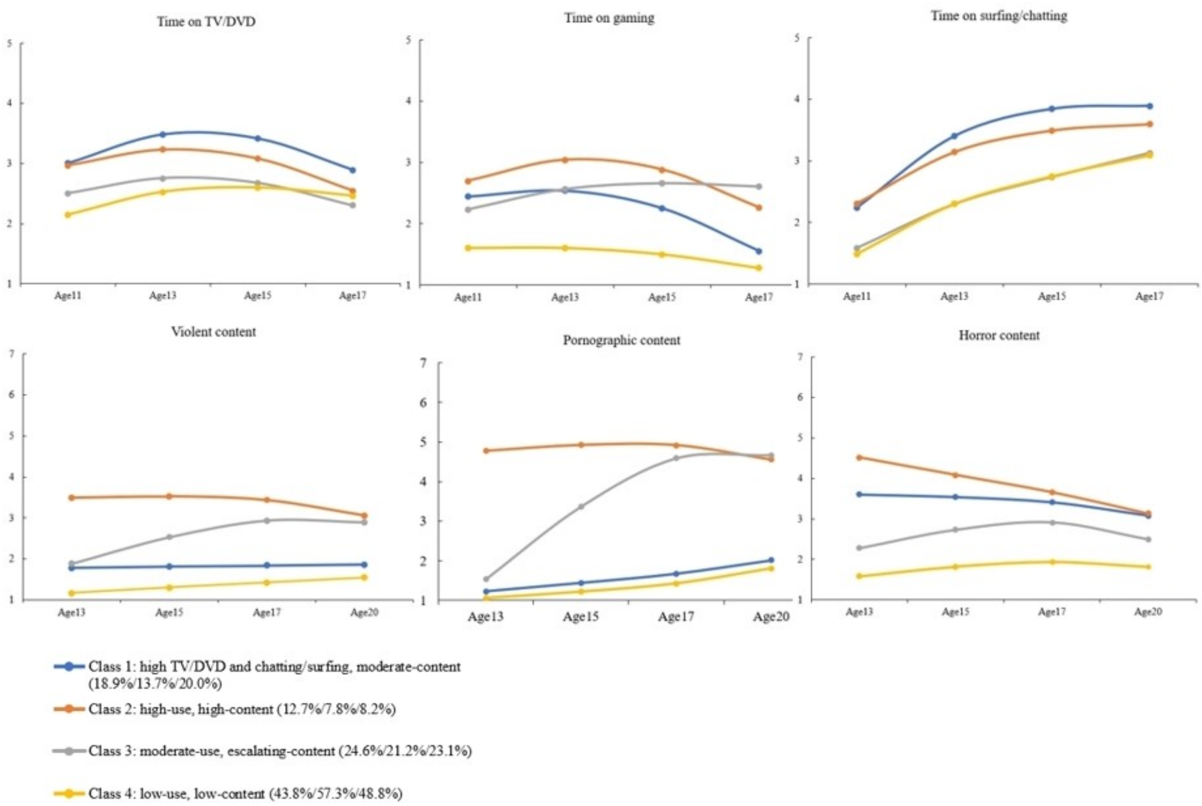

Figure 1. Four-class model of screen time and screen content trajectories.

Note. The vertical axis for screen time represents hours per day: 1=never, 2=1 hour, 3=2 hours, 4=3 hours, 5=more than 3 hours per day. The vertical axis for screen content represents frequency of viewing or engagement, on a 1–7 response scale: 1=never, 2=1–2 times, 3=3–12 times, 4=several times per month, 5=once per week, 6=several times per week, 7=daily. The percentages displayed in each class label indicate the proportion of participants in the main z-proso/D2M burst 1/D2M burst 2.