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Generative Artificial Intelligence Applications Use Among US Youth

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Abstract

IMPORTANCE As generative artificial intelligence (GenAI) tools become increasingly integrated into the daily lives of youth, it is critical to study their usage patterns and potential implications for mental health. While there is evidence of a rapid pace of adoption among adults, rates of GenAI use among youth remains largely undocumented.

OBJECTIVE To characterize GenAI application (app) usage among US youth, including adoption rates and time spent.

DESIGN, SETTING, AND PARTICIPANTS This cross-sectional study documented digital behavior of US youth extracted from a parental monitoring app. Participants were ages 4 to 17 years and were in families using a commercially available Aura app in the US. No identifying information was collected about the child except year of birth. Data were collected using passive sensing methods from naturalistic smart device use between September 2024 and April 2025. Data were analyzed in May and June 2025.

MAIN OUTCOME AND MEASURES Adoption rates (ie, number of youth ever accessing GenAI apps on their device) and time spent using GenAI (ie, average minutes accessing GenAI apps), measured by age and time period.

RESULTS In a cohort of 6488 participants, nearly 2072 youths (31.9%) used GenAI apps on their device. GenAI use was highest among teens (age 13 to 14 years, 899 of 2139 [42.0%]; age 15 to 17 years, 628 of 1246 [50.4%]), although adoption among preteens (age 10 to 12 years, 484 of 2366 [20.5%]) and school-aged children (age 8 to 9 years, 49 of 522 [9.4%]) was not trivial. GenAI usage was higher after school than at nighttime or during school. Overall, users spent a mean (SD) 2.37 (10.55) and a median (IQR) 0.18 (0.04-0.84) minutes a day using GenAI, yet large variances and skewed distributions suggest that a small subset of youth use GenAI extensively, with the heaviest users accessing GenAI for over 40 minutes a day.

CONCLUSIONS AND RELEVANCE In this cross-sectional study, Gen AI app use varied widely among participants, with up to half of adolescents having some use and a small subset engaging in heavy use. Future research must address individual differences in GenAI use to determine impacts on development.

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Key Points

Question What are the adoption rates and usage patterns of generative artificial intelligence (GenAI) applications (apps) among US youth?

Findings In this cross-sectional study of 6488 US youths aged 4 to 17 years, a third used GenAI apps on their devices, including 50% of teens aged 15 to 17 years, 20% among children aged 10 to 12 years, and 9% among children aged 8 to 9 years. Daily use was a mean 2.37 minutes and a median 0.18 minutes, although a small subset of youth engaged for over 40 minutes per day.

Meaning The widespread use of GenAI apps among youths, including vulnerable younger users, underscores the urgent need to understand its potential developmental and mental health implications.

+ Supplemental content

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Introduction

Generative artificial intelligence (GenAI) refers to AI tools that generate content, affording interaction with a highly flexible, conversational agent.[1] GenAI has the potential to upend the context of human development,[2] and has been called the fastest adopted technology among adults.[3] However, adoption rates and usage patterns among youth remain unclear and no prior studies have leveraged passive sensing data to characterize youth GenAI use.

GenAI use poses both potential risks and benefits to youth well-being.[2] Understanding patterns of GenAI use among youth—including across different ages and times of day—is a critical first step toward evaluating the developmental risks or opportunities presented by this technology. GenAI can offer benefits related to learning or structured self-reflection.[2] GenAI is also designed to be reliable, sycophantic, personalized, and gamified,[4] which may lead some youth to use GenAI excessively. Heavy GenAI use may displace healthy offline activities, such as when used during school or at nighttime.[5] Moreover, among adults, a small subset of heavy users use GenAI for emotionally intimate conversations,[6] suggesting that heavy-using youth may be at risk of socioemotional reliance on chatbot companions.

Additionally, younger users may be more vulnerable to negative effects of technology.[7,8] Older teens (ages 15 to 18 years) are more likely than 13-to-14-year-olds to report GenAI-related media literacy skills and resist using GenAI when it might undermine skill-building.[9] Despite US privacy regulations restricting most online applications (apps) to users older than 13 years, many children and preteens easily surmount age verification processes to access social media.[10] It remains unknown how many children and preteens similarly access GenAI.

