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Timing Matters: Age of Onset in Online Child Sexual Solicitation and Abuse and Young Adults' Well-Being

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Abstract

Online child sexual solicitation and abuse (OCSSA) is a widespread phenomenon with first exposure clustering in adolescence. While accumulating evidence documents adverse psychological correlates, the role of developmental timing across the spectrum of OCSSA subtypes remains poorly understood. Data were drawn from a nationally representative German survey of *N* = 1,006 young adults aged 18 to 29 years. Nine OCSSA subtypes and age at first exposure were assessed retrospectively and operationalized as single-year onset indicators. Psychological well-being was measured using the WHO-5 Well-Being Index. A dual machine learning approach combining LASSO and Random Forest regression was used to identify robust predictors, controlling for offline CM, age, gender, education, and equivalized household income. A post-hoc multiple linear regression provided interpretable effect estimates. 32.3% of participants reported at least one form of OCSSA before age 18. Offline CM was the dominant predictor of reduced well-being ($B = -17.66$, $p < .001$). Three age of OCSSA onset predictors were identified: unwanted exposure to pornographic/sexualized material at ages 13 and 15, and unwanted sexualized talk at age 15. Of these, exposure to pornographic/sexualized material at age 13 remained statistically significant in the post-hoc regression ($B = -11.22$, $p = .005$). Specific OCSSA subtypes at particular ages may relate to long-term well-being, with early-to-mid adolescence emerging as a potentially sensitive developmental period.

Introduction

Globally, approximately one-third of young adults report having experienced at least one form of online child sexual solicitation and abuse (OCSSA) before age 18 [1]. OCSSA includes solicitation-based behaviors like unwanted sexualized communication and abusive forms such as coercive interactions and image-based sexual abuse (IBSA), the latter referring to coercive obtaining, creation, or non-consensual distribution of sexualized material [2–4]. Different OCSSA subtypes may exert distinct effects due to variations in boundary violation nature, interactional context, and psychological burden. While sharing similarities with offline sexual abuse - such as loss of control, humiliation, and trauma-related stress – OCSSA has unique digital characteristics that may intensify harm. The permanence, replicability, and potential for rapid, uncontrollable dissemination of digital material can exacerbate victims' psychological burden [5, 6]. The enduring accessibility of such material impedes psychological closure and sustains ongoing victimization [7]. Emerging evidence indicates OCSSA may form part of broader poly-victimization patterns, with some individuals reporting both online and offline child maltreatment (CM) [8].

Prevalence, Age of First Exposure, and Long-Term Psychological Burden

Lifetime prevalence of sexual violence in childhood and adolescence is estimated at 12.7% in a representative German adult sample, with 61.9% of those affected additionally reporting OCSSA [9].

Using the same validated questionnaire in young adults, approximately 33% reported exposure to at least one OCSSA form before age 18, with unwanted exposure to pornographic material (up to 22%), unwanted sexualized talk (16%), and unwanted sexualized questions (13.5%) being most prevalent [8]. In a U.S. survey of young adults aged 18–28, prevalence rates reached 3.5% for threatened image sharing and 4.9% for forced sexualized image production [3]. In an Australian study of individuals aged 16–24, non-consensual image sharing victimization was reported by 7.6% [10]. Additionally, very recent evidence emerged that in Africa and Asia approx. 17% of children ages 12–17 experienced at least one form of technology-facilitated child sexual exploitation and abuse, equivalent to over 10 million children in in the 12 countries included [11].

First OCSSA exposure is concentrated in mid-to-late adolescence, with most initial exposure occurring between 12 and 17 years [3, 12]. Australian data indicate 67% of first exposures cluster within ages 12–15, with median ages of 15 years for non-consensual distribution of sexual material and 14 years for unwanted solicitation to engage in sexual acts [10]. This concentration during mid-adolescence may be significant, as it coincides with intensified online engagement, emerging sexuality, and heightened peer orientation [13, 14], making individuals particularly exposed to technology-facilitated sexual boundary violations [15]. These patterns raise the question of whether the concentration of first exposure in adolescence corresponds to the period of greatest long-term psychological vulnerability, or whether earlier exposure may be associated with stronger later psychological burden.

The psychological burden of OCSSA overlaps with adverse outcomes reported in offline sexual victimization contexts [16, 17]. A systematic review identified consistent adverse outcomes, including elevated stress, depressive symptoms, shame, emotional dysregulation, diminished self-esteem, and behavioral problems [18]. The enduring accessibility of digital material intensifies feelings of loss of control and ongoing threat, contributing to sustained anxiety and hypervigilance [19, 20]. While most report transient consequences, a substantial minority experiences enduring functional impairment [21]. Colburn et al. [21] found long-term impact of IBSA varies with developmental timing: individuals victimized at or before age 12 report higher rates of long-term adverse effects (nearly 50%) compared to those first exposed in later adolescence (less than 20%). Particularly enduring psychological effects into adulthood have been observed following non-consensual creation or distribution of sexual material [21]. However, these findings focus exclusively on IBSA and rely on a dichotomized age of onset measure, providing limited insight into comparable timing-related differences across more prevalent solicitation-based forms.

Developmental Timing and the Sensitive Periods Hypothesis

The sensitive periods hypothesis suggests that the long-term psychological and biological consequences of adverse experiences depend on the specific developmental window of first exposure [22]. Early work shows that the age of onset of child maltreatment (CM) is linked to long-term mental health outcomes [23], though recent evidence indicates no single peak vulnerability period consistently emerges across outcomes, implying timing effects vary by adversity type and outcome [24].

Neurobiologically, the brain's shifting plasticity means OCSSA interacts with neural circuits undergoing peak maturation, rather than leaving a uniform imprint [25]. This aligns with the principle of multifinality: similar adverse experiences may yield different long-term outcomes depending on developmental timing [26]. In childhood, rapid maturation of limbic structures like the amygdala and hippocampus - central to threat processing and emotional memory - makes early OCSSA exposure particularly likely to affect stress-reactive circuits, potentially leading to later hypervigilance and emotional dysregulation [25, 27, 28].

Adolescence, however, is marked by a "dual-systems" dynamic: a fully reactive limbic system, sensitized by pubertal hormones, contrasts with the protracted maturation of the prefrontal cortex (PFC), responsible for cognitive control [25, 29]. This imbalance increases vulnerability to social-evaluative stress, as adolescents lack the neural "brakes" to modulate intense emotional responses [29, 30]

This vulnerability extends online, where protracted PFC maturation and heightened emotional reactivity may amplify susceptibility to emotion-arousing media [31]. There is longitudinal evidence that adverse childhood experiences predict problematic social media use in adolescents (reviewed in Pazdur et al. [32]. Further, adolescent females with substantiated CSA were overrepresented in high-risk online profiles, predicting subsequent online sexual solicitations [33] and intentional exposure to online sexual content was revealed to differentiate resilient from chronic PTSS trajectories among adolescent females exposed to potentially traumatic events, including CSA [34].

OCSSA's social manipulation and trust violations may be particularly salient during adolescence, when sensitivity to social signals coincides with immature regulatory control [30, 35]. Social relationships become central to well-being and identity, while digital environments intensify the visibility of social feedback, embedding sexual boundary violations in self-evaluation and identity construction [36–38]. Thus, OCSSA's psychological consequences may vary by developmental stage, as exposure interacts with neural, social, and emotional maturation.

The Current Study

Despite growing evidence documenting the prevalence and psychological consequences of OCSSA, limited attention has been paid to whether the timing of first exposure contributes to differences in long-term psychological well-being. Most empirical studies conceptualize exposure dichotomously, focusing on whether victimization occurred rather than when it first occurred. Existing evidence for age-related gradients derives primarily from image-based forms of victimization. Consequently, it remains unclear whether comparable timing-related patterns extend across the broader range of OCSSA subtypes, including high-prevalence solicitation-based experiences [21]. Moreover, prior studies have rarely isolated the contribution of OCSSA timing to psychological burden from that of co-occurring offline maltreatment, leaving the independent prognostic relevance of developmental timing unestablished. Because OCSSA sometimes forms part of broader patterns of poly-victimization, it is necessary to account for offline CM when examining long-term psychological outcomes [2].

