Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Digital traces of child maltreatment: Investigating TikTok data donations and predicting depressive symptoms in adolescents

Ann-Christin Haag

ann-christin.haag@uniklinik-ulm.de

Ulm University Hospital https://orcid.org/0000-0002-3865-8727

Olivia Dimitrijevic

Ulm University Hospital

Tanmay Nayyar

Ulm University Hospital

Dunja Tutus

Ulm University Hospital https://orcid.org/0000-0003-2569-761X

Julian Schwab

Ulm University

Hans Kestler

Ulm University

Jörg Fegert

Department of Child and Adolescent Psychiatry/Psychotherapy, Ulm University

Article

Keywords: social media use, adolescents, child maltreatment, depression

Posted Date: April 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9018980/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: There is **NO** Competing Interest.

Abstract

While the debate about social media and adolescent mental health is ongoing, there is growing consensus about exacerbated effects for vulnerable adolescents, e.g., after child maltreatment (CM). Existing research predominantly relies on self-reports, cross-sectional designs, and lacks analyses of specific social media activities. In a participatory digital data donation design, 129 adolescents (ages 13-18years, 31.8% exposed to CM) shared parts of their TikTok data archives capturing objective usage (e.g., videos viewed, posts, likes). Machine learning identified the average number of weekly searches as the most important TikTok behavior classifying CM status, followed by TikTok session length and the mean number of posts per week. Longitudinal analyses of identified TikTok behaviors with depressive symptoms revealed more followers and less posting activity as significant predictors of increased depression six months later. Findings will inform our understanding of how CM-exposed adolescents use TikTok differently from their peers and provide opportunities for targeted prevention.

Introduction

Adolescence is a sensitive developmental period marked by socioemotional and neurobiological change, during which social experiences become particularly influential for mental health and behavioral development[1–3]. At the same time, adolescence coincides with increased exposure to digital social environments, which now constitute a central context for peer interaction, identity exploration, and affect regulation in adolescents' everyday life[4]. Social media platforms are used by nearly all adolescents, typically on a daily basis and often repeatedly throughout the day[5]. Notably, almost half of U.S. teens report being online "almost constantly," highlighting how embedded digital environments are in adolescents' routines[5].

Among these platforms, TikTok has emerged as one of the most dominant, with around 61% of adolescents reporting daily use and many adolescents describing their engagement as near constant[5]. TikTok use unfolds primarily within a highly personalized, algorithmically curated "For You" feed of short-form videos, characterized by rapid content turnover and immersive recommendation dynamics[6,7]. Importantly, TikTok engagement extends beyond passive viewing. Adolescents may rapidly switch between distinct behavioral streams including content exposure (watching, skipping, rewatching), social interaction (likes, comments, shares, following), and private communication (direct messaging). As a result, overall time spent on the platform may mask qualitatively different patterns of engagement with distinct implications for socioemotional development and mental health[4,7].

Social media use and mental health

Empirical research linking social media use to adolescent mental health has yielded mixed findings. Across large-scale studies and meta-analytic work, average associations between global indicators of use and mental health outcomes tend to be small, while effects vary substantially across individuals and contexts[8,9]. A recent prospective cohort analysis suggests modest associations between overall screen time and later mental health symptoms, with variation across specific screen-based activities rather than uniform effects of total exposure[10]. Longitudinal within-person evidence further indicates that increases in time spent on social media are not reliably accompanied by increases in depressive or anxiety symptoms across adolescence, underscoring the limited explanatory value of duration-based metrics alone[11,12]. Recent methodological work argues that adolescent well-being may be better understood through digital phenotypes derived from objective trace data, particularly when combined with traditional self-report measures[13].

A recent systematic review of research on TikTok use suggests that problematic or addiction-like TikTok use is frequently associated with higher depressive and anxiety symptoms, particularly in younger users[14]. Complementing this, trajectory-based analyses focusing on depressive symptoms and distinct screen activities suggest that the effects may vary depending on the developmental course of symptoms. Furthermore, reciprocal associations often appear small or inconsistent once stable between-person differences are taken into account[15]. Instead, emerging work suggests that risk may be concentrated in specific, problem-related patterns of engagement rather than overall intensity of use[16]. Activity-specific indicators such as browsing vs. posting show differential associations with depressive symptoms, in which browsing on Instagram at baseline was related to longitudinal increases in adolescents' depressed mood and adolescents' depressive symptoms at baseline was related to later increases in Instagram posting[17].

Mirroring this broader pattern, TikTok-specific evidence is still emerging but similarly points to activity-dependent associations with mental health and well-being[18]. For instance, in objective platform data from a similar social short-form video service, passive viewing time predicted lower life satisfaction and reduced positive affect, whereas active content creation (posting) predicted higher life satisfaction[19].

Because such associations do not clarify direction, recent research has examined whether mental health predicts patterns of use over time or vice versa. Longitudinal network analyses suggest that effects may primarily run from psychological states to patterns of TikTok

engagement, rather than the other way around[20]. The study found that problematic TikTok use was primarily driven by pre-existing depressive symptoms and social anxiety. Specifically, participatory use (e.g., commenting, liking, or sharing content) was predicted by higher life satisfaction, an increased negative self-view, and reduced social anxiety, whereas contributory use (e.g., producing videos) was predicted by life satisfaction. In contrast, passive viewing showed only minimal prospective links to mental health outcomes once other effects were controlled for[20].

Together, these findings underscore that short-form video "use" comprises heterogeneous behavioral streams that cannot be captured by duration metrics alone. At the same time, TikTok may also provide opportunities for creativity and social play, suggesting that engagement can reflect both adaptive and maladaptive processes depending on individual vulnerability and context[6].

Child maltreatment and digital vulnerability

Childhood maltreatment (CM), a subtype of violence against children, refers to harmful acts or omissions by caregivers or other responsible persons that cause (or have the potential to cause) harm and includes emotional, physical, and sexual abuse as well as neglect[21,22]. CM is a potent developmental risk factor associated with lasting alterations in emotion regulation[23], increased stress sensitivity and dysregulated neurobiological reactivity to threat[24], and impairments in interpersonal functioning[25.] Across the lifespan, CM is related to several negative mental health outcomes, including a greater risk for depression[26], anxiety[27], posttraumatic stress disorder[28,29], eating disorder[30], substance abuse[31], as well as altered neurocognitive development, including poorer inhibitory control and working memory[32]. CM is also linked to an elevated likelihood of later revictimization in adolescence and adulthood[33]. These alterations may influence how adolescents navigate online environments and increase susceptibility to maladaptive or risk-laden patterns of social media use[34–36]. Meta-analytic evidence indicates robust associations between CM and problematic or addiction-like forms of internet use, suggesting that digital engagement may function as a maladaptive coping strategy in the context of prior adversity[36].

Consistent with this notion, adolescents who experienced CM appear disproportionately exposed to digital risks, including online victimization, sexual solicitations, and compulsive patterns of online behavior[37,38]. Objective digital trace studies further suggest that high-risk online behaviors can cluster with psychosocial vulnerability among CM-exposed youth, including online sexual solicitations and meeting strangers offline, first met online, underscoring that online behavior may serve as a behavioral signature of broader developmental risk processes[34,39]. However, most existing evidence relies on self-reported media use and focuses on aggregate indicators such as time spent online, providing limited insight into how specific platform-level behaviors are patterned as a function of CM.

In summary, there are critical gaps in the current literature. First, few studies have examined whether adolescents with and without histories of CM differ systematically in various platform-specific social media behaviors and which behavioral features are most informative for distinguishing CM-exposed from non-exposed adolescents. Second, from a methodological perspective, although subjective reports of adolescent social media use have been shown to be inaccurate and imprecise[40], objective data on use remain extremely sparse. Meanwhile, digital data donations haven been proven to be feasible in adolescents and offer great opportunity to gain a deepened understanding of online behaviors[41]. Third, although CM is a well-established risk factor for depression, especially during adolescence, longitudinal evidence linking objective social media behaviors to subsequent depressive symptoms while accounting for CM is missing. Recent evidence in adults' objective web-use data demonstrates that digital behavioral traces can capture affect-related processes over time, illustrating the potential of such data for modelling clinically relevant outcomes[42]. To date, it has not been tested whether comparable behavioral traces prospectively predict depressive symptoms in adolescents, particularly when accounting for CM-related vulnerability.