Objective usage patterns are necessary to inform future research on the impacts of GenAI on youth development. The current project uses passive sensing observations from a parental monitoring app to demonstrate rates of adoption and minutes of GenAI use among users, split by developmental stage, days of the week, and time of day.

Methods

Data were collected from the Aura parental monitoring app, a commercial product that allows parents to download to their child's internet-capable devices.[11] Data are aggregated for each child across all devices.

As part of the onboarding process, parents or caregivers agree to the terms and conditions as well as the privacy policy. Important features of these policies for this study include: (1) parents attest that they are the legally authorized caregiver for their child on whose device the app is being installed, and (2) parents are informed that deidentified, aggregated data may be used for scientific purposes. This approach removes self-selection bias. A waiver of consent has been granted for analysis of the aggregated, deidentified data by the WCG Clinical Services institutional review board. This use of a waiver of parental consent and child assent by the institutional review board, operating under the Common Rule, required a determination that the research posed no more than minimal risk; the waiver would not adversely affect the rights and welfare of participants; the research could not practicably be carried out without the waiver; and the data used were appropriately deidentified. Users retain the ability to request deletion of their data at any time through the platform's existing privacy controls. Our reporting approach follows Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline for cross-sectional research. In line with these recommendations, we clearly describe our study design, sample selection, measurement procedures, analytic approach, and potential sources of bias.

The app uses virtual private network (VPN) and keystroke data (ie, data inputted into a custom overlay keyboard within an app) collected passively from the device. For the current analysis, app use was classified using keystroke data for all apps and supplemented with VPN data for ChatGPT. To date, given its high traffic, only ChatGPT has been accurately identified among app users using VPN data due to the dynamic nature of app availability and the resource-intensive nature of VPN classification. Keystroke data are more robust and consistently classifiable via unique app store identifiers, although it requires users to opt in to the overlay keyboard. A strength of using keystroke data is that this approach isolated instances in which youth are actively typing into a chatbot interface, reducing noise from moments when they may open an application without providing any input.

Data for the current project were from September 1, 2024, to April 1, 2025. We excluded holiday breaks (ie, November 24 to November 30, 2024, and December 22, 2024, to January 1, 2025). During this time, children's supervision and structured activities vary, adding noise to GenAI use estimates. Although the exact dates of school closures and holiday observances vary by region, school, and family, most US public schools are closed on these dates. Among participants with any keyboard input data (indicating that app data collection was functioning; 8218 participants), those with at least 14 total days and 10 school days of keyboard data (to ensure generalizable data per user; 6488 participants) were included in analyses, resulting in 914 812 days of participant data.

The convenience sampling strategy recruited only families using the app, which does not collect information about users other than year of birth. We infer participant's age using year of birth. A small subset of users (1263 [19.5%]) self-reported US state, representing regions in the Southeast (380 [30.1%]), West (251 [19.9%]), Southwest (232 [18.4%]), Midwest (223 [17.7%]), and Northeast (177 [14.0%]). The deidentified analysis process maximizes participant privacy but limits information about demographics or representativeness of the sample.

GenAI and social apps (non-AI) were identified with both top-down (researchers identified a list of current apps available on app stores) and bottom-up (ie, researchers inspected the list of apps that users accessed and identified apps from that list) methods. We identified the most commonly used apps. New or less-used apps required a minimum of 1000 reviews for inclusion (eAppendix 3 in Supplement 1). GenAI app information (eg, app store product pages) was coded by PhD-level researchers to determine apps that are marketed for companionship. Research assistants trained in app assessment reviewed and double-coded the apps to ensure accurate ratings.

We categorized temporal contexts by (1) weekday and (2) weekend day, as well as separately by (3) school hours (defined as Monday through Friday, 8 AM to 3 PM; following prior work[12]), (4) after school (Monday through Friday, 3 PM to 10 PM), and (5) nighttime (10 PM to 4 AM). Sleep onset times vary substantially, particularly across age groups; thus, we define the nighttime range based on evidence of typical sleep onset and late-night media use that displaces sleep onset. Bedtimes for most youth ages 4 to 17 years range between 8 PM and 10:30 PM.[13-15] We extend the window through 4 AM to capture the full span of late-night media use that might displace sleep onset, building on research linking technology use after around 1 AM to sleep disruption.[16,17] The goal of distinguishing these temporal contexts was to disaggregate when youth GenAI use may replace healthy behaviors (eg, paying attention in school, sleeping) and explore if GenAI use differs by presumed adult supervision or structured activities (eg, across weekdays vs weekends).