The present study examines whether the age of first exposure to different forms of OCSSA is differentially associated with psychological well-being in young adulthood within a population-based sample. Given the absence of prior empirical evidence on timing-specific effects across OCSSA subtypes and the high-dimensional predictor space generated by crossing various OCSSA forms with 18 possible ages of first exposure, the present study adopted an exploratory design without a priori hypotheses regarding specific age-of-onset combinations. The primary aim was to identify OCSSA age of onset indicators associated with reduced psychological well-being in young adulthood, while accounting for offline CM and sociodemographic characteristics. Thereby, mid-adolescence (approximately 14 to 16 years) appears theoretically salient given both the concentration of first exposure and developmental vulnerability during this period. However, the design of the present study examines associations across the full range to avoid restricting detection to anticipated windows.

Results

Sample characteristics

The sample comprised *N* = 1,006 participants aged 18 to 29 years, of whom 50.8% (n = 511) identified as male. The mean age was 23.65 (*SD* = 3.51). The study utilized a multi-stage design combining a representative probability sample with a stratified quota-boost for young adults (ages 18–29). The final sample was recruited to be nationally representative with respect to age, gender, and geographic region. An overview of sociodemographic and socioeconomic characteristics is presented in Table 1.

Table 1
Sociodemographic characteristics of the sample

Age (*M, SD*, Range in years)	**Total sample (*N* = 1,006)** *n* **(%)**
	23.65 (3.51) [18–29]
Gender	
Female	493 (49.0)
Male	511 (50.8)
Diverse	2 (0.2)
Highest level of education	
Basic education	643 (64)
Advanced education	362 (36)
Equivalence income	
Below poverty risk threshold (< €1381.55)	248 (25.4)
Above poverty risk threshold (> €1381.55)	727 (74.6)
Notes. *M* = mean; *SD* = standard deviation.	
Descriptive Statistics	

Descriptive characteristics of OCSSA, offline CM, and psychological well-being across gender are presented in Table 2. Overall, 32.3% of all participants reported experiencing at least one form of OCSSA before the age of 18. Among those affected, female and male gender were distributed relatively equally (52.6% female, 47.1% male, 0.3% diverse). Given the single representation within the diverse category, statistical stratifications for this subgroup were not feasible. The most frequently reported experiences were unwanted confrontation with pornographic or sexualized material (21.9%), unwanted sexualized talk (15.7%), and unwanted sexualized questions (13.5%). Prevalence estimates for specific OCSSA types for adults aged 18–96 years of the same study have been previously reported [8]. Overall, 18.9% of participants had experienced at least one form of offline CM. The mean WHO-5-well-being score in the total sample was rather elevated with *M* = 72 (*SD* = 20.7). Approximately 16.2% (*n* = 163) of participants scored below the established cut-off of 50, indicating reduced psychological well-being [39].

Table 2
Descriptive characteristics of OCSSA, offline CM, and WHO-5 well-being by gender

OCSSA	**Total sample (*N* = 1,006)** *n* (%) or *M* (*SD*)	**Male (*n* = 511)** *n* (%) or *M* (*SD*)	**Female (*n* = 493)** *n* (%) or *M* (*SD*)
Any form of OCSSA	325 (32.3)	153 (29.9)	171 (34.7)
WHO-5 Index	72 (20.7)	72.9 (19.5)	71.1 (22.0)
[Range]	[0-100]	[16–100]	[0-100]
≥ 50	843 (83.8)	438 (85.7)	403 (81.7)
< 50	163 (16.2)	73 (14.3)	90 (18.3)
Offline Child Maltreatment			
Yes	190 (18.9)	93 (18.2)	97 (19.6)
No	816 (81.1)	418 (81.8)	396 (80.4)

Notes. *M* = mean; *SD* = standard deviation.

Age Distribution of First OCSSA Exposure

Figure 1 illustrates the distribution of reported ages at first OCSSA exposure. Table 3 summarizes descriptive statistics. Observed age ranges extended from 8 to 18 years, although early onset reports were infrequent. Across all OCSSA categories, first exposure was most reported during mid-adolescence, with most onsets occurring between 13 and 17 years. Mean age of onset ranged from 14.8 years (unwanted confrontation with pornographic/sexualized material) to 15.9 years (non-consensual taking of sexualized material). Median onset ages were consistently 15 or 16 years across categories, suggesting a relatively concentrated developmental window. Unwanted confrontation with pornographic/sexualized material and unwanted sexualized talk showed the highest overall frequencies and broadest age distribution, with elevated case numbers from ages 13 through 17. Image-based victimization forms (OCSSA items 1–3) showed more concentrated distributions in later adolescence (ages 15–17), while commercial sexual activities remained rare across all ages (*n* = 6).

Table 3
Descriptive statistics for age of onset across OCSSA categories

OCSSA Item	Endorsed[a] *n* (%)	Age of onset *M (SD)*	Median	Range
Non-consensual sharing of sexualized material	26 (2.6)	14.9 (1.7)	15	10–18
Non-consensual taking of sexualized material	31 (3.1)	15.9 (1.4)	16	13–18
Forced sexualized material	40 (4)	15.4 (1.7)	16	10–18
Sextortion	32 (3.2)	15.9 (1.3)	16	13–18
Unwanted sexualized talk	158 (15.7)	15.1 (1.6)	15	10–18
Unwanted sexualized questions	136 (13.5)	15.2 (1.5)	16	11–18
Request to engage in unwanted sexual acts	78 (7.8)	15.2 (1.5)	16	12–17
Commercial sexual talk/material/activity	6 (0.6)	15.5 (1.8)	16	13–17
Unwanted confrontation with pornographic/sexualized material	220 (21.9)	14.8 (1.8)	15	8–18
Notes. [a] *n* (%) indicates the number and percentage of participants who endorsed the respective OCSSA item and reported a valid age of first exposure. *M* = mean; *SD* = standard deviation.				
LASSO Regression				

Using 10-fold cross-validation, the optimal penalty parameter was identified at λ = 0.76 (lambda.min). At this level of regularization, 11 of the 29 potential predictors retained non-zero coefficients. The cross-validated model explained 15% of variance in WHO-5 well-being scores (R^2 =.15) with a root mean squared error (RMSE) of 19.05.

All retained predictors were negatively associated with well-being scores, indicating that the presence of these predictors correspond to decreased psychological well-being. The strongest predictor was the experience of at least one form of offline CM (*B* = -16.49), followed by onset of unwanted confrontation with pornographic/sexualized material at age 13 (*B* = -6.30) and equivalence income below the poverty risk threshold (*B* = -5.85). Notably, several selected predictors clustered in early to mid-adolescence with ages ranging between 13 and 16 years. An overview of predictors ranked by absolute coefficient magnitude is presented in Table 4.

Table 4

Predictors selected by LASSO regression (λ = 0.76) for WHO-5 well-being, ranked by variable importance

Predictor	B_{minMSE}[a]
Offline child maltreatment (at least one type[b])	-16.49
Age 13 – Unwanted confrontation with pornographic / sexualized material	-6.30
Equivalence income (below poverty risk threshold)	-5.85
Age 15 – Unwanted sexualized talk	-4.84
Age 16 – Request to engage in unwanted sexual acts	-3.31
Age 13 – Request to engage in unwanted sexual acts	-3.04
Age 15 – Unwanted confrontation with pornographic / sexualized material	-2.34
Age 16 – Forced sexualized material	-0.98
Educational attainment (advanced education)	-0.82
Age 17 – Request to engage in unwanted sexual acts	-0.61
Age 14 – Unwanted sexualized talk	-0.38
Notes. [a]B_{minMSE} = beta estimates based on the optimal lambda to find the minimum mean squared error in LASSO regression analysis. [b] types: emotional abuse, physical abuse, sexual abuse, emotional neglect, physical neglect.	
Random Forest Regression	

The Random Forest model explained 16% of variance in WHO-5 well-being scores (OOB R^2 = .16) with an out-of-bag RMSE of 19.02, indicating predictive performance comparable to the LASSO model. Variable importance analysis based on permutation importance (%IncMSE) identified offline CM exposure as the most influential predictor (%IncMSE = 88.93), followed by equivalence income below the poverty risk threshold (%IncMSE = 40.18) and gender (%IncMSE = 20.71). Higher %IncMSE values indicate a stronger decrease in predictive accuracy when the variable is permuted. Among the age of onset variables, onset of unwanted confrontation with pornographic / sexualized material at age 13 (%IncMSE = 13.97) and unwanted sexualized talk at age 15 (%IncMSE = 10.49) showed the highest importance values. Table 5 provides detailed importance metrics for the top 15 predictors.