The current study

The present study addresses these gaps by analyzing objective TikTok usage data in a naturalistic setting, i.e., derived from adolescents' data archives within an innovative participatory data-donation framework[43]. Focusing on CM as a central vulnerability factor, we pursue three complementary aims. First, we describe objective TikTok use indicators (e.g., number of videos watched, posts, likes, favorites, messages, followers) gathered from data archives as well as self-reported TikTok experiences and explore differences between adolescents with and without self-reported histories of CM. Second, we apply machine learning to identify which features differentiate CM-exposed from non-exposed adolescents when considering a holistic set of TikTok use metrics. Thereby, while we pursue an explorative approach in identifying which objective TikTok activities represent important features in classifying CM status, we expect that at-risk experiences, such as receiving sexual solicitations via TikTok, will be amongst the relevant features. Third, based on the identified features characterizing CM-exposed adolescents, we investigate which objective TikTok activities represent longitudinal risk factors of depressive symptoms over a six-month follow-up. Together, this approach provides a fine-grained, data-driven characterization of how TikTok engagement is patterned following CM and how these patterns are associated with subsequent mental health impairment. Findings of the

present study will inform preventive and targeted preventive intervention strategies for vulnerable adolescents after CM, ultimately fostering resilience navigating the digital world.

Results

Sample characteristics and descriptive statistics

The final sample consisted of 129 adolescents, with the slight majority being girls (56.6%). Ages ranged between 13 and 18 years, with a mean of 15.90 (*SD* = 1.47). Participants reported a mean socioeconomic status (SES) of 15.17 (range: 3-25). Demographic characteristics and study group comparisons across CM status are presented in Table 1.

Approximately half of the participants (45.0%, *n* = 58) attended a grammar school (academically oriented secondary school), followed by secondary schools offering intermediate qualifications (30.2%, *n* = 39) and other types of schools (24.8%, *n* = 32), including comprehensive, vocational, or special education schools. Participants were on average in grade/year 10 (*M = 9.89*, *SD* = 1.37; range: 7-13).

About one third of the sample (31.8%, *n* = 41) reported moderate to extreme CM exposure. Frequencies of experienced types of CM are reported in the supplementary material. With regards to at least moderate to severe CM, adolescents reported incidences of childhood emotional abuse most frequently, followed by emotional neglect, physical neglect and sexual abuse (Table S4). Comparisons between CM-exposed and non-CM study groups revealed no statistically significant differences in gender or SES. However, participants in the CM group were older on average (Table 1).

Table 2 presents descriptive information on objective and self-reported TikTok use variables in the complete sample and across study groups. Based on their data archives, adolescents viewed, on average, over 2,000 videos per week, which corresponds to about 313 videos per day. They skipped over 1,000 videos on average per week (approx. 148 per day), i.e., they spent less than 3 seconds looking at a video. The vast majority of videos (86.5%) were viewed only once. Adolescents spend time on TikTok in about 36 sessions per week. A session was defined as viewing interrupted by ≥10 minutes. A session was on average approx. 17 minutes long. Ten percent of all videos were viewed during nighttime hours between 10 pm and 6 am. Adolescents, on average, liked about 406 videos per week and favorited 28 videos per week. On average, they shared about 34 videos, executed 27 searches, and wrote 7 comments per week. Further, participants had on average more than 300 followers and followed more than 800 accounts. The total number of likes on their profile ranged from 0 to 364,067, with a mean of more than 11,000 received likes and a median of 0, indicating high interindividual variability. Adolescents sent on average 23 direct messages per week via TikTok and received 26. About 45% of adolescents had private accounts.

Regarding self-reported TikTok use variables, approximately half of adolescents (49.6%, n = 64) reported using TikTok between 1-3 hours per day, 32.6% (*n* = 42) less than 1 hour per day and 17.9% (*n* = 23) more than 3 hours per day. Further, they reported low mean frequencies of participation in TikTok challenges or trends and few TikTok only friends. 20.9% (*n* = 27) of adolescents reported having received sexual solicitations on TikTok at least once and 11.6% (*n* = 15) report having met with someone offline whom they had first met on TikTok. Lastly, adolescents reported very low mean levels of parental control. However, all variables show wide ranges indicating interindividual variability (see Table S1).

Exploring study group differences

Comparing adolescents exposed to CM versus non-exposed peers, several statistically significant differences were revealed based on exploratory non-adjusted group comparisons (see Table 2). Adolescents with a history of CM viewed significantly more videos per week on average than their non-exposed peers. In addition, adolescents exposed to CM performed almost twice as many searches per week on average and posted more than twice as much content. Adolescents after CM also self-reported higher frequencies of sexual solicitations via TikTok. Trending towards statistical significance were differences regarding the mean weekly number of videos skipped, the average session length and the percentage of videos watched at night, all greater in the CM group compared to the non-exposed group. Lastly, while only marginally significant (*p* = .057), the odds of meeting strangers offline first met on TikTok were 2.81 times greater for CM-exposed adolescents compared to non-exposed peers. After FDR adjustment for multiple comparisons, no differences were statistically significant. However, rank-biserial correlation effect sizes were of medium size for searches per week (r_{rb} = .30) and in the small-to-medium range for videos viewed per week (r_{rb} = .23), the proportion of videos viewed at night (r_{rb} = .22), and posts per week (r_{rb} = .23).

Identifying TikTok use patterns associated with CM

The refined XGBoost model, optimized via nested leave-one-out cross-validation (LOOCV) across 129 folds, achieved a mean outer macro F1 score of 0.713 (95% CI: [0.636, 0.791]). Feature importance analysis, conducted using SHAP values, identified the following variables as

the top three contributors to CM status classification, in descending order of impact: searches per week, age, and socioeconomic status (SES) (see Figures 1 and 2).

Among TikTok user activity-based metrics, the three most influential variables were the number of searches per week, average session length, and the average number of posts per week, ranking 1st, 4th, and 5th overall, respectively. Figure 1 visualizes the distribution and directionality of the top 20 feature impacts. Notably, a higher number of average searches per week (mean absolute SHAP = 0.058; Figure 2) is consistently associated with an increased predicted risk of CM exposure. Similarly, longer average session lengths are linked to classification into the CM-exposed group, while shorter sessions are associated with the non-exposed category. This pattern is also observed for the mean number of posts per week.

Following these metrics, feature importance diminishes considerably (Figure 2). The presence of parental controls, ranking 6th in importance, is associated with classification into the non-exposed category, whereas its absence aligns with the CM-exposed group. Additionally, receiving sexual solicitations via TikTok and meeting strangers offline after initial contact on the platform are both clearly associated with CM status. The composite index for video engagement – which includes the average number of videos watched, skipped, rewatched, and liked per week – ranks lower in importance compared to other indicators of active platform engagement, such as searches, posts, and direct messages.

Predicting depression at follow-up based on identified TikTok use variables

To examine whether the most important TikTok use indicators identified above predict depression over time, SHAP-selected features were analyzed with depressive symptoms at 6-month follow-up (T2) as the outcome.Table 3 depicts the results of the path analysis. The model explained a substantial proportion of variance in T2 depressive symptoms (R^2 = .65).

Controlling for demographic variables, baseline depressive symptoms, and CM, two TikTok use indicators emerged as significant predictors of T2 depression (Table 3). Specifically, a higher number of followers and a lowered average number of posts per week were associated with more elevated subsequent depressive symptoms. Baseline depression and exposure to CM were robust significant predictors of depressive symptoms at T2, whereas socio-demographic characteristics were not.