Cochran *Q* tests assessed whether adoption proportions differed significantly across temporal contexts within each age group (a repeated measures analysis). χ^2 Tests of homogeneity evaluated if adoption proportions differed significantly across the age groups for each specific temporal context. For minutes of use, we performed nonparametric (given non-normal and zero-inflated distributions) post hoc pairwise comparisons (following significant omnibus tests) with the full sample. For intragroup comparisons (eg, comparing weekday vs weekend within 1 age group), we used Wilcoxon signed-rank tests. For intergroup comparisons (eg, comparing weekday usage between 2 age groups), we used the Mann-Whitney *U* test. A family-wise Bonferroni correction was applied to post hoc tests. Nonparametric Spearman rank-order correlations tested associations between GenAI and social apps.

Results

In our sample of 6488 US youth (age range, 4-17 years), nearly a third (2072 [31.9%]) had accessed a GenAI app from their device, and the majority of these (1682 [25.9% of full sample]) had used a GenAI app for at least 3 minutes (**Table 1**). ChatGPT was by far the most common app, accessed by 1632 participants (78.8% of GenAI users). Of the 17 apps used by 10 or more participants, 7 (41%) are marketed to provide social companionship (**Table 2**). Approximately 1 in 5 participants (1382 [21.3%]) had ever used GenAI during school hours, whereas about 1 in 4 (1655 [25.5%]) used GenAI after school. Relatively fewer (811 [12.5%]) used GenAI at night.

By age category, 628 midteens (50.4%), 899 young teens (42.0%), 484 preteens (20.5%), 49 school-aged children (9.4%), and 12 young children (5.6%) had ever used GenAI (Table 1). Intragroup and intergroup differences emerged when comparing adoption rates within age categories and across temporal contexts (Table 1; **Figure**). When looking specifically at adoption rates for youth with at least 3 minutes of GenAI use, percentage of youth using GenAI increased with age across all temporal contexts, with only a few exceptions. For all age categories, the smallest percentage of youth used GenAI at nighttime, whereas the largest percentage used GenAI on weekdays.

Among those with any GenAI use, users spent a mean (SD) 2.37 (10.55) minutes per day using GenAI (median [IQR], 0.18 [0.04-0.84] min/d), indicating that those at the high end of the distribution (ie, 3 SDs) access GenAI for over 30 minutes per day and the heaviest user using GenAI for nearly 3 hours per day (maximum, 172.50 min/d) (**Table 3**). This included a mean (SD) 2.23 (9.90) minutes on weekdays (maximum, 183.00 min/d), 2.71 (13.57) minutes on weekends (maximum, 286.33 min/d), 0.71 (3.54) minutes during school hours (maximum, 90.55 min/d), 1.24 (5.84) minutes after school (maximum, 123.11 min/d), and 0.56 (3.43) minutes at nighttime (maximum, 84.25 min/d). Variances were highest during weekends for preteens (mean [SD], 3.10 [13.53] min/d;

Table 1. Percentage of Sample Using Generative Artificial Intelligence (GenAI)