Table 5
Predictors ranked by variable importance in the Random Forest model

Predictor	%IncMSE[a]
Offline child maltreatment	88.93
Equivalence income	40.18
Gender	20.71
Age 13 – Unwanted confrontation with pornographic sexualized material	13.97
Age 15 – Unwanted sexualized talk	10.49
Age 16 – Forced sexualized material	8.26
Age 17 – Request to engage in unwanted sexual acts	7.92
Age (continuous)	7.60
Age 16 – Unwanted sexualized questions	6.74
Age 17 – Unwanted sexualized talk	5.74
Educational attainment	4.04
Age 16 – Unwanted confrontation with pornographic/sexualized material	4.00
Age 15 – Unwanted confrontation with pornographic/sexualized material	3.58
Age 15 – Unwanted sexualized questions	3.06
Age 14 – Unwanted confrontation with pornographic/sexualized material	2.80

Notes. [a]%IncMSE represents the percentage increase in mean squared error after random permutation of a predictor.

Several predictors identified in the LASSO model (Fig. 2A), including offline CM, unwanted confrontation with pornographic material age 13 and 15, equivalence income, highest level of Education, unwanted sexualized talk age 15, forced sexualized material age 16 and request to engage in unwanted sexual acts age 17 were also ranked among the most important variables in the Random Forest analysis (Fig. 2B), indicating convergence across modelling approaches. Predictors identified by both modelling approaches are presented in Table 6.

Table 6
Convergence of predictors of well-being identified by both LASSO and Random Forest models

Predictor	**LASSO (|*B*|)**	**Random Forest (%IncMSE)**
Offline child maltreatment	16.49	88.93
Equivalence income	5.85	40.18
Educational attainment	0.82	4.04
Age 13 – Unwanted confrontation with pornographic/sexualized material	6.30	13.97
Age 15 – Unwanted confrontation with pornographic/sexualized material	2.34	3.58
Age 15 – Unwanted sexualized talk	4.84	10.49
Age 16 – Forced sexualized material	0.98	8.26
Age 17 – Request to engage in unwanted sexual acts	0.61	7.92
Notes. *|B|* = absolute unstandardized regression coefficient from LASSO model; %IncMSE represents the percentage increase in mean squared error after random permutation of a predictor.		
Post-Hoc Linear Regression		

To obtain interpretable effect estimates and formal significance tests, a post-hoc multiple linear regression was conducted including the 15 predictors with the highest %IncMSE values identified in the Random Forest analysis (see Table 6). Random Forest, rather than LASSO, was used for this screening step, as it explained slightly more variance and provides a continuous, λ-independent importance measure [40, 41]. The overall regression model was statistically significant, $F(16, 989) = 14.38$, $p < .001$, explaining 17% of the variance in WHO-5 well-being scores (adjusted R^2 =.17). Experiences of at least one form of offline CM were significantly associated with lower psychological well-being ($B = -17.66$, $SE = 1.60$, $p < .001$) representing the strongest association in the model. Similarly, an equivalence income below the poverty risk threshold predicted reduced well-being ($B = -7.11$, $SE = 1.38$, $p < .001$). Among the age of onset variables, onset of unwanted confrontation with pornographic material at age 13 showed significant negative associations with WHO-5 scores ($B = -11.22$, $SE = 3.94$, $p = .005$), indicating that first exposure at age 13 was associated with lower psychological well-being in young adulthood. Onset of unwanted sexualized talk at the age of 15 showed a marginal association ($B = -6.93$, $SE = 3.76$, $p = .065$). All remaining predictors did not reach statistical significance in the multivariable model. Detailed model estimates are shown in Table 7. The direction and relative pattern of standardized coefficients were consistent with the importance rankings observed in both the LASSO and Random Forest models, supporting convergence across analytical approaches.

Table 7
Post-hoc multiple linear regression predicting WHO-5 well-being

Predictor	***B***	***β***	***SE***	**95% CI**	***t***	***p***
Offline child maltreatment (at least one type[a])	-17.66	-0.33	1.59	[-20.97, -14.53]	-11.07	< .001
Equivalence income (below poverty risk threshold)	-7.11	-0.14	1.38	[-9.82, -4.39]	-5.13	< .001
Gender[b] (female)	-0.72	-0.01	1.21	[-3.10, 1.64]	-0.60	.547
Gender[b] (diverse)	-1.02	-0.00	13.37	[-27.27, 25.23]	-0.07	.939
Age (continuous)	0.13	0.02	0.17	[-0.19, 0.47]	0.79	.425
Educational attainment (advanced education)	-2.24	-0.05	1.35	[-4.70, 0.22]	-1.78	.07
Age 13 – Unwanted confrontation with pornographic/sexualized material	-11.22	-0.08	3.94	[-18.95, -3.47]	-2.84	.005
Age 14 – Unwanted confrontation with pornographic/sexualized material	-0.25	-0.00	3.25	[-6.63, 6.12]	-0.07	.937
Age 15 – Unwanted confrontation with pornographic/sexualized material	-5.83	-0.05	3.03	[-12.32, 0.64]	-1.76	.077
Age 15 – Unwanted sexualized talk	-6.93	-0.06	3.76	[-14.31, 0.45]	-1.84	.065
Age 15 – Unwanted sexualized questions	-2.58	-0.01	4.41	[-11.24, 6.08]	-0.58	.558
Age 16 – Unwanted confrontation with pornographic/sexualized material	-0.69	-0.01	2.64	[-5.88, 4.48]	-0.26	.791

Notes. adj. R^2 = .17, $F(16, 989) = 14.38$, $p < .001$. [a] types: emotional abuse, physical abuse, sexual abuse, emotional neglect, physical neglect; [b] male gender serves as reference category. *B* = unstandardized coefficient; β = standardized coefficient; *SE* = standard error; CI = confidence interval.

Predictor	*B*	*β*	*SE*	95% CI	*t*	*p*
Age 16 – Forced sexualized material	-6.99	-0.03	5.83	[-18.44, 4.46]	-1.19	.231
Age 16 – Unwanted sexualized questions	-2.62	-0.02	3.09	[-8.69, 3.44]	-0.84	.396
Age 17 – Unwanted sexualized talk	-0.46	-0.00	3.91	[-8.14, 7.22]	-0.11	.906
Age 17 – Request to engage in unwanted sexual acts	-3.79	-0.02	4.87	[-13.35, 5.76]	-0.77	.436

Notes. adj. R^2 = .17, $F(16, 989) = 14.38$, $p < .001$. [a] types: emotional abuse, physical abuse, sexual abuse, emotional neglect, physical neglect; [b] male gender serves as reference category. *B* = unstandardized coefficient; β = standardized coefficient; *SE* = standard error; CI = confidence interval.

Discussion

The present study examined whether the developmental timing of first exposure to OCSSA is associated with psychological well-being in young adulthood within a nationally representative German sample. OCSSA was common, with 32.3% of young adults reporting at least one form before age 18, with first exposure clustering primarily between ages 13 and 17. Unwanted exposure to pornographic/sexualized material at ages 13 and 15 and unwanted sexualized talk at age 15 showed the strongest associations with lowered psychological well-being. Taken together, the findings suggest that developmental timing may be relevant for comparatively prevalent and often underestimated forms of OCSSA. The most consistent OCSSA-specific finding, beyond offline CM and household income, was the negative association between unwanted pornographic/sexualized material exposure at age 13 and reduced young adult well-being. Selected by LASSO and Random Forest, it reached significance in post-hoc regression, suggesting age 13 may represent a specific window where such exposure is linked to greater long-term psychological burden than later exposure. Neurodevelopmentally, early adolescence features highly reactive limbic structures sensitized by pubertal hormones, while prefrontal regulatory capacity remains immature [25, 29]. Exposure to threatening or premature sexualized content during this phase may thus be more closely linked to alterations in stress-reactive and self-evaluative circuits than later exposure, when regulatory mechanisms are more consolidated [28, 30]. Age 13 also coincides with normative sexual development onset, when cognitive readiness for interpreting sexuality, intimacy, and relational boundaries is incomplete [42]. Premature confrontation with sexualized material may interfere with developmental scaffolding for sexual self-concept and relational expectations [36, 37].