Discussion

Findings from the present study indicate that specific TikTok activities distinguish adolescent users who reported CM experiences from those without such experiences. As such, the average number of TikTok searches per week was revealed as the most important feature classifying CM status. In addition, mean session length and the mean number of posts per week emerged as important factors characterizing TikTok use of adolescents exposed to CM versus non-exposed peers. In subsequent longitudinal analyses controlling for CM status, T1 depression, and socio-demographic characteristics, our findings show that a greater number of TikTok followers at T1, as well as fewer average posts per week, are risk factors for greater levels of depression at T2.

Collectively, our findings highlight the interplay between user behaviour and platform-specific activities in characterizing adolescents exposed to CM. Interestingly, while active behaviors, such as searches and posts, ranked higher in feature importance for classifying CM status than the composite score of video engagement, which serves as an indicator of time spent on TikTok. This mirrors recent calls for more nuanced investigations of online activities and a shift away from the concept of screentime[44].

Our finding that the weekly number of TikTok searches and posts characterizes CM-exposed adolescents may reflect mechanisms of disclosure and support seeking. A recent investigation found that about half of adult participants reported discussing their exposure to CM on social media[45]. Searching for specific material and postings could also represent ways to get social support and connection[46]. Another potential coping mechanism could be emotion regulation, similar to reports of how adolescents used social media to cope with feelings of loneliness and anxiety during the COVID-19 pandemic[47]. In order to get a sense of the contents of adolescents' TikTok activities, we asked participants at follow-up whether they interacted with others on TikTok about mental health or trauma, and adolescents exposed to CM reported they did so more frequently compared to non-exposed adolescents (mental health U = 482.00, p = .003; trauma U = 552.00, p = .022).

In addition, session length was identified as an important feature, whereas the number of sessions per week only ranked lower in feature importance. This indicates that prolonged sessions are more likely to characterize adolescents exposed to CM, rather than checking TikTok more often. Prolonged TikTok sessions relate to the attention-capturing dark pattern of infinite scrolling, where content endlessly loads as users scroll[48]. Results presented here indicate that adolescents after CM might be particularly sensitive to this manipulative interaction design.

Considering that adolescents exposed to CM primarily reported experiences of emotional abuse and neglect in the present sample, less parental control regarding their smartphone use seems intuitive. This may be indicative of a negative emotional family climate, reduced parental monitoring, as well as impaired parent-child relationship quality, all risk factors in families of children exposed to CM[49]. This is especially concerning, as the lack of parental monitoring may leave adolescents without a protective buffer against TikTok's high-frequency rewards and social pressures[14]. Without parental guidance, the compulsive need to maintain digital visibility and constant exposure to idealized content can overwhelm the already strained self-regulatory capacities of youth exposed to CM, thereby fueling a cycle of social comparison and increasing the risk for mental health problems.

Finally, our results confirmed the relationship between CM and online sexual solicitations, as well as meeting strangers from TikTok offline. This is consistent with previous research that identified CM as a unique risk factor for high-risk Internet behaviors in adolescents[38]. Furthermore, females who had experienced child sexual abuse were at increased odds of being represented in a "high-risk" profile, which predicted exposure to Internet-initiated victimizations, such as receiving online sexual solicitations [39].

Our finding that a higher follower count predicted an increase in depression six months later aligns with previous research that observed a positive relationship between social network size and symptoms of depression[50]. Additionally, an increased follower count has been linked to increased negative emotions in social media influencers[51]. While having more followers may indicate higher social connections, acceptance, and reward, it can also increase pressure on users to constantly deliver new material on TikTok to maintain relevance for a large audience. More followers can also lead to negative social comparisons among users and the fear of missing out[14,52]. It has been shown that TikTok may provide users with validation that momentarily boosts self-esteem but may also increase symptoms of depression through excessive engagement and social comparison. Therefore, on TikTok, where emotional investment in metrics (such as likes and followers) is high, a large base of followers may transition from a source of validation to a source of evaluation apprehension[53].

This is further compounded by the finding that less frequent posting also predicted higher T2 depression in the present study. Less posting may reflect more passive consumption, which has been found to reduce life satisfaction compared to active content creation[19]. The combination of high social visibility (many followers) and low active engagement (fewer posts) may exacerbate feelings of distress, as users endure the pressures of a large digital presence without the self-expressive benefits of active participation[51].

This study benefits from a participatory data-sharing approach, which facilitated the investigation of objectively assessed TT behaviors in a naturalistic setting. It further focuses on a subsample of adolescents exposed to CM who have previously been identified of being vulnerable to detrimental effects of digital media use[34–36].

Despite these strengths, several limitations are worth noting. First, the sample included is limited. As a result, the number of adolescents exposed to CM is also limited. The CM prevalence rate in the present sample is, however, comparable to a previous empirical investigation based on representative German samples, that reports a prevalence rate of 31.0%[54]. Relatedly, attrition and missingness at T2 (total 34.9%) may limit generalizability and introduce bias in the estimates, despite the statistical adequacy of FIML under a MAR assumption. Attrition further poses a methodological challenge because it can be assumed that participants with higher levels of psychological distress or lower motivation were primarily responsible for not continuing their participation at T2. Finally, potential confounding effects of psychopathology need warrant acknowledgement. Although we specifically re-classified known CM status, disentangling the effects of psychopathology and CM and their associations with social media should be a focus of future investigations.

While the current study provides valuable insights into TikTok metrics among adolescents exposed to CM on TikTok, there remains a critical need for further investigation into the actual content of their online activities. Specifically, future research should delve deeper into the contents of searches, posts, and viewed videos to gain a more comprehensive understanding of the digital experiences of CM-exposed adolescents. Future research should also investigate potential mechanisms underlying different patterns of digital media use among CM-exposed adolescents. Thereby, social media use among adolescents exposed to CM can serve both adaptive and maladaptive coping functions. While social media platforms provide critical spaces for disclosure, support seeking, and emotional regulation[55], they also pose risks of excessive use and problematic internet behaviors that can exacerbate psychological distress[35]. Psychological mechanisms such as mood management, emotional dysregulation, and sense of control underpin how adolescents use social media to cope with maltreatment-related stress and loneliness. Lastly, there is a need to examine bidirectional influences between mental health and social media behaviors. While this study showed that specific social media behaviors relevant to CM-exposed adolescents longitudinally impact symptoms of depression, there is also evidence that psychological states shape social media behaviors[20].

Findings presented here are also of great clinical relevance as they can foster selective and indicative prevention strategies for vulnerable adolescents, such as those with a history of CM. Understanding how CM-exposed adolescents use TikTok differently from their peers

provides a crucial opportunity for targeted interventions. The average number of searches per week emerges as a key predictor of CM exposure among youth, underscoring the importance of monitoring and interpreting online behavior patterns in clinical settings. This insight can inform therapeutic approaches by incorporating specific behaviours, such as search frequency, session length, and posting activity, into counseling and therapy sessions. Moreover, recognizing the potential at-risk activities associated with TikTok use, such as receiving sexual solicitations online and meeting strangers offline, is essential for developing comprehensive prevention and intervention programs. Additionally, an increased presence of mental health providers directly on social media platforms is crucial, as these are the spaces where adolescents increasingly spend time and seek information. Such a presence provides an opportunity for mental health professionals to connect with adolescents and disseminate accurate information. It can facilitate early intervention, provide support, and guide adolescents towards appropriate mental health resources. While TikTok has been used for a range of public health purposes, institutional accounts remain poorly engaged[56].

By linking objective digital trace data to self-reported CM exposure and longitudinal impacts on mental health, this study moves beyond the scope of previous investigations. Our findings show that distinct platform behaviors, not general time spent using TikTok, differentiate CM-exposed adolescents from their peers and relate to later depressive symptoms. For youth with CM experiences, online activity may therefore reflect both coping efforts and increased vulnerability within their everyday digital lives. Collectively, these findings demonstrate the importance of utilizing detailed digital data donations to comprehend how childhood adversity manifests in adolescents' online behavior. This perspective can inform targeted prevention strategies, clinical interventions, and the development of digital environments that more effectively support vulnerable populations youth.