		Youths, No. (%)						Intragroup Usage Test	
Cohort	No.	Total	Weekday	Weekend	Nighttime (10 PM-4 AM)	School hours (weekdays 8 AM-3 PM)	After school (weekdays, 3 PM-10 PM)	Cochran Q	*P* value
Any GenAI use[a]									
All (ages 4-17 y)	6488	2072 (31.9)	1934 (29.8)	1482 (22.8)	811 (12.5)	1382 (21.3)	1655 (25.5)	1840.07	<.001
Young children (4-7 y)	215	12 (5.6)	11 (5.1)	8 (3.7)	2 (0.9)	8 (3.7)	5 (2.3)	15.10	<.001
School-aged children (8-9 y)	522	49 (9.4)	40 (7.7)	34 (6.5)	11 (2.1)	19 (3.6)	36 (6.9)	57.38	<.001
Preteens (10-12 y)	2366	484 (20.5)	440 (18.6)	344 (14.5)	171 (7.2)	272 (11.5)	385 (16.3)	471.17	<.001
Young teens (13-14 y)	2139	899 (42.0)	845 (39.5)	650 (30.4)	350 (16.4)	610 (28.5)	732 (34.2)	834.19	<.001
Midteens (15-17 y)	1246	628 (50.4)	598 (48.0)	446 (35.8)	277 (22.2)	473 (38.0)	497 (39.9)	511.32	<.001
Intergroup homogeneity test		629.93	620.19	403.83	275.06	545.22	483.23	NA	NA
χ^2 *P* value		<.001	<.001	<.001	<.001	<.001	<.001	NA	NA
≥3 min of GenAI use[b]									
All (4-17 y)	6488	1682 (25.9)	1545 (23.8)	1059 (16.3)	543 (8.4)	1033 (15.9)	1248 (19.2)	1656.80	<.001
Young children (4-7 y)	215	9 (4.2)	7 (3.3)	3 (1.4)	1 (0.5)	4 (1.9)	5 (2.3)	10.00	.04
School-aged children (8-9 y)	522	36 (6.9)	30 (5.8)	20 (3.8)	8 (1.5)	16 (3.1)	25 (4.8)	36.51	<.001
Preteens (10-12 y)	2366	375 (15.9)	335 (14.2)	245 (10.4)	122 (5.2)	188 (8.0)	279 (11.8)	365.95	<.001
Young teens (13-14 y)	2139	743 (34.7)	694 (32.5)	474 (22.2)	226 (10.6)	454 (21.2)	561 (26.2)	804.71	<.001
Midteens (15-17 y)	1246	519 (41.7)	479 (38.4)	317 (25.4)	186 (14.9)	371 (29.8)	378 (30.3)	490.14	<.001
Intergroup homogeneity test	NA	523.38	500.38	285.62	164.52	432.21	360.23	NA	NA
χ^2 *P* value	NA	<.001	<.001	<.001	<.001	<.001	<.001	NA	NA

Abbreviation: NA, not applicable.

[a] Users with any GenAI use are categorized as those with any (ie, at least 1 minute) active keyboard data collected on an app researchers categorized as GenAI.

[b] Users with at least 3 minutes of GenAI use are those with at least 3 minutes of active keyboard data collected on an app researchers categorized as GenAI. For example, 30 school-aged children (5.8% of the full sample of school-aged children) have spent at least 3 minutes using GenAI on weekdays.

maximum, 171.83 min/d), young teens (mean [SD], 2.96 [15.53] min/d; maximum, 286.33 min/d), and midteens (mean [SD], 2.21 [10.97] min/d; maximum, 199.53 min/d) with those at the high end of the distribution (ie, 3 SDs) accessing GenAI for over 40 minutes per weekend day and the heaviest user accessing GenAI for over 4 hours and 45 minutes.

GenAI use was significantly higher on weekdays vs weekends, weekends vs after school, and after school vs nighttime or during school. For overall use and each temporal context, each age group spent more minutes using GenAI than those younger than them with one exception: young children and school-aged children did not significantly differ for any context.