Three negative associations clustered at age 15: unwanted pornographic/sexualized material exposure, unwanted sexualized talk, and - in LASSO only - requests to engage in unwanted sexual acts. None reached significance in post-hoc regression, but the first two approached this threshold and converged across both models. This pattern aligns with theoretical accounts of heightened mid-adolescent vulnerability, marked by maximal limbic-prefrontal mismatch [29], intensifying peer orientation, and increasing salience of social-evaluative experiences [36, 38]. Increasing cognitive capacity may heighten adversity impacts, as adolescents internalize and ruminate on experiences [43].

OCSSA's psychological burden may be amplified during this window due to trust violations, social manipulation, and exposure threats in peer contexts [30, 35]. Digital environments further intensify this, as peer orientation and self-presentation unfold through platforms quantifying social feedback [15, 44], embedding boundary violations in identity construction [37]. The age-15 clustering across subtypes may reflect broader sensitivity to social-evaluative stress rather than subtype-specific effects. This aligns with research on in-person CM identifying mid-to-late adolescence as a sensitive window for adult psychopathology [45]. However, age 15 approximates the modal first OCSSA exposure age in this sample, so larger cell sizes may partly explain the clustering. Disentangling true developmental sensitivity from detection asymmetry requires future oversampling of less common onset ages.

A central conceptual contribution is positioning solicitation-based OCSSA within the broader victimization landscape. Prior timing-related evidence focused almost exclusively on IBSA, notably Colburn et al. [21], who compared exposure before vs. after age 12. Like the present study, their work relied on retrospective self-reports, documenting associations rather than causal effects. The present results extend this evidence in two ways. First, convergence across pornographic exposure and unwanted sexualized talk indicates timing-related well-being differences also apply to solicitation-based experiences. Second, using single-year onset categories reveals more discrete age-related patterns, suggesting the developmental gradient may also be observable in mid-adolescence, not solely a "before-or-after-age-12" phenomenon. This is clinically relevant because solicitation-based OCSSA is most prevalent in population-based samples [2, 3, 10] and is often minimized as less severe than coercive or image-based forms. However, the present findings suggest that at specific developmental ages, non-coercive solicitation-based experiences are associated with lower well-being in young adulthood, consistent with Page et al. [18].

Notably, gender was not a significant predictor in post-hoc regression. This aligns with evidence from the same sample showing no significant gender difference in OCSSA experience, contrasting with the pronounced female predominance in offline sexual abuse [8]. Thus, OCSSA may differ from contact-based sexual victimization in form, prevalence, and demographic profile.

Although convergence between LASSO and Random Forest strengthens confidence in selected findings, divergences also emerged. Some predictors important in Random Forest, such as gender, did not reach significance in post-hoc OLS, likely reflecting nonlinear contributions not captured by additive models. Similarly, some LASSO-selected predictors did not rank highly in Random Forest. These discrepancies

highlight that convergent findings should be interpreted as the most robust signal, while non-convergent findings remain provisional.

Strengths and Limitations

The present study has several strengths. The analyses used a large, nationally representative sample of young adults aged 18–29, enhancing external validity. The dual machine learning strategy enabled cross-method validation of predictor importance in a high-dimensional, exploratory context where traditional regression models risk overfitting. Explicit adjustment for offline CM addresses a critical confounder rarely controlled in prior OCSSA timing research; the persistence of independent OCSSA associations beyond this adjustment indicates online victimization is not merely a marker of broader adversity. The fine-grained year-by-year operationalization of age at first exposure advances prior dichotomized approaches [18, 21], enabling identification of discrete vulnerability windows. To our knowledge, this is among the first population-based studies to examine timing associations across the full OCSSA spectrum.

These strengths must be weighed against limitations. First, retrospective OCSSA reports introduce recall bias and non-disclosure [46], and the cross-sectional design precludes causal conclusions. Second, the WHO-5 captures subjective well-being over the preceding two weeks and is more sensitive to current mood than stable trauma-related sequelae. Third, analyses lacked information on relevant moderators, including social support, resilience, therapeutic experiences, and victimization characteristics [4, 18]. Statistical power for individual age-of-onset cells was limited, particularly for less prevalent subtypes. Finally, post-hoc OLS analyses should be interpreted cautiously, as predictors were selected based on prior machine learning rather than a priori specifications, so estimates are better understood as descriptive indications than confirmatory tests.

Implications for Research and Practice

The findings carry implications for research, prevention, and clinical practice. Future studies should use prospective and longitudinal designs to address retrospective self-report limitations. Oversampling less common onset ages and rarer OCSSA subtypes may clarify whether findings reflect discrete developmental sensitivity or statistical detectability differences. Research should also examine moderating factors such as social support, resilience, and victimization characteristics; given that many solicitations involve same-age peers, the relational context warrants attention [4, 47, 48].

Preventively, the findings argue against focusing only on late adolescence, where OCSSA exposures peak. Instead, they support earlier, developmentally timed interventions. The age-13 association for unwanted pornographic exposure suggests age-appropriate digital sexual literacy should be established before this age, while the age-15 convergence indicates mid-adolescent programs should address the broader OCSSA spectrum, including solicitation- and exposure-based experiences often unrecognized as sexual violence [9]. However, the strong role of offline CM and socioeconomic disadvantage cautions

against treating OCSSA prevention as a stand-alone digital safety issue. Effective prevention should be embedded in broader child protection, family support, and socioeconomic systems.

Clinically, the findings support routine assessment of whether sexual victimization occurred, when it first occurred, and whether digital components were involved [16, 20]. This is important because online victimization may be overlooked or minimized in therapeutic settings [7]. Given the limited evidence base for OCSSA-specific interventions, clinical standards and child protection frameworks should adapt to digital victimization's specific features, including the persistence and replicability of abusive material [49, 50].

Finally, the findings highlight platform governance as a structural prevention target. Blanket age bans have shown limited effectiveness, as minors often circumvent them, migrating to less regulated spaces [51]. More promising are integrated models combining age verification, safety-by-design obligations, and educational strategies, locating responsibility with both individuals/families and platform providers. Recent debates around AI-mediated digital environments further underline the need for regulatory frameworks addressing emerging risks such as personalized interaction, simulated grooming, and AI-generated abusive material [52].

Conclusions

This study provides initial population-based evidence that the developmental timing of first exposure to specific OCSSA subtypes is associated with psychological well-being in young adulthood, independently of offline CM and sociodemographic factors. While offline CM and socioeconomic disadvantage remained the strongest predictors, unwanted exposure to pornographic or sexualized material at age 13 and unwanted sexualized talk at age 15 emerged as factors associated with lower psychological well-being. These findings suggest that prevention should begin before early adolescence and address OCSSA, with a focus on solicitation-based OCSSA types. Findings can further inform public health policy in light of recent debates around age-related recommendations for online media use.

Methods

Procedure

Data were drawn from a nationwide population-based survey conducted in Germany between October 2023 and April 2024. USUMA (www.usuma.com), specializing in demographic analysis, gathered responses from a representative cohort of the German-speaking population aged 16 and above. A full description of the sampling framework and survey procedures is provided elsewhere [2].

Ethical approval

for this research was granted by the University of Leipzig's Ethics Committee. For the present analyses, the sample was restricted to participants aged 18–29 years corresponding to the United Nations age

definition used for indicator 16.2.3, which retrospectively measures childhood sexual violence as part of monitoring Sustainable Development Goal target 16.2 [53].

Measures

Sociodemographic Characteristics

Information regarding age, gender, and educational attainment was assessed via questionnaires. Socioeconomic status was operationalized using equivalized household income, which was calculated by dividing the reported net household income by the square root of household size [54]. To facilitate interpretation, equivalized income was categorized relative to the national poverty risk threshold, defined as 60% of the median equivalized income. Participants were classified as living below or above the poverty risk threshold. Educational attainment was dichotomized into basic (no school qualification, lower secondary education, or polytechnical high school completion) and advanced education (technical college diplomas, university entrance qualifications, or university degrees). Given the single representation within the diverse gender category, stratified descriptive analyses were restricted to male and female participants. For regression analyses, diverse participants were retained and dummy-coded (male as reference category).

