Social media’s enduring effect on adolescent life satisfaction

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In this study, we used large-scale representative panel data to disentangle the between-person and within-person relations linking adolescent social media use and well-being. We found that social media use is not, in and of itself, a strong predictor of life satisfaction across the adolescent population. Instead, social media effects are nuanced, small at best, reciprocal over time, gender specific, and contingent on analytic methods.

Does the increasing amount of time adolescents devote to social media negatively affect their satisfaction with life? Set against the rapid pace of technological innovation, this simple question has grown into a pressing concern for scientists, caregivers, and policymakers. Research, however, has not kept pace (1). Focused on cross-sectional relations, scientists have few means of parsing longitudinal effects from artifacts introduced by common statistical modeling methodologies (2). Furthermore, the volume of data under analysis, paired with unchecked analytical flexibility, enables selective research reporting, biasing the literature toward statistically significant effects (3, 4). Nevertheless, trivial trends are routinely overinterpreted by those under increasing pressure to rapidly craft evidence-based policies.

Our understanding of social media effects is predominately shaped by analyses of cross-sectional associations between social media use measures and self-reported youth outcomes. Studies highlight modest negative correlations (3), but many of their conclusions are problematic. It is not tenable to assume that observations of between-person associations—comparing different people at the same time point—translate into within-person effects—tracking an individual, and what affects them, over time (2). Drawing this flawed inference risks misinforming the public or shaping policy on the basis of unsuitable evidence.

To disentangle between-person associations from within-person effects, we analyzed an eight-wave, large-scale, and nationally representative panel dataset (Understanding Society, the UK Household Longitudinal Study, 2009–2016) using random-intercept cross-lagged panel models (2). We adopted a specification curve analysis framework (3, 5)—a computational method which minimizes the risk that a specific profile of analytical decisions yields false-positive results. In place of a single model, we tested a wide range of theoretically grounded analysis options (data is available on the UK data service (6); code is available on the Open Science Framework (7)). The University of Essex Ethics Committee has approved all data collection on Understanding Society main study and innovation panel waves, including asking the Open Science Framework (7). The authors declare no conflict of interest.

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Data deposition: The dataset is available from the UK Data Service (doi.org/10.5255/UKDA-SN-6614-1). The underlying code for this paper is available on the Open Science Framework (doi.org/10.17605/OSF.IO/J4X9P).

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satisfaction with friends, predicted slightly reduced social media use ($b = -0.17$ to $-0.05$ or $\beta = -0.11$ to $-0.07$; Fig. 2, Right).

However, some caution is warranted: When comparing both genders, the effects’ confidence intervals overlap, and the lower incidence of significant effects in males alone is not evidence that the effects are therefore substantial in females (10), especially as they are very small in size. Further, the yearly interval between measurements in these data might not be optimal for understanding reciprocal social media effects over time, underlining how no single study can capture the full causal picture. We also highlight that self-report measures only partially reflect the objective time adolescents spend engaging with social media (11), yet they form the foundation of technological assessments included in the best-practice models (white indicates $P < 0.05$, black indicates $P < 0.05$). For the unabridged figure, including the complete set of analytic decisions and underlying code, see doi.org/10.17605/OSF.IO/4XP3V.

With the unknowns of social media effects still substantially outnumbering the knowns, it is critical that independent scientists, policymakers, and industry researchers cooperate more closely. Scientists must embrace circumspection, transparency, and robust ways of working that safeguard against bias and analytical flexibility. Doing so will provide parents and policymakers with the reliable insights they need on a topic most often characterized by unfounded media hype. Finally, and most importantly, social media companies must support independent research by sharing granular user engagement data and participating in large-scale team-based open science. Only then will we truly unravel the complex constellations of effects shaping young people in the digital age.

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