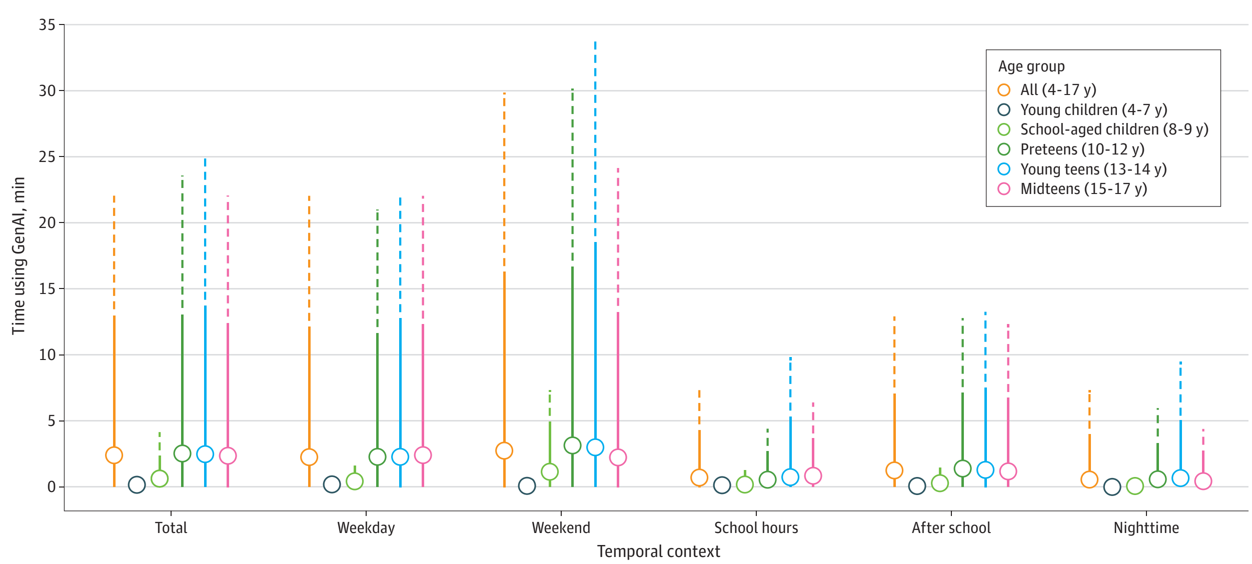
Across the full sample, GenAI use represented a mean (SD) 0.40% (0.03%) of all smartphone use. Time on GenAI and social apps (non-AI) were positively correlated (Spearman $\rho = 0.20$; $P < .001$). For every 100 minutes spent on social apps, youth used GenAI for a mean (SD) of just 1.50 (0.43) minutes.

Table 2. Generative Artificial Intelligence (GenAI) Applications Use With 10 or More Users

GenAI application name (N = 17)	No. of users	GenAI users, % (n = 2072)	Full sample, % (n = 6488)
ChatGPT	1632	78.8	25.2
Gauth (AI study companion)	219	10.6	3.4
PolyBuzz (formerly Poly.AI)[a]	172	8.3	2.7
Character AI (chat, talk, text)[a]	128	6.2	2.0
Google Gemini	60	2.9	0.9
Pengu (AI raise virtual AI pets)	58	2.8	0.9
Talkie (personalized AI chats)[a]	58	2.8	0.9
Microsoft Copilot	49	2.4	0.8
CHAI (social AI platform-chat)[a]	28	1.4	0.4
AI Chatbot (AI chat smith 4)	17	0.8	0.3
Spicychat AI (roleplay chat)[a]	17	0.8	0.3
ChatOn AI (chat bot assistant)	14	0.7	0.2
AI ChatNow (AI chat assistant)	13	0.6	0.2
DeepSeek (AI assistant)	12	0.6	0.2
Parallel Live (fake live)	12	0.6	0.2
Linky AI (chat, play, connect)[a]	10	0.5	0.2
Museland AI (AI character chat)[a]	10	0.5	0.2

[a] Marketed as a social companionship app.

Figure. Mean Time and Distribution of Generative Artificial Intelligence (GenAI) Use by Temporal Context and Age Group



Circles indicate mean measures, with solid lines representing 1 SD and dashed lines 2 SDs.

Discussion

Nearly 1 in 3 youth use GenAI on their device and users spend a mean of 2.37 minutes a day using GenAI, with notable variability. Although average use time was relatively low, most youth with any GenAI use had used GenAI apps for at least 3 minutes and the variances and maximum values indicate that a subset of youth use these tools heavily, underscoring the need to examine the impacts of such use and the individual difference factors that predict it. Moreover, at the time of data collection, ChatGPT had been available for only roughly 2 years,[3] signaling that these adoption rates and usage patterns may continue grow if tools become more accessible and functional in the future. Results also suggest that adoption of and minutes using GenAI increases with age and that youth use GenAI in diverse temporal contexts.