Offline Child Maltreatment

Experiences of CM were assessed using the German version of the *Adverse Childhood Experiences Questionnaire* [55], a reliable, valid, and widely used screening instrument for retrospective assessment of adverse experiences during childhood. The questionnaire comprises five items addressing CM and five items focusing on household dysfunction. Each item uses a binary response scale (yes/no) to capture the occurrence of various adverse experiences, with higher cumulative scores reflecting greater exposure to childhood adversity. For the present investigation, we specifically utilized the five CM-related items – covering physical abuse, emotional abuse, contact sexual abuse, physical and emotional neglect – while excluding items pertaining to household dysfunction. CM exposure was dichotomized (yes/no) to compare participants who experienced at least one form of maltreatment versus those who reported no maltreatment experiences (see Table 2). In the present sample, internal consistency for the selected five-item subset was $\alpha = .69$ indicating satisfactory reliability for this reduced scale.

Online Child Sexual Solicitation and Abuse

OCSSA was assessed using screening questions developed by Finkelhor et al. [3]. The original items were translated into German through a systematic back-translation process and supplemented with an additional question addressing exposure to pornographic material, reflecting considerations specific to German legal framework. The resulting screening tool is presented in full detail in previous work [2]. It employs a binary response format (yes/no) to document the occurrence of various OCSSA experiences,

including commercial sexual exploitation online, IBSA, and online sexual solicitation. Positive responses were followed by questions on frequency, age at first occurrence and age at termination. This 9-item screening tool showed acceptable internal consistency (Cronbach's α = .72) in the present sample.

Well-Being

Psychological well-being was assessed using the *World Health Organization Well-Being Index* (WHO-5) [56], an internationally established and validated five-item measure evaluating subjective well-being over the past two weeks [39, 57]. Items are rated on a six-point Likert scale (0 = “at no time” to 5 = “all of the time”), with raw scores multiplied by four to create an index ranging from 0 to 100, where higher scores indicate better well-being. Internal consistency in the present sample was excellent (α = .92). Its established cut-off score of below 50 indicates relevant impairment and is widely used as a screening indicator for depressive symptomatology [39, 57]. The WHO-5 has proven sensitive to victimization-related differences in comparable German samples [9].

Statistical Analysis

All statistical analyses were performed in R Version 4.5.2 [58]. The analyses were implemented using the *glmnet* [59], *randomForest* [60], *VIM* [61], *psych* [62], *car* [63], *lm.beta* [64] and *ggplot2* [65] packages.

Predictor Variables

To examine the potential impact of developmental timing of OCSSA exposure, age of onset variables were transformed into year-specific dummy variables. For each of the nine OCSSA items, the continuous age of onset variable (ranging from 1–18 years, reflecting the ages during which OCSSA experiences could have occurred for the first time before adulthood) was recoded into 18 binary dummy variables, each representing whether the individual experienced the particular form of OCSSA for the first time at a specific age. This transformation yielded a total of 162 age-of-onset dummy variables. To minimize the influence of sparsely populated predictors, only age-of-onset variables with at least 10 observations ($n \geq 10$) were retained for analysis, as sparse data and rare categorical predictor levels can compromise the stability of regression-based estimates [66]. In consequence, 24 age-of-onset dummy variables were included for analyses, along with five covariates (age, gender, educational attainment, socioeconomic status, and offline CM exposure), resulting in a total of 29 predictor variables.

Missing Data and Imputation

Missing data patterns were examined descriptively and formally tested using Little's MCAR test ($\chi^2(917) = 1417$, $p < .001$) [67]. As the null hypothesis of data being missing completely at random (MCAR) was rejected, missing data were classified as missing at random (MAR). Of the $N = 1{,}006$ participants, 930 (92.4%) had complete data on all analysis variables. Missing values were identified in the age of onset variables ($n = 17$), WHO-5 well-being items ($n = 4$), offline CM items, and covariates (equivalized income $n = 31$; school graduation $n = 1$). The equivalized income variable exhibited the highest number of missing values, which is consistent with general patterns in survey research where income-related questions often elicit lower response rates due to sensitivity concerns [68]. Missing values were imputed

using K-Nearest Neighbor (KNN) imputation. The number of neighbors was set to k = 5, a commonly recommended value that balances bias and variance in imputation [61].

Analytical Strategy

High-dimensional predictor space and substantial intercorrelations among predictors pose a challenge for traditional regression approaches due to increased risks of overfitting and multicollinearity. To address these issues, a sequential analytical strategy combining two machine learning approaches was applied: LASSO regression and Random Forest regression. Both techniques are robust to large numbers of correlated predictors and small sample sizes relative to the number of predictors [40, 69]. This dual-method approach was implemented to cross-validate findings and ensure that identified predictors were consistently important across different statistical frameworks. Convergence of results across both methods provides stronger evidence for robust associations with psychological well-being, as it reduces the likelihood of method-specific artifacts.

Lasso Regression. LASSO (Least Absolute Shrinkage and Selection Operator) regression was used to identify relevant predictors. LASSO uses L1 regularization to penalize the absolute magnitude of regression coefficients, shrinking less important coefficients to zero and thus enabling automatic variable selection [69, 70]. This shrinkage property is particularly advantageous for data with multicollinearity, as LASSO tends to retain only one representative variable from a set of highly correlated predictors, reducing redundancy while preserving predictive information. All 24 age-of-onset dummy variables and five covariates were entered as potential predictors of the WHO-5 Well-Being Index. Predictors were automatically standardized internally by the glmnet algorithm (standardize = TRUE) to ensure comparable penalization across variables with different scales. The regularization strength is controlled by the penalty parameter lambda. The optimal lambda value was determined through 10-fold cross-validation by selecting lambda.min, the value that minimized mean cross-validated prediction error. Model performance was evaluated using root mean square error (RMSE) and the coefficient of determination (R^2) from cross-validation. Variables with non-zero coefficients at the optimal lambda were identified as selected predictors and ranked by the absolute magnitude of their coefficients to determine their relative importance in predicting well-being.

Random Forest Regression. To complement the LASSO analysis and to capture potential non-linear relationships and higher-order interactions between predictors, Random Forest regression was applied. Random Forest is an ensemble machine learning method that constructs multiple decision trees during training and outputs the average prediction across all trees, thereby reducing variance and improving prediction accuracy [41]. This approach requires no assumptions about the distributional form of the data [40, 41]. The Random Forest model included the same set of predictors as the LASSO regression, comprising 24 age-of-onset variables and five covariates, to predict the WHO-5 Well-Being Index. The Forest was grown with 1,000 trees (ntree = 1000). Following standard recommendations, the number of variables randomly sampled as candidates at each split (mtry) was set to the square root of the total number of predictors, rounded down to the nearest integer (mtry = 5; [41]. Model performance was evaluated using out-of-bag (OOB) estimation, an internal cross-validation procedure inherent to Random

Forest. Each tree is trained on a bootstrap sample, and predictions for each observation are made using only the trees for which that observation was not included in training. This provides unbiased prediction error estimates without requiring a separate test set [41]. OOB root mean squared error (RMSE) and OOB R^2 were computed as measures of predictive accuracy. Variable importance was assessed using the percentage increase in mean squared error (%IncMSE), which reflects the increase in prediction error when a predictor is randomly permuted. Higher values indicate greater importance for model accuracy.

Post-Hoc Linear Regression. Following the Random Forest analysis, a post-hoc ordinary least square (OLS) multiple regression was conducted to obtain interpretable effect sizes, establish the direction of relationships, and conduct formal hypothesis tests. The variables with the highest %IncMSE values in the Random Forest model were entered simultaneously as predictors of the WHO-5 Well-Being Index. For each predictor, unstandardized regression coefficients (*B*), standard errors (*SE*), t-values, p-values, and 95% confidence intervals were calculated. Model fit was evaluated using R^2, adjusted R^2 and the F-statistic. The significance level was set at $\alpha = .05$ for all statistical tests.

Prior to interpretation, regression assumptions were examined. Visual inspection of Q-Q plots and residuals-versus-fitted plots did not indicate substantial non-normality or heteroscedasticity. Multicollinearity diagnostics revealed low variance inflation factors (all VIFs < 1.2), indicating no problematic collinearity among predictors.

Declarations

Ethics approval and consent to participate:

Participants provided written informed consent in accordance with the Declaration of Helsinki. All procedures were approved by the University of Leipzig's Ethics Committee (reference number 278/23-ek).

Consent for publication:

Not applicable.

Competing interests:

The authors have no relevant financial or non-financial interests to disclose.