Methods

Participants

A total of 154 adolescents aged 13 to 18 years were enrolled between December 2023 and June 2025 and completed baseline questionnaire assessments (T1). Of these, 129 participants (83.8%) provided their TikTok data archives, constituting the analytical baseline sample. Among participants who did not provide TikTok archives, two explicitly declined data archive sharing, whereas the remaining participants did not submit their archives despite repeated reminders. At the 6-month follow-up (T2), questionnaire data were available for a subsample of 84 participants, corresponding to a retention rate of 65.1% relative to the baseline sample. Participants were required to have used TikTok for at least the past six months.

Procedures and Design

The *TikTalk Teens Study* is a longitudinal observational project. Recruitment took place in youth centers, schools as well as the clinical settings via flyers, personal contact and a TikTok account specifically created for the purposes of the present study. After providing informed consent, participants completed a set of online questionnaires. A central feature of the project is its participatory data-donation design: participants shared their TikTok data archives, which contain objective usage data gathered by the platform. These data offer naturalistic insights into social media behaviors while reducing common biases introduced by self-report (Parry et al., 2022).

Participants downloaded their personal TikTok archives and shared parts of them with the study team. During study participation, adolescents followed the study team's TikTok account and vice-versa. After six months, participants were asked to fill out a set of questionnaires online (T2). Participants were compensated with a gift voucher of €20 for baseline and follow-up each. For adolescents younger than 16 years, caregivers provided written informed consent. Adolescents provided written assent or consent if 16 or older. Procedures were approved by the Ethics Committee of Ulm University (292/23).

Measures

Demographic characteristics were assessed via self-report questionnaires. SES was calculated as a composite score including parental education and parental occupation, with higher scores indicating higher SES.

Childhood Maltreatment (CM) experiences were assessed using the German version of the Childhood Trauma Questionnaire (CTQ[57]), a widely used measure. The CTQ consists of 28 items assessing five different types of CM, i.e., emotional, physical and sexual abuse as well as emotional and physical neglect. Participants responded to each item on a 5-point Likert scale (1 = "never true" to 5 = "very often true"). CM subtype scores were calculated using the sum score of the five items, ranging from 5 to 25, with higher scores indicating more severe childhood abuse and/or neglect. Based on the subtype scores, categorical severity levels were calculated according to the cut-off values previously reported[58].

Severity scores ranged from 1 “none to minimal,” 2 “minimal to moderate,” 3 “moderate to severe,” to 4 “severe to extreme”. For the purposes of the present study, exposure to CM was considered met and clinically relevant when scores were at or above the “moderate to severe” (3) severity threshold in at least one of the five subscales. Consequently, a binary variable was created to indicate the exposure to CM (0 = “no”, 1 = “yes”). Internal consistencies of the CTQ subscales ranged from good to excellent in the present sample (Cronbach’s α: emotional abuse = .91; physical abuse = .70; sexual abuse = .91; emotional neglect = .84), except for the physical neglect subscale, which showed lowered internal consistency (α = .64). The CTQ total scale showed excellent internal consistency (α = .93) in the present sample.

Objective TikTok Use Data. Adolescents shared parts of their TikTok data archives. Shared data files included the browsing history, favorite videos, like list, posts, searches, share history, comments, direct messages, followers, following, block list, and settings (private account enabled or disabled). Variables obtained from data archives and used in the present study are detailed in Supplementary Table S1. Variables have been divided by the number of weeks a TikTok behavior was used to obtain comparable estimates across participants. In addition, several variables were calculated, including the number of sessions, session length and the percentage of videos watched at night. The number of likes adolescents received was collected manually by checking the account profile.

Self-Report TikTok Use and Experiences & Parental Control. Self-reported TikTok use was assessed via items created specifically for the purposes of the present study: 1) Duration of daily TikTok use (answers 0 = “15 minutes or less” - 4 = “More than 3 hours”); 2) Participation in TikTok challenges and trends (0 = “No, never” - “Yes, often"); 3) TikTok-only friendships (0 = “none” - 2 = “many”). Further, potential at-risk TikTok experiences were assessed, including the frequency of unwanted sexual solicitations via TikTok (0 = “No, never” - 2 = “Yes, happened several times”) and whether adolescents have met someone offline whom they first met on TikTok (0 = “No” 1 = “Yes”). Lastly, the degree of parental control over adolescents’ smartphone use was assessed on a 5-point scale (0 = “Not at all” - 4 = “Very strong”). More details on all items are presented in Supplementary Table S2.

Depression. Depressive symptoms were assessed using the Short Mood and Feelings Questionnaire (SMFQ), a widely used self-report measure of depression symptoms in children and adolescents (Angold et al., 1995). The SMFQ consists of 13 items that cover various aspects of depressive symptomatology over the past month. Participants respond on a 3-point Likert scale: “Not true” (1), “Sometimes” (2), and “True” (3). A total score is calculated by summing up the responses, resulting in a score ranging between 13 to 39, with higher scores indicating greater severity of depressive symptoms. Internal consistency of the SMFQ was excellent (α = .92) in the present sample.

Data Analyses

Data analyses were conducted with R (version 4.3.3) using the packages lavaan (0.6.17), readxl (1.4.3) and dplyr (1.1.4) as well as Python (version 3.10.11) using the packages xgboost (3.1.2), scikit-learn (1.7.2), pandas (2.2.3), numpy (2.0.1), optuna (4.5.0), shap (0.49.1), and torch (2.9.1). To examine whether TikTok use variables differed between adolescents exposed to CM and non-exposed adolescents, non-parametric Mann-Whitney U- and Chi-Square tests were computed, taking into account that assumptions of normality were violated. Shapiro-Wilk tests indicated significant deviations from normality for all continuous variables (all p-values < .05). False Discovery Rate (FDR) adjustment for multiple comparisons was applied. Effect sizes for Mann-Whitney-U tests are reported as rank-biserial correlations (r_{rb}) while odds ratios (OR) are reported for categorical comparisons.

To identify TikTok behaviors that are specific to CM-exposed adolescents, supervised machine learning was used based on objective and self-report TikTok use variables. Predictive models for CM status (0/1) were developed. Leave-One-Out Cross-Validation (LOOCV) with a 3-fold inner CV was employed for hyperparameter optimization to maximize data utility and minimize bias/variance in performance estimates. Data preprocessing included encoding categorical variables, binarizing sparse counts (0=absence, 1=presence), and transforming continuous variables (log1p) with Winsorization (0.5–99.5%). Missing values (<5%) were imputed via k-Nearest Neighbors (k=5). Twenty-four TikTok use features, based on both TikTok data archives and self-reported information, were entered into the models. Age, gender, SES and the number of weeks videos were favorited on TikTok were included to control for socio-demographic factors as well as for the period of time users have been interacting with TikTok. Principal Component Analysis was used on highly correlated features, retaining the first principal component for latent constructs (i.e., Video Engagement Index and Favorites Index), which helped to reduce multi-collinearity. Variance Inflation Factor (VIF) analysis excluded one collinear feature (Direct Messages Sent/Week). All variables entered into the machine learning models including the respective preprocessing methods are detailed in the supplementary material (Table S3).

Seven models, namely generalized additive models (EBM), gradient boosting (XGBoost), bagging-based ensembles, logistic regression, kernel methods, and conditional inference trees, were evaluated using nested LOOCV. The primary metric was the mean macro F1 score. To address class imbalance, a lightweight Wasserstein Generative Adversarial Network (WGAN) was used to generate synthetic samples within each fold. XGBoost achieved the highest performance (mean macro F1 = 0.713, 95% CI: [0.636, 0.791]) with optimized hyperparameters (learning rate = 0.0094, n_estimators = 389, max_depth = 4). SHAP values were used to quantify feature importance. More detailed information about preprocessing and machine learning analyses is provided in the Supplementary Methods.