The current study extends prior survey work among teens by using passive sensing and sampling a wider age range to characterize youth GenAI use.[9,18] In prior survey studies, 51% of 13-to-18-year-olds reported using GenAI chatbots,[9] mirroring our findings among similar-aged youth. Our results show that many preteens and school-aged children are also using GenAI, despite US privacy regulations currently intended to restrict access for youth younger than 13 years. Further research addressing GenAI use during early and middle childhood will be critical to examine potential risks and benefits among these potentially vulnerable groups that are often missed in technology research.

The most popular app was ChatGPT, a multipurpose chatbot that can provide entertainment, information, and academic support.[9,18,19] However, versatile chatbots can be used in myriad ways, and several of participants' top apps are marketed for companionship. Companionship features (eg, personalization, emotional expressivity), coupled with gamification and potentially inappropriate content exposure, pose significant risks to adolescents' socioemotional development.[2,4,20]

GenAI use among participants is especially common after school, perhaps to support (or circumvent) academic work. Without careful scaffolding, GenAI can undermine learning.[2,9,18,19] Few participants use GenAI during nighttime hours. However, large variances suggests that for a small subset of youth, time spent on GenAI apps may be substantial, particularly during weekends for preteen and young teen users. Users may be inclined to access GenAI during unstructured or unsupervised weekend time. This reliance on chatbots can pose significant risks to young users' well-being and social relationships.[2]

Critically, the current study addresses the quantity of GenAI use across youth, but questions about how and why youth use GenAI remain. The field of social media research is increasingly shifting

Table 3. Generative Artificial Intelligence (GenAI) Use Among GenAI Users

Age group	No.	Average use time, mean (SD) or median (IQR), min					
		Total	Weekday	Weekend	Nighttime (10 PM-4 AM)	School hours (M-F 8 AM-3 PM)	After school (M-F 3 PM-10 PM)
Mean							
All (4-17)	2072	2.37 (10.55)	2.23 (9.90)	2.71 (13.57)	0.56 (3.43)	0.71 (3.54)	1.24 (5.84)
Young children (4-7)	12	0.17 (0.22)	0.20 (0.27)	0.09 (0.12)	0.01 (0.02)	0.14 (0.23)	0.08 (0.14)
School-aged children (8-9)	49	0.63 (1.75)	0.43 (1.18)	1.14 (3.78)	0.08 (0.30)	0.19 (0.54)	0.29 (0.79)
Pre-teens (10-12)	484	2.50 (10.52)	2.25 (9.38)	3.10 (13.53)	0.58 (2.70)	0.55 (2.19)	1.38 (5.72)
Young teens (13-14)	899	2.45 (11.24)	2.25 (10.49)	2.96 (15.53)	0.67 (4.40)	0.74 (4.56)	1.28 (6.25)
Mid-teens (15-17)	628	2.33 (10.04)	2.38 (9.90)	2.21 (10.97)	0.44 (2.33)	0.84 (2.80)	1.17 (5.58)
Median							
All (4-17)	2072	0.18 (0.04-0.84)	0.18 (0.04-0.86)	0.1 (0-0.70)	0 (0-0.06)	0.04 (0-0.30)	0.08 (0.01-0.43)
Young children (4-7)	12	0.05 (0.04-0.25)	0.07 (0.03-0.27)	0.04 (0-0.11)	0 (0-0)	0.03 (0-0.13)	0 (0-0.08)
School-aged children (8-9)	49	0.09 (0.04-0.16)	0.1 (0.01-0.20)	0.04 (0-0.21)	0 (0-0)	0 (0-0.09)	0.06 (0-0.16)
Pre-teens (10-12)	484	0.14 (0.03-0.76)	0.1 (0.02-0.71)	0.08 (0-0.70)	0 (0-0.06)	0.01 (0-0.16)	0.06 (0.01-0.41)
Young teens (13-14)	899	0.17 (0.04-0.80)	0.18 (0.04-0.77)	0.11 (0-0.71)	0 (0-0.05)	0.04 (0-0.23)	0.08 (0.01-0.45)
Mid-teens (15-17)	628	0.28 (0.05-1.11)	0.3 (0.05-1.20)	0.13 (0-0.79)	0 (0-0.09)	0.1 (0-0.5)	0.1 (0.01-0.46)

to focus on more precise digital experiences.[21,22] The current results provide a foundation for the field regarding prevalence rates and how developmental stage, context, and apps may be associated with use patterns. Future research must address GenAI motivations (eg, emotional support, task automation), beliefs and attitudes (eg, idealizing AI or believing AI can substitute human relationships), and the specific content youth input into GenAI apps and are exposed to in return.