Author Contribution

A.C.H: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft; K.C.G: Conceptualization, Data curation, Methodology, Project administration, Validation, Writing – review &

editing; E.P.: Formal analysis, Writing – original draft; M.R.: Writing – review & editing; J.M.F: Conceptualization, Project administration, Supervision, Writing – review & editing

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Data Availability

Availability of data and materials: The individual-level data reported in this article cannot be publicly shared due to ethical and legal restrictions. These data contain highly sensitive information that could compromise participant privacy. However, to support transparency and reproducibility, we commit to sharing a minimum aggregated dataset necessary to reproduce the main analyses (e.g., group-level statistics, model outputs) upon reasonable request to the corresponding author (A.C.H.). The data analysis scripts are available on GitHub (https://github.com/annhaag/OCSSA_ageofonset).

References

1. Fry D, Krzeczkowska A, Ren J, Lu M, Fang X, Krzeczkowska A, et al. Prevalence estimates and nature of online child sexual exploitation and abuse: a systematic review and meta-analysis. Lancet Child Adolesc Health. 2025;9:184–93. https://doi.org/10.1016/S2352-4642(24)00329-8.
2. Chauviré-Geib K, Gerke J, Haag A-C, Sachser C, Finkelhor D, Rassenhofer M, et al. The increase in online child sexual solicitation and abuse: Indicator 16.2.3 of the UN Sustainable Development Goals (SDG) documents a hidden and growing pandemic. Population-based surveys fail to capture the full picture. Child Abuse Negl. 2025;164:107452. https://doi.org/10.1016/j.chiabu.2025.107452.
3. Finkelhor D, Turner H, Colburn D. Prevalence of Online Sexual Offenses Against Children in the US. JAMA Netw Open. 2022;5:e2234471. https://doi.org/10.1001/jamanetworkopen.2022.34471.
4. Turner HA, Finkelhor D, Colburn D. Contexts and Characteristics of Imaged-Based Sexual Exploitation and Abuse of Children: Incident Dynamics in a National Sample. Child Maltreat. 2025;30:68–81. https://doi.org/10.1177/10775595241233970.
5. Hellevik PM, Haugen L-EA, Överlien C. Outcomes of image-based sexual abuse among young people: a systematic review. Front Psychol. 2025;16:1599087. https://doi.org/10.3389/fpsyg.2025.1599087.
6. Knipschild R, Covers M, Bicanic IAE. From digital harm to recovery: a multidisciplinary framework for First Aid after Online Sexual Abuse. Eur J Psychotraumatology. 2025;16:2465083. https://doi.org/10.1080/20008066.2025.2465083.
7. Schmidt F, Varese F, Bucci S. Understanding the prolonged impact of online sexual abuse occurring in childhood. Front Psychol. 2023;14:1281996. https://doi.org/10.3389/fpsyg.2023.1281996.

8. Chauviré-Geib K, Haag A-C, Gerke J, Sachser C, Rassenhofer M, Fegert JM. Associations between online child sexual solicitation and abuse and offline child maltreatment: A latent class analysis. Eur Child Adolesc Psychiatry. 2025;35:869–81. https://doi.org/10.1007/s00787-025-02885-5.
9. Dreßing H, Hoell A, Scharmann L, Simon AM, Haag A-C, Dölling D, et al. Sexual violence against children and adolescents: A German nationwide representative survey on its prevalence, situational context, and consequences. Dtsch Ärztebl Int. 2025. https://doi.org/10.3238/arztebl.m2025.0076.
10. Walsh K, Mathews B, Parvin K, Smith R, Burton M, Nicholas M, et al. Prevalence and characteristics of online child sexual victimization: Findings from the Australian Child Maltreatment Study. Child Abuse Negl. 2025;160:107186. https://doi.org/10.1016/j.chiabu.2024.107186.
11. Ghai S, Vuorre M, Kardefelt-Winther D, Ferguson AM, Kurten S, Livingstone S, et al. Technology mediation in child sexual exploitation and abuse in Africa and Asia. Nature. 2026;654:408–18. https://doi.org/10.1038/s41586-026-10525-4.
12. Ferragut M, Ortiz-Tallo M, Blanca MJ. Non-contact child sexual abuse: Characteristics in a representative Spanish sample. Int Rev Vict. 2026;32:152–66. https://doi.org/10.1177/02697580251374720.
13. Chrillesen N. Living in a Sextech Era: Normalisation of Violence during Sex and of Image-Based Sexual Abuse. SSRN Electron J. 2023. https://doi.org/10.2139/ssrn.4559149.
14. De Ridder S. Social Media and Young People's Sexualities: Values, Norms, and Battlegrounds. Soc Media Soc. 2017;3:2056305117738992. https://doi.org/10.1177/2056305117738992.
15. Odgers CL, Jensen MR. Annual Research Review: Adolescent mental health in the digital age: facts, fears, and future directions. J Child Psychol Psychiatry. 2020;61:336–48. https://doi.org/10.1111/jcpp.13190.
16. Joleby M, Landström S, Lunde C, Jonsson LS. Experiences and psychological health among children exposed to online child sexual abuse – a mixed methods study of court verdicts. Psychol Crime Law. 2021;27:159–81. https://doi.org/10.1080/1068316X.2020.1781120.
17. Jonsson LS, Fredlund C, Priebe G, Wadsby M, Svedin CG. Online sexual abuse of adolescents by a perpetrator met online: a cross-sectional study. Child Adolesc Psychiatry Ment Health. 2019;13:32. https://doi.org/10.1186/s13034-019-0292-1.
18. Page S, McFeeters A, Rani NHM, Slater C, Stevenson J, Quayle E, et al. Psychological and Emotional Harms of Online Child Sexual Exploitation and Abuse in Children Under the Age of 18: A Systematic Review of the Evidence. Child Abuse Rev. 2025;34:e70048. https://doi.org/10.1002/car.70048.
19. Joleby M, Lunde C, Landström S, Jonsson LS. "All of Me Is Completely Different": Experiences and Consequences Among Victims of Technology-Assisted Child Sexual Abuse. Front Psychol. 2020;11:606218. https://doi.org/10.3389/fpsyg.2020.606218.
20. Schmidt F, Varese F, Larkin A, Bucci S. The Mental Health and Social Implications of Nonconsensual Sharing of Intimate Images on Youth: A Systematic Review. Trauma Violence Abuse. 2024;25:2158–72. https://doi.org/10.1177/15248380231207896.

21. Colburn D, Mitchell KJ, Gewirtz-Meydan A, Finkelhor D, Turner HA, O'Brien JE. Life impact following childhood Image-Based Sexual Abuse victimization among a sample of young adults. Child Abuse Negl. 2025;167:107584. https://doi.org/10.1016/j.chiabu.2025.107584.
22. Dunn E, Busso DS, Davis KA, Smith ADAC, Mitchell C, Tiemeier H, et al. Sensitive Periods for the Effect of Child Maltreatment on Psychopathology Symptoms in Adolescence. Complex Psychiatry. 2023;9:145–53. https://doi.org/10.1159/000530120.
23. Kaplow JB, Widom CS. Age of onset of child maltreatment predicts long-term mental health outcomes. J Abnorm Psychol. 2007;116:176–87. https://doi.org/10.1037/0021-843X.116.1.176.
24. Schaefer JD, Cheng TW, Dunn EC. Sensitive periods in development and risk for psychiatric disorders and related endpoints: a systematic review of child maltreatment findings. Lancet Psychiatry. 2022;9:978–91. https://doi.org/10.1016/S2215-0366(22)00362-5.
25. Teicher MH, Samson JA, Anderson CM, Ohashi K. The effects of childhood maltreatment on brain structure, function and connectivity. Nat Rev Neurosci. 2016;17:652–66. https://doi.org/10.1038/nrn.2016.111.
26. Cicchetti D, Rogosch FA. Equifinality and multifinality in developmental psychopathology. Dev Psychopathol. 1996;8:597–600. https://doi.org/10.1017/S0954579400007318.
27. McLaughlin KA, Weissman D, Bitrán D. Childhood Adversity and Neural Development: A Systematic Review. Annu Rev Dev Psychol. 2019;1:277–312. https://doi.org/10.1146/annurev-devpsych-121318-084950.
28. Nelson CA, Sullivan EF, Valdes V. Early adversity alters brain architecture and increases susceptibility to mental health disorders. Nat Rev Neurosci. 2025;26:642–56. https://doi.org/10.1038/s41583-025-00948-9.
29. Tottenham N, Galván A. Stress and the adolescent brain. Neurosci Biobehav Rev. 2016;70:217–27. https://doi.org/10.1016/j.neubiorev.2016.07.030.
30. Telzer EH, Escalante E, Jack DB, Tsai RY-H. How Social and Cultural Processes Shape Adolescents: An Ecocultural Transactional Framework of Adolescent Brain Development. Annu Rev Dev Psychol. 2025;7:315–37.
31. Crone EA, Konijn EA. Media use and brain development during adolescence. Nat Commun. 2018;9:588. https://doi.org/10.1038/s41467-018-03126-x.
32. 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. 2025;10:237–53. https://doi.org/10.1007/s40894-025-00264-4.
33. Noll JG, Haag A-C, Shenk CE, Wright MF, Barnes JE, Kohram M, et al. An observational study of Internet behaviours for adolescent females following sexual abuse. Nat Hum Behav. 2021;6:74–87. https://doi.org/10.1038/s41562-021-01187-5.
34. Haag A-C, Bonanno GA, Chen S, Herd T, Strong-Jones S, S. S, 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. 2023;35:1794–807. https://doi.org/10.1017/S0954579422000475.