Patterns of missing data were examined prior to the longitudinal analyses. Little's MCAR test indicated that missingness was not completely at random ($\chi^2(21) = 37.40$, $p = .015$). To assess whether missingness was consistent with a missing-at-random (MAR) mechanism, attrition analyses compared participants with ($n = 81$) and without ($n = 48$) follow-up depression data across all included study variables. No differences emerged for any TikTok indicators or covariates (all $ps > .05$), except for parental control and gender. Adolescents reporting higher parental control were more likely to provide follow-up data ($\chi^2(1) = 4.58$, $p = .032$). In addition, girls were more likely than boys to skip follow-up assessments ($\chi^2(1) = 13.78$, $p < .001$; 55.6% dropout among girls vs. 21.9% among boys). Overall, missingness was associated with only a small number of observed variables, consistent with the MAR assumption.

Path analysis was used to investigate the impacts of TikTok use variables on T2 depressive symptoms. Variables previously identified as relevant in the SHAP-based feature selection procedure (i.e., SHAP > 0.02) were included as predictors. Demographic information (age, gender, SES), baseline depression (T1), and CM were entered as covariates. Parameters were estimated using robust maximum likelihood (MLR) with full information maximum likelihood (FIML) to account for missing data under a missing-at-random assumption (Schafer & Graham, 2002).

Declarations

Consent: For adolescents younger than 16 years, caregivers provided written informed consent and adolescents provided written assent in accordance with the Declaration of Helsinki and German ethical guidelines. Adolescents aged 16 years or older provided written informed consent independently. By the vote of our University Ethics committee adolescents were allowed to provide informed consent from 16 years. Meaning parental consent was only needed for this younger than 16.

Data Availability

The data reported in this article are not publicly available because they contain extremely sensitive information that could compromise the privacy and confidentiality of research participants. We cannot provide individual-level data from this project due to the limits of our confidentiality agreement with participants. Data are available on reasonable request from A.C.H.

Code Availability

The data analysis script is available from A.C.H. upon request.

Acknowledgements

A.C.H. acknowledges support from a grant from the Porticus Foundation. A.C.H. and D.T acknowledge support from the European Social Fund Plus (ESF Plus) and the Ministry of Science, Research and Arts Baden-Wuerttemberg through the Margarete von Wrangell-Program. The views and opinions expressed in this publication are solely those of the author and do not necessarily reflect the official position of the funders.

Author contributions

AC.H. was the principal investigator of the study, was involved in the conception and design of the study, participated in data acquisition, directed the analysis and interpretation of findings, produced drafts and revisions, and provided final approval of the manuscript.

O.D. participated in data acquisition, contributed to the conception of the manuscript, to data analyses, the interpretation of findings, and produced drafts.

T.N. participated in data acquisition, performed data analyses, aided in interpretation of findings, and contributed to drafts.

D.T. aided in the interpretation of findings, and contributed to drafts and revisions.

J.S. extracted the variables from data archives and contributed to revisions of the manuscript.

H.A.K. supervised the analyses of the data archives and contributed to revisions of the manuscript.

J.M.F. was involved in the conception of the study, aided in interpretation of findings, and contributed to drafts and revisions.

All authors have approved the submitted version.

Competing interests

The authors declare no competing interests.

References

1. Kessler, R. C. *et al.* Lifetime Prevalence and Age-of-Onset Distributions of DSM-IV Disorders in the National Comorbidity Survey Replication. *Arch. Gen. Psychiatry* **62**, 593 (2005).
2. Blakemore, S.-J. & Mills, K. L. Is Adolescence a Sensitive Period for Sociocultural Processing? *Annu. Rev. Psychol.* **65**, 187–207 (2014).
3. Shulman, S. & Scharf, M. Adolescent psychopathology in Times of Change: The need for integrating a developmental psychopathology perspective. *J. Adolesc.* **65**, 95–100 (2018).
4. Orben, A., Meier, A., Dalgleish, T. & Blakemore, S. J. Mechanisms linking social media use to adolescent mental health vulnerability. *Nature Reviews Psychology* vol. 3 407–423 Preprint at https://doi.org/10.1038/s44159-024-00307-y (2024).
5. Faverio, M. & Sidoti, O. Teens, Social Media and AI Chatbots 2025. *Pew Research Center* (2025).
6. Burke, A., Kumpulainen, K. & Smith, C. Children's digital play as collective family resilience in the face of the pandemic. *Journal of Early Childhood Literacy* **23**, 8–34 (2023).
7. Montag, C., Yang, H. & Elhai, J. D. On the Psychology of TikTok Use: A First Glimpse From Empirical Findings. *Front. Public Health* **9**, 641673 (2021).
8. Fassi, L., Ferguson, A. M., Przybylski, A. K., Ford, T. J. & Orben, A. Social media use in adolescents with and without mental health conditions. *Nat. Hum. Behav.* **9**, 1283–1299 (2025).
9. Orben, A. & Przybylski, A. K. The association between adolescent well-being and digital technology use. *Nat. Hum. Behav.* **3**, 173–182 (2019).
10. Nagata, J. M. *et al.* Screen time and mental health: a prospective analysis of the Adolescent Brain Cognitive Development (ABCD) Study. *BMC Public Health* **24**, (2024).
11. Coyne, S. M., Rogers, A. A., Zurcher, J. D., Stockdale, L. & Booth, M. Does time spent using social media impact mental health?: An eight year longitudinal study. *Comput. Human Behav.* **104**, (2020).
12. Plackett, R., Sheringham, J. & Dykxhoorn, J. The Longitudinal Impact of Social Media Use on UK Adolescents' Mental Health: Longitudinal Observational Study. *J. Med. Internet Res.* **25**, (2023).
13. Sultan, M., Scholz, C. & van den Bos, W. Leaving traces behind: Using social media digital trace data to study adolescent wellbeing. *Computers in Human Behavior Reports* vol. 10 Preprint at https://doi.org/10.1016/j.chbr.2023.100281 (2023).
14. Jain, L. *et al.* Exploring Problematic TikTok Use and Mental Health Issues: A Systematic Review of Empirical Studies. *Journal of Primary Care and Community Health* vol. 16 Preprint at https://doi.org/10.1177/21501319251327303 (2025).
15. Houghton, S. *et al.* Reciprocal Relationships between Trajectories of Depressive Symptoms and Screen Media Use during Adolescence. *J. Youth Adolesc.* **47**, 2453–2467 (2018).
16. Boer, M., Stevens, G. W. J. M., Finkenauer, C., de Looze, M. E. & van den Eijnden, R. J. J. M. Social media use intensity, social media use problems, and mental health among adolescents: Investigating directionality and mediating processes. *Comput. Human Behav.* **116**, (2021).
17. Frison, E. & Eggermont, S. Browsing, Posting, and Liking on Instagram: The Reciprocal Relationships Between Different Types of Instagram Use and Adolescents' Depressed Mood. *Cyberpsychol. Behav. Soc. Netw.* **20**, 603–609 (2017).
18. Conte, G. *et al.* Scrolling through adolescence: a systematic review of the impact of TikTok on adolescent mental health. *Eur. Child Adolesc. Psychiatry* **34**, 1511–1527 (2025).
19. Wu, Y. *et al.* The Relationship Between Social Short-Form Videos and Youth's Well-Being: It Depends on Usage Types and Content Categories. *Psychology of Popular Media* **10**, 467–477 (2021).
20. Yao, N. & Chen, J. TikTok use in relation to mental health and well-being: A longitudinal network analysis. *Computers in Human Behavior Reports* **20**, (2025).
21. Cowley, L. E. *et al. Defining Child Maltreatment for Research and Surveillance: An International, Multi-Sectoral, Delphi Consensus Study in 34 Countries in Europe and Surrounding Regions*. www.thelancet.com (2025).
22. World Health Organization. *Responding to Child Maltreatment: A Clinical Handbook for Health Professionals.* (2022).
23. Cicchetti, D. Socioemotional, personality, and biological development: Illustrations from a multilevel developmental psychopathology perspective on child maltreatment. *Annu. Rev. Psychol.* **67**, 187–211 (2016).
24. McLaughlin, K. A., Sheridan, M. A., Alves, S. & Mendes, W. B. Child Maltreatment and Autonomic Nervous System Reactivity: Identifying Dysregulated Stress Reactivity Patterns using the Biopsychosocial Model of Challenge and Threat. *Psychosom Med* **7**, 538–546 (2014).