Importantly, this study demonstrates how responsibly governed industry–academic partnerships can leverage deidentified behavioral data for public-interest research. Industry data on youth are commonly used for commercial purposes, where corporate incentives often prioritize maximizing engagement over partnering with researchers or minimizing potential harm. Youth report strong interest in sharing their personal deidentified data for research that aims to understand and promote youth well-being.[24] Future partnerships can follow this model by establishing clear ethical oversight, ensuring transparency, and aligning research goals with youth well-being.

Limitations

This study had several limitations. These data represent objective behavioral observations, avoiding self-report biases. However, aspects of the sampling strategy limit generalizability. First, sociodemographic information was unavailable. This preserves privacy but limits our understanding of external validity to the US youth population or ability to conduct subgroup analyses. Second, our text-based application passive sensing methods—although they capture digital behavior on potentially multiple mobile devices per child—exclude browser-based activity and voice inputs with chatbots. It is possible that youth use GenAI via mobile applications more when they are alone or with peers, possibly yielding more companionship or risky use, whereas web browser-based use may yield more task support and homework help. Outcomes may also vary according to whether users input text prompts or voice-based prompts, particularly for preliterate children. Future research can explore these contextual factors more. Third, given the large number and dynamic availability of AI applications, our scope was necessarily focused on identifying the most used and high-risk apps. Therefore, some apps may not be included in the current analysis. Fourth, our temporal context cut-offs, although useful to understand patterns across our large sample, may obfuscate individual and group-level differences in daily behaviors (eg, older youth engage in more extracurriculars, go to bed later), adding noise to our estimates.

Finally, the sample of youth may be biased because the tracking app requires purchasing and caregiver setup, likely selecting for families with higher parental monitoring tendencies. Nationally representative data suggests that over half of US parents monitor their child's digital behaviors and 39% use digital parental controls,[23] indicating that most studies of US adolescent digital behaviors today are likely complicated by parents' direct oversight of such use. The Aura app cost may restrict the sample to affluent families. Aura advertises in a range of outlets (eg, website searches, social media) and the pricing scale includes economical options (currently $4.99 to $15.99 per month or $99 to $199 annually), making the app accessible to diverse families.

To our knowledge, the current study is the first to use passive sensing to measure GenAI use among US adolescents; thus, the representativeness or bias in the current sample is challenging to test directly. Nationally representative self-report data indicate similar adoption rates as those found in the current study: 51% of 13-to-18-year-olds in a representative poll[9] vs 42% of 13-to-14-year-olds and 50% of 15-to-17-year-olds in our passive sensing data. Notably, social desirability and misremembering biases may add noise to survey-based estimates. In contrast, features of the current study (ie, the exclusion of browser-based GenAI activity, the tracking app's built-in restrictions, limiting analyses to apps with a primary purpose of GenAI interaction as determined by the research team) likely systematically suppress estimates of GenAI use. Thus, although similarities with nationally representative data may signal that the current sample is not inappropriately biased, we believe our estimates are likely conservative. Critically, if true, the high adoption observed in this lower-bound sample suggests rates in the broader youth population may be even higher.

Conclusions

To our knowledge, large-scale objective data on youth GenAI use are currently unavailable, and this dataset offers a valuable preliminary opportunity to examine adoption patterns. These findings provide a critical foundation for understanding patterns of GenAI use. Future work must address individual differences, context, and age-related effects of GenAI use.[2,7]

ARTICLE INFORMATION

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Administrative, technical, or material support: Akre-Bhide, Boeldt, Richardson, Burnell.

Supervision: Flannery, Kollins.

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Data Sharing Statement: See Supplement 2.

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SUPPLEMENT 1.

eAppendix 1. Application classification and risk assessment methodology
eAppendix 2. List of generative AI apps used for analysis
eAppendix 3. List of social (non-AI) apps used for analysis

SUPPLEMENT 2.

Data Sharing Statement