35. Stänicke LI, Reiremo GK, Scheie SI, Jessen RS, Jensen TK. Navigating, being tricked, and blaming oneself—A meta-synthesis of youth's experience of involvement in online child sexual abuse. Child Fam Soc Work. 2024;29:1096–114. https://doi.org/10.1111/cfs.13152.
36. Clark DA, Durbin CE, Heitzeg MM, Iacono WG, McGue M, Hicks BM. Adolescent Sexual Development and Peer Groups: Reciprocal Associations and Shared Genetic and Environmental Influences. Arch Sex Behav. 2021;50:141–60. https://doi.org/10.1007/s10508-020-01697-9.
37. Maes C, Van Oosten JMF, Vandenbosch L. Adolescents' Digital Media Interactions within the Context of Sexuality Development. In: Nesi J, Telzer EH, Prinstein MJ, editors. Handbook of Adolescent Digital Media Use and Mental Health. 1st edition. Cambridge University Press; 2022. p. 135–61. https://doi.org/10.1017/9781108976237.009.
38. Nesi J, Telzer EH, Prinstein MJ. Adolescent Development in the Digital Media Context. Psychol Inq. 2020;31:229–34. https://doi.org/10.1080/1047840X.2020.1820219.
39. Topp CW, Østergaard SD, Søndergaard S, Bech P. The WHO-5 Well-Being Index: A Systematic Review of the Literature. Psychother Psychosom. 2015;84:167–76. https://doi.org/10.1159/000376585.
40. Strobl C, Boulesteix A-L, Zeileis A, Hothorn T. Bias in random forest variable importance measures: Illustrations, sources and a solution. BMC Bioinformatics. 2007;8:25. https://doi.org/10.1186/1471-2105-8-25.
41. Breiman L. Random Forest. Mach Learn. 2001;45:5–32.
42. Sravanti L, Velusamy AJP, Rajendra KM, Kommu JVS. Childhood Digital Exposure to Sexual Content: Through the Lens of Developmental Psychopathology. J Psychosexual Health. 2025;7:115–9. https://doi.org/10.1177/26318318251322555.
43. Newbury JB, Arseneault L, Moffitt TE, Caspi A, Danese A, Baldwin JR, et al. Measuring childhood maltreatment to predict early-adult psychopathology: Comparison of prospective informant-reports and retrospective self-reports. J Psychiatr Res. 2018;96:57–64. https://doi.org/10.1016/j.jpsychires.2017.09.020.
44. Orben A, Meier A, Dalgleish T, Blakemore S-J. Mechanisms linking social media use to adolescent mental health vulnerability. Nat Rev Psychol. 2024;3:407–23. https://doi.org/10.1038/s44159-024-00307-y.
45. Meier M, Schalinski I, Boonmann C, Jenkel N, Seker S, d'Huart D, et al. Differential effects of childhood maltreatment types and timing on psychopathology in formerly out-of-home placed young adults. 2024. https://doi.org/10.31234/osf.io/2vrjt.
46. Hardt J, Rutter M. Validity of adult retrospective reports of adverse childhood experiences: review of the evidence. J Child Psychol Psychiatry. 2004;45:260–73. https://doi.org/10.1111/j.1469-7610.2004.00218.x.
47. Fiedler M, Otten D, Jud A, Brähler E, Fegert JM, Clemens V. Associations between perpetrator characteristics of child maltreatment, age of onset, and physical and mental health. Child Adolesc

Psychiatry Ment Health. 2026;20:28. https://doi.org/10.1186/s13034-026-01049-w.

48. Finkelhor D, Colburn D, Gewirtz-Meydan A, O'Brien JE, Jones LM, Turner HA, et al. Youth-Produced Images Are the Majority of Child Sexual Abuse Materials: Categories of Youth and Adult Perpetrators From a Victim Based Study. Sex Abuse. 2026;38:337–53. https://doi.org/10.1177/10790632261415819.
49. Fegert JM. European child and adolescent psychiatry in a digital world. Eur Child Adolesc Psychiatry. 2025. https://doi.org/10.1007/s00787-025-02910-7.
50. Menhart R, Stellermann-Strehlow K, Helling-Bakki A, Horvay R, Dippel N, Winter SM. A systematic review and meta-analysis of medical and psychosocial care procedures for children and adolescents after (online) sexual abuse. Child Abuse Negl. 2025;166:107540. https://doi.org/10.1016/j.chiabu.2025.107540.
51. Montag C, Demetrovics Z, Elhai JD, Grant D, Koning I, Rumpf H-J, et al. Social Media Use in Childhood and Adolescence: Minimizing Its Adverse Effects Through Corporate Social Responsibility and European Union Regulations. In: Christakis DA, Hale L, editors. Handbook of Children and Screens. Cham: Springer Nature Switzerland; 2025. p. 477–84. https://doi.org/10.1007/978-3-031-69362-5_65.
52. Haag A-C, Bui E. Beyond the algorithm: rethinking child protection in the digital age. Int J Ment Health. 2025;54:152–3. https://doi.org/10.1080/00207411.2025.2493992.
53. United Nations. The sustainable development goals report 2024. 2024.
54. OECD, editor. OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth. Paris: OECD Publishing; 2013. https://doi.org/10.1787/9789264194830-en.
55. Schäfer I, Wingenfeld K, Spitzer C. Deutsche Version des "Adverse Childhood Experiences Questionnaire (ACE)." 2009.
56. World Health Organization. WHO-5. 1998.
57. Brähler E, Mühlan H, Albani C, Schmidt S. Teststatistische Prüfung und Normierung der deutschen Versionen des EUROHIS-QOL Lebensqualität-Index und des WHO-5 Wohlbefindens-Index. Diagnostica. 2007;53:83–96. https://doi.org/10.1026/0012-1924.53.2.83.
58. R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing; 2024.
59. Friedman J, Hastie T, Tibshirani R. Regularization Paths for Generalized Linear Models via Coordinate Descent. J Stat Softw. 2010;33. https://doi.org/10.18637/jss.v033.i01.
60. Liaw A, Wiener M. Classification and Regression by randomForest. R News. 2002;2:18–22.
61. Kowarik A, Templ M. Imputation with the R Package VIM. J Stat Softw. 2016;74:1–16. https://doi.org/10.18637/jss.v074.i07.
62. Revelle W. psych: Procedures for Psychological, Psychometric, and Personality Research. Evanston, Illinois: Northwestern University; 2026.
63. Fox J, Weisberg S. An R Companion to Applied Regression. Third. Thousand Oaks CA: Sage; 2019.

64. Behrendt S. lm.beta: Add Standardized Regression Coefficients to Linear-Model-Objects. 2025.
65. Wickham H. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York; 2016.
66. Greenland S, Mansournia MA, Altman DG. Sparse data bias: a problem hiding in plain sight. BMJ. 2016;353:i1981. https://doi.org/10.1136/bmj.i1981.
67. Tierney N, Cook D. Expanding Tidy Data Principles to Facilitate Missing Data Exploration, Visualization and Assessment of Imputations. J Stat Softw. 2023;105. https://doi.org/10.18637/jss.v105.i07.
68. Tourangeau R, Yan T. Sensitive questions in surveys. Psychol Bull. 2007;133:859–83. https://doi.org/10.1037/0033-2909.133.5.859.
69. Tibshirani R. Regression Shrinkage and Selection Via the Lasso. J R Stat Soc Ser B Stat Methodol. 1996;58:267–88. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x.
70. Hastie T, Tibshirani R, Friedman J. The Elements of Statistical Learning. New York, NY: Springer New York; 2009. https://doi.org/10.1007/978-0-387-84858-7.