25. Teicher, M. H., Samson, J. A., Anderson, C. M. & Ohashi, K. The effects of childhood maltreatment on brain structure, function and connectivity. *Nature Reviews Neuroscience* vol. 17 652–666 Preprint at https://doi.org/10.1038/nrn.2016.111 (2016).
26. Humphreys, K. L. *et al.* Child maltreatment and depression: A meta-analysis of studies using the Childhood Trauma Questionnaire. *Child Abuse Negl.* **102**, 104361 (2020).
27. Zhang, Y., Liao, H., Gu, J. & Wang, J. Anxiety and depression related to childhood maltreatment in teenagers: Comparing multiple individual risk model, cumulative risk model and latent profile analysis. *Child Abuse Negl.* **128**, (2022).
28. Breslau, N. *et al.* Childhood maltreatment, juvenile disorders and adult post-traumatic stress disorder: A prospective investigation. *Psychol. Med.* **44**, 1937–1945 (2014).
29. Noll, J. G. Child Sexual Abuse as a Unique Risk Factor for the Development of Psychopathology: The Compounded Convergence of Mechanisms. *Annual Review of Clinical Psychology* vol. 17 439–464 Preprint at https://doi.org/10.1146/annurev-clinpsy-081219-112621 (2021).
30. Johnson, J. G., Cohen, P., Kasen, S. & Brook, J. S. Childhood Adversities Associated With Risk for Eating Disorders or Weight Problems During Adolescence or Early Adulthood. *American Journal of Psychiatry* **159**, 394–400 (2002).
31. Cicchetti, D. & Handley, E. D. Child maltreatment and the development of substance use and disorder. *Neurobiol. Stress* **10**, 100144 (2019).
32. Cowell, R. A., Cicchetti, D., Rogosch, F. A. & Toth, S. L. Childhood maltreatment and its effect on neurocognitive functioning: Timing and chronicity matter. *Dev. Psychopathol.* **27**, 521–533 (2015).
33. Walker, H. E., Freud, J. S., Ellis, R. A., Fraine, S. M. & Wilson, L. C. The Prevalence of Sexual Revictimization: A Meta-Analytic Review. *Trauma Violence Abuse* **20**, 67–80 (2019).
34. Haag, A. C. *et al.* Understanding posttraumatic stress trajectories in adolescent females: A strength-based machine learning approach examining risk and protective factors including online behaviors. *Dev. Psychopathol.* **35**, 1794–1807 (2023).
35. Pazdur, M., Tutus, D. & Haag, A. C. Risk Factors for Problematic Social Media Use in Youth: A Systematic Review of Longitudinal Studies. *Adolesc. Res. Rev.* **10**, 237–253 (2025).
36. Tang, H. *et al.* The relationship between childhood trauma and internet addiction in adolescents: A meta-analysis. *J. Behav. Addict.* **13**, 36–50 (2024).
37. Kennedy, R. S., Font, S. A., Haag, A. C. & Noll, J. G. Childhood Sexual Abuse and Exposure to Peer Bullying Victimization. *J. Interpers. Violence* **37**, NP18589–NP18613 (2022).
38. Noll, J. G., Shenk, C. E., Barnes, J. E. & Haralson, K. J. Association of Maltreatment With High-Risk Internet Behaviors and Offline Encounters. *Pediatrics* **131**, e510–e517 (2013).
39. Noll, J. G. *et al.* An observational study of Internet behaviours for adolescent females following sexual abuse. *Nat. Hum. Behav.* **6**, 74–87 (2022).
40. Verbeij, T., Pouwels, J. L., Beyens, I. & Valkenburg, P. M. The accuracy and validity of self-reported social media use measures among adolescents. *Computers in Human Behavior Reports* **3**, (2021).
41. Yap, V. Z. Y. *et al.* Digital Data Donation With Adolescents. *Ann. N. Y. Acad. Sci.* **1554**, 251–266 (2025).
42. Kelly, C. A. & Sharot, T. Web-browsing patterns reflect and shape mood and mental health. *Nat. Hum. Behav.* **9**, 133–146 (2024).
43. van Driel, I. I. *et al.* Promises and Pitfalls of Social Media Data Donations. *Commun. Methods Meas.* **16**, 266–282 (2022).
44. Maheux, A. J. *et al.* Annual Research Review: Adolescent social media use is not a monolith: toward the study of specific social media components and individual differences. *Journal of Child Psychology and Psychiatry and Allied Disciplines* vol. 66 440–459 Preprint at https://doi.org/10.1111/jcpp.14085 (2025).
45. Schwab-Reese, L. M., PettyJohn, M. E., Tasnim, R. & Fingerman, M. Social media facilitates disclosure among people experiencing child maltreatment: A brief report. *Child Protection and Practice* **5**, (2025).
46. Kotozaki, Y., Manmohan Galagali, P. & Maftei, A. *Social Media Use as a Coping Mechanism during the COVID-19 Pandemic: A Multidimensional Perspective on Adolescents' Well-Being*.
47. Cauberghe, V., Van Wesenbeeck, I., De Jans, S., Hudders, L. & Ponnet, K. How Adolescents Use Social Media to Cope with Feelings of Loneliness and Anxiety during COVID-19 Lockdown. *Cyberpsychol. Behav. Soc. Netw.* **24**, 250–257 (2021).
48. Monge Roffarello, A. & De Russis, L. Towards Understanding the Dark Patterns That Steal Our Attention. in *Conference on Human Factors in Computing Systems - Proceedings* (Association for Computing Machinery, 2022). doi:10.1145/3491101.3519829.
49. Olson, A. E. *et al. Child Maltreatment, Parent-Child Relationship Quality, and Parental Monitoring in Relation to Adolescent Behavior Problems: Disaggregating Between and Within Person Effects*. (2022).

50. Limniou, M., Ascroft, Y. & McLean, S. Differences between Facebook and Instagram Usage in Regard to Problematic Use and Well-Being. *J. Technol. Behav. Sci.* **7**, 141–150 (2022).
51. Azayem, A. K., Nawaz, F. A., Jeyaseelan, L., Kair, H. M. & Sultan, M. A. Beyond the filter: Impact of popularity on the mental health of social media influencers. *Digit. Health* **10**, (2024).
52. Sala, A., Porcaro, L. & Gómez, E. Social Media Use and adolescents' mental health and well-being: An umbrella review. *Computers in Human Behavior Reports* vol. 14 Preprint at https://doi.org/10.1016/j.chbr.2024.100404 (2024).
53. Hendrikse, C. & Limniou, M. The Use of Instagram and TikTok in Relation to Problematic Use and Well-Being. *J. Technol. Behav. Sci.* **9**, 846–857 (2024).
54. Witt, A., Brown, R. C., Plener, P. L., Brähler, E. & Fegert, J. M. Child maltreatment in Germany: Prevalence rates in the general population. *Child Adolesc. Psychiatry Ment. Health* **11**, (2017).
55. Schwab-Reese, L. *et al.* "If I Stay Silent, It Doesn't Help Anyone": Understanding How People Use TikTok to Talk About Sexual Violence. *Violence Against Women* **31**, 3311–3329 (2025).
56. McCashin, D. & Murphy, C. M. Using TikTok for public and youth mental health – A systematic review and content analysis. *Clin. Child Psychol. Psychiatry* **28**, 279–306 (2023).
57. Klinitzke, G., Romppel, M., Häuser, W., Brähler, E. & Glaesmer, H. [The German Version of the Childhood Trauma Questionnaire (CTQ): psychometric characteristics in a representative sample of the general population]. *Psychother. Psychosom. Med. Psychol.* **62**, 47–51 (2012).
58. Häuser, W., Schmutzer, G., Brähler, E. & Glaesmer, H. Misshandlungen in Kindheit und Jugend: Ergebnisse einer Umfrage in einer repräsentativen Stichprobe der Deutschen Bevölkerung. *Dtsch. Arztebl.* **108**, 287–294 (2011).

Tables

Table 1. Demographic characteristics and study group comparisons

	Total sample		CM		Non-exposed		
	M / n	*SD / %*	*M / n*	*SD / %*	*M / n*	*SD / %*	Test statistic
Age	15.90	1.47	16.37	1.28	15.68	1.51	*U* = 1317, *p* adj. = .036
Gender							$\chi^2(1) = 1.94$[a], *p* adj =.163
Female	73	56.59	26	63.41	47	53.41	
Male	54	41.86	13	31.71	41	46.59	
Diverse	2	1.55	2	4.88	0	0.00	
SES	15.17	3.99	14.03	4.46	15.70	3.66	*U* = 1359, *p* adj = .087

***Notes*.** *N* = 126 – 129. CM = Child maltreatment. SES = Socio-economic status. Adjustment for multiple comparisons using false discovery rate. [a]Comparison includes only participants of female and male gender. The diverse category had to be excluded due to low cell count.

Table 2. Descriptive statistics and study group comparisons across objective and self-report TikTok use variables

		Total sample (*N* = 129)			Child maltreatment (*n* = 41)		Non-exposed (n = 88)		U-test / Chi^2-test		
	N[b]	*Mean* (*n*)	*Median*	*SD* (%)	*M* (n)	*SD* (%)	*M* (*n*)	*SD* (%)	*p*-value	*adj. p*-value	Effect size (r_{rb} / OR)
Objective TikTok use variables extracted from data archives											
Videos Viewed / Week	116[b]	2190.21	1754.14	1718.93	2734.65	2167.20	1954.95	1437.20	0.047	.206	0.23
Videos Skipped / Week	116	1038.05	503.34	1332.10	1349.67	1489.10	903.40	1244.01	0.055	.206	0.23
Unique Videos Viewed / Week	116	1893.89	1548.81	1465.01	2372.02	1871.77	1687.29	1205.41	0.047	.206	0.23
Multiply-Viewed Videos / Week	116	152.75	74.47	210.44	183.60	187.23	139.41	219.47	0.112	.261	0.19
Sessions / Week	116	36.22	35.96	19.11	38.37	20.43	35.30	18.57	0.472	.575	0.08
Session Length (Seconds)	116	1040.63	1000.11	415.72	1091.95	308.86	1018.45	454.13	0.077	.240	0.21
Follower	127	325.77	76.00	658.77	515.50	976.04	238.54	423.52	0.161	.301	0.16
Following	129	844.07	234.00	1474.29	696.80	1228.55	912.68	1577.63	0.889	.889	0.02
Number Of Videos Liked / Week	128	406.19	280.79	419.95	459.33	407.04	382.03	425.77	0.145	.301	0.16
Number Of Videos Favorited / Week	126	28.00	9.49	70.50	41.42	111.90	21.98	39.65	0.197	.345	0.14
Proportion Of Videos Viewed At Night	116	0.10	0.08	0.10	0.13	0.12	0.09	0.10	0.059	.206	0.22
Shares / Week	125	33.46	7.21	132.97	65.67	234.61	19.39	33.99	0.092	.255	0.19
Searches / Week	118	27.11	14.87	34.55	39.52	46.71	21.88	26.56	0.010	.206	0.30
Accounts Blocked / Week	127	0.30	0.09	0.45	0.34	0.57	0.28	0.39	0.538	.628	0.07
Comments / Week	122	7.14	4.13	11.37	7.68	10.65	6.88	11.75	0.439	.559	0.09
Direct Messages Sent / Week	124	23.33	6.00	53.56	30.59	58.56	19.87	51.01	0.156	.301	0.16
Direct Messages Received / Week	124	26.10	10.00	54.95	39.93	80.25	19.52	36.23	0.413	.559	0.09

		Total sample (*N* = 129)			Child maltreatment (*n* = 41)		Non-exposed (n = 88)		U-test / Chi^2-test		
	N[b]	*Mean* (*n*)	*Median*	*SD* (%)	*M* (n)	*SD* (%)	*M* (*n*)	*SD* (%)	*p*-value	*adj. p*-value	Effect size (r_{rb} / OR)
Chat Partners / Week	124	0.93	0.69	0.85	0.82	0.62	0.98	0.94	0.609	.656	0.06
Single Contacts / Week	124	0.10	0.00	0.21	0.07	0.15	0.11	0.23	0.439	.559	0.08
Posts / Week	128	1.24	0.00	3.76	1.95	5.21	0.90	2.80	0.021	.206	0.23
Likes Received On Profile	129	11742.25	0.00	47047.37	27997.76	78516.38	4168.66	15480.03	0.312	.460	0.10
Private Account Status (yes)	127	57	NA	44.9	17	43.6	40	45.5	0.846	.877	0.93[a]
Self-reported TikTok use variables from questionnaires											
Parental Control	129	0.78	1.00	0.82	0.71	0.93	0.81	0.77	0.218	.359	0.12
Self-Report Daily Usage Duration	129	2.74	3.00	0.92	2.93	0.91	2.65	0.92	0.100	.255	0.17
Participation in TikTok Trends /Challenges (yes)[c]	129	45	NA	34.88	17	13.18	28	21.71	0.285	.443	1.52[a]
Online-Only Friends	129	0.32	0.00	0.57	0.37	0.62	0.30	0.55	0.574	.643	0.05
Sexual Solicitations On TikTok	129	0.25	0.00	0.52	0.41	0.67	0.17	0.41	0.029	.206	0.17
Meeting TikTok-Strangers Offline (yes)	129	15	NA	11.63	8	19.51	7	7.95	0.057	.206	2.81[a]

Notes. r_{rb} = Rank biserial correlation. [a] OR = Odds Ratio presented. [b] *N* varies due to technical TikTok data archive transmission issues. [c] Although participation in TikTok challenges and trends was assessed on a three-point scale (see Table S2), no participant chose the third category. Therefore, the variable was treated as dichotomous. Adj. *p*-values are adjusted for multiple comparison using false discovery rate. NA = Not available.

Table 3. Results of path analysis predicting Time 2 depressive symptoms

Predictors	B	SE	z-value	*p*-value	*β*
Searches / Week	-0.39	0.37	-1.04	.298	-0.06
Session Length (Seconds)	0.45	0.51	0.88	.381	0.07
Posts / Week	-1.22	0.55	-2.21	.027	-0.18
Parental Control	-0.23	0.96	-0.24	.812	-0.02
Sexual Solicitations On TikTok	0.58	1.25	0.46	.644	0.04
Number Of Weeks Favorites Recorded	-0.09	0.48	-0.20	.846	-0.01
Follower Count	1.39	0.48	2.90	.004	0.21
Chat Partners / Week	0.30	0.50	0.59	.554	0.04
Direct Messages Received / Week	-0.35	0.57	-0.61	.543	-0.05
Meeting TikTok-Strangers Offline	-2.07	1.57	-1.32	.188	-0.10
Control Variables					
Age (T1)	-0.86	0.63	-1.37	.172	-0.13
Gender [a]	-2.17	1.14	-1.90	.058	-0.17
Socioeconomic Status (SES)	-0.67	0.59	-1.15	.249	-0.10
Childhood Maltreatment (CTQ)	4.08	1.09	3.74	<.001	0.28
T1 Depression	3.94	0.51	7.79	<.001	0.59

Notes. *N* = 129. *B* = unstandardized coefficient; *SE* = standard error; *z-value* = Wald test statistic; *β* = standardized coefficient. Estimates obtained from an observed-variable path model estimated with full information maximum likelihood. [a] Gender was treated as a categorical variable and coded as 0 = female, 1 = male, 2 = diverse.