Figures

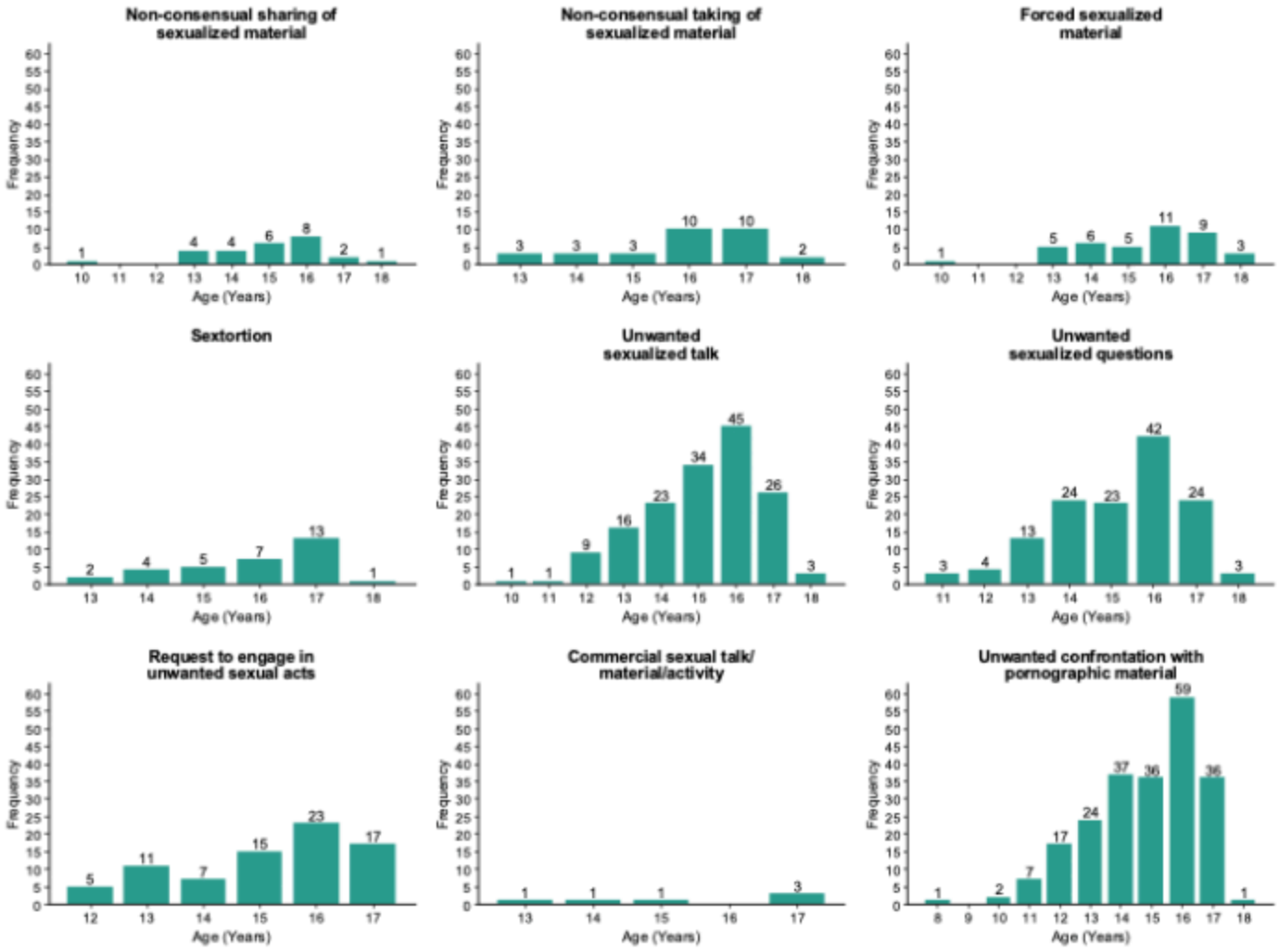

Figure 1

Age-of-onset distribution for different types of OCSSA

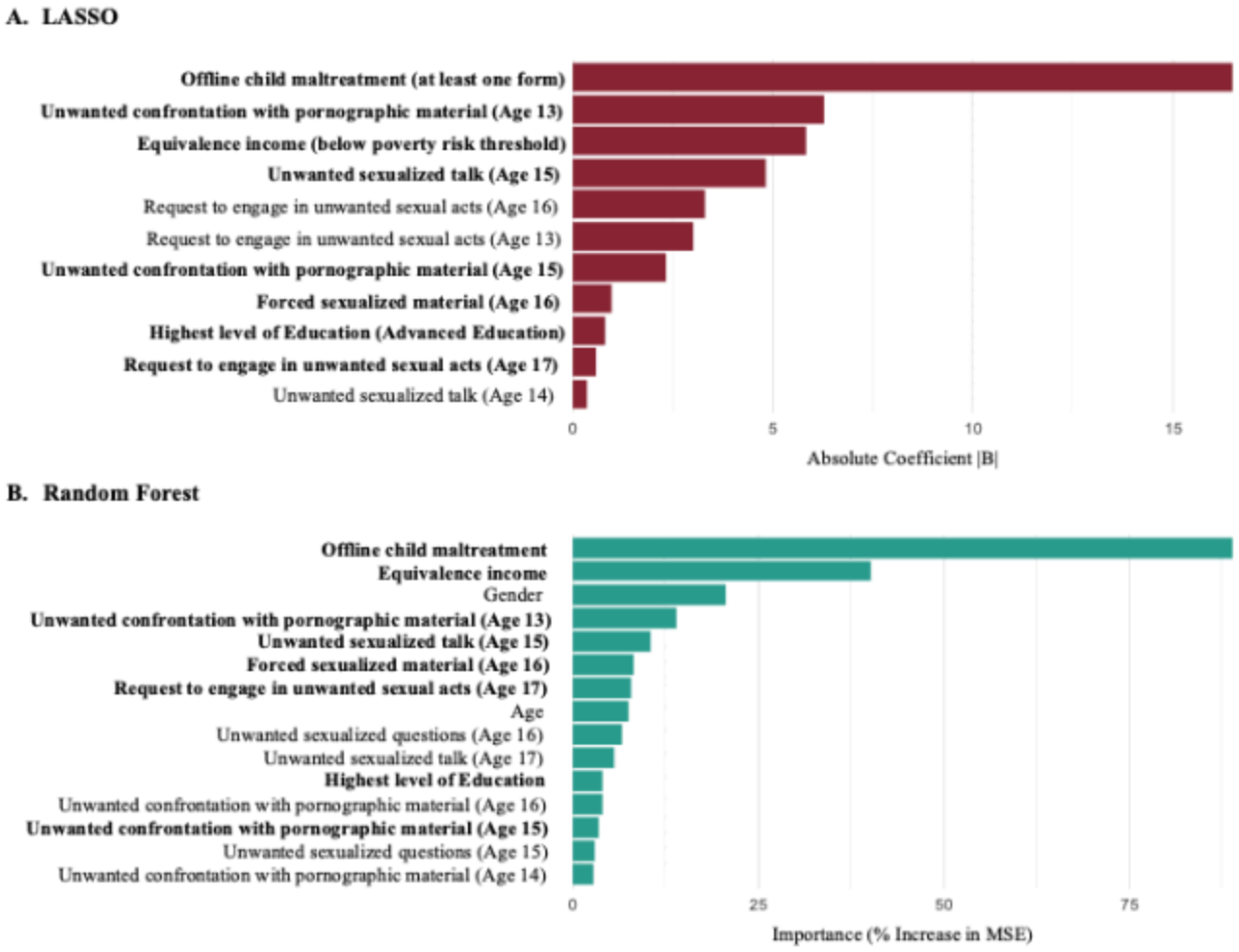

Figure 2

Predictor importance for psychological well-being (WHO-5). (A) Absolute unstandardized coefficients |*B*| from LASSO regression based on the optimal lambda (λ = .76). All displayed coefficients indicate a negative association with well-being. (B) Relative variable importance from Random Forest regression, measured as the percentage increase in Mean Squared Error (%IncMSE) when the variable is permuted. Predictors shown in bold were identified by both the LASSO and Random Forest models