Figures

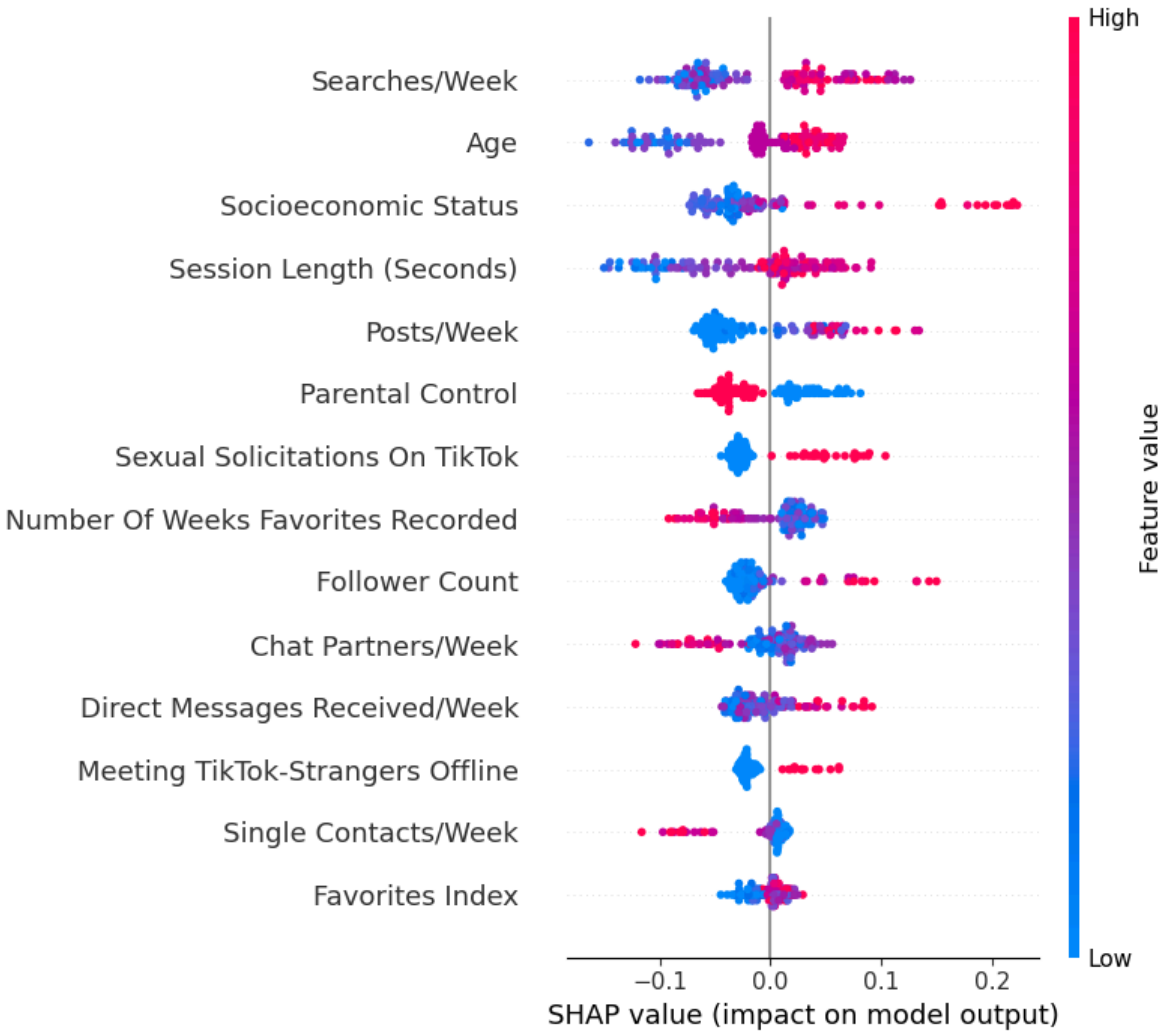

Figure 1

Beeswarm SHAP value distribution of the top features classifying child maltreatment (CM) status. Distribution of SHAP values for the top 14 features influencing CM status classification. Each dot represents an individual observation, with color indicating feature value (red = high, blue = low). Positive feature impact on model outcome indicates increased predicted risk, while negative feature impact indicates decreased predicted risk. Features are ranked by their mean absolute SHAP value.

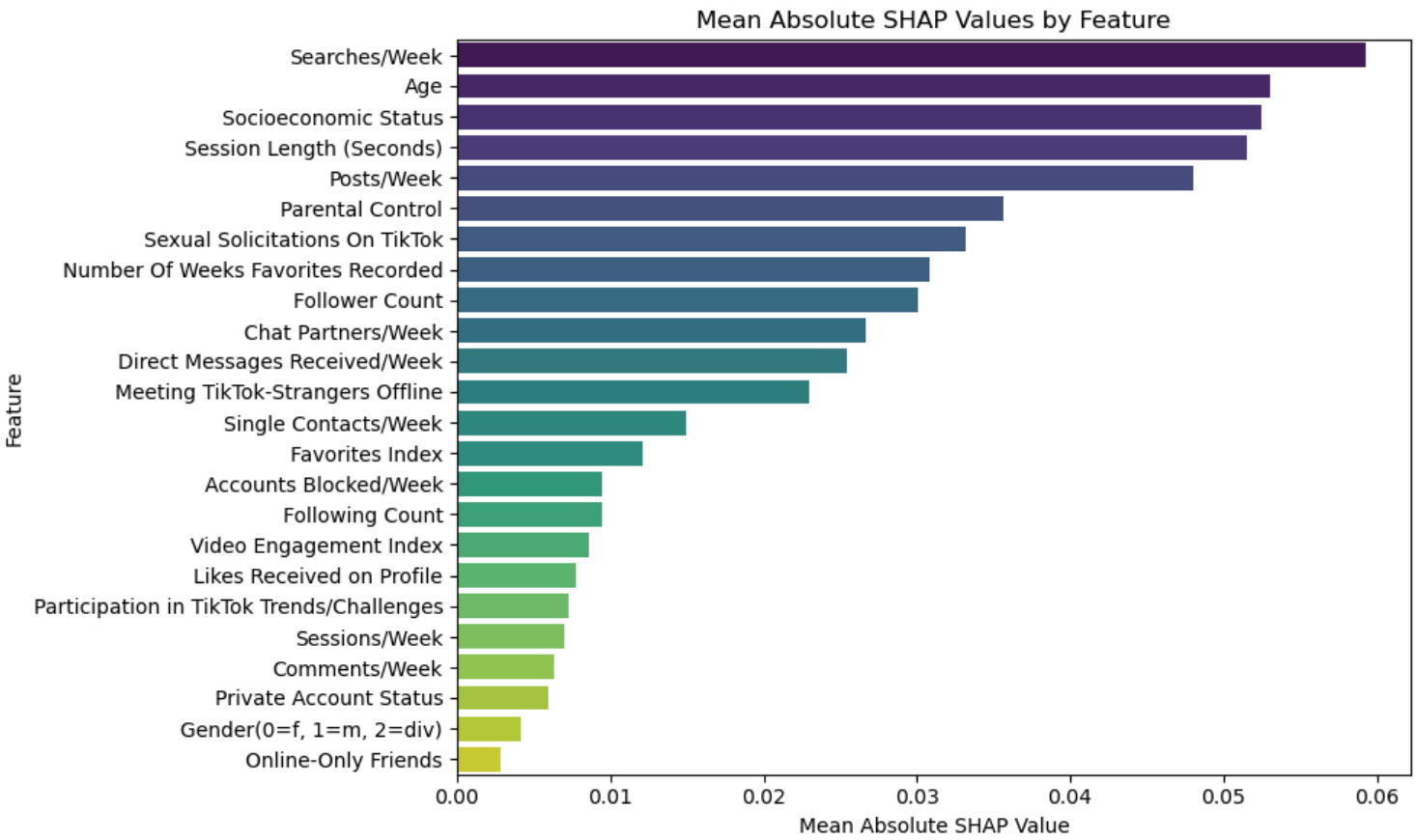

Figure 2

Mean absolute SHAP values of all included features classifying child maltreatment (CM) status. Mean absolute SHAP values for all 24 features, quantifying their relative contribution to CM status predictions. Features are ordered by their average impact on model output. The magnitude of each bar reflects the average contribution of the corresponding feature to the model's prediction across all observations.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- supplmaterial.docx