Social Media Use in the United States and Its Educational Effects on Young Adults: A Longitudinal Study

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Abstract: This paper uses the Panel Study of Income Dynamics (PSID) data, particularly its Child Development Supplement (CDS) and Transition into Adulthood Supplement (TAS) data from 2017 and 2019 to form a longitudinal dataset, to study how social media used by young people causally affect their academic achievement, while controlling for their background characteristics and parents' education and marital status. We estimate our model by using the panel data ordered probit estimation method. Our results show that the infrequent use of social media has no impact on educational outcomes, the daily use of social media has a negative effect on the educational achievement of those pursuing doctoral, medical, and law degrees. It is possible that the time spent on social media could crowd out time that could have been spent with family, friends, or on other activities which promote individual education, health and wellbeing.

Résumé : Cet article utilise les données du Panel Study of Income Dynamics (PSID), en particulier les données du Child Development Supplement (CDS) et du Transition into Adulthood Supplement (TAS) de 2017 et 2019 pour constituer un ensemble de données longitudinales et étudier l'impact causal des médias sociaux sur la réussite scolaire des jeunes, tout en contrôlant leurs caractéristiques sociodémographiques, le niveau d'éducation et la situation matrimoniale de leurs parents. Nous estimons notre modèle en utilisant la méthode d'estimation probit ordonnée des données de panel. Nos résultats montrent qu'une utilisation

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peu fréquente des médias sociaux n'a pas d'impact sur les résultats scolaires, tandis qu'une utilisation quotidienne a un effet négatif sur la réussite scolaire des personnes poursuivant des études de doctorat, de médecine et de droit. Il est possible que le temps passé sur les médias sociaux empiète sur le temps qui aurait pu être consacré à la famille, aux amis ou à d'autres activités favorisant l'éducation, la santé et le bien-être individuels.

JEL Codes: L82 (Entertainment • Media), L86 (Information and Internet Services • Computer Software), I20 (Education and Research Institutions: General)

1. Introduction

Computer technology, internet connectivity, and social media use permeate the fabric of contemporary society. For many years, scholars have studied the impact of TV viewing on young people's academic achievement, health, and other measures of individual wellbeing (Hofferth et al. (2018), Supper, Guay, and Talbot (2021)). Today the use of social media (Facebook, Instagram, Twitter, TikTok, etc.) by adolescents or young adults and their participation in other internet activities are at least as time consuming as TV was in the past. Scholars from around the world have used longitudinal survey data from many countries to study the causal effects of social media use by adolescents on their mental health (Thorisdottir et al. 2019; Puukko et al. 2020) and life satisfaction (Orben, Dienlin, and Przybylski, 2019). This study builds on the existing research by using the Panel Study of Income Dynamics (PSID) core, Child Development Supplement (CDS), and Transition into Adulthood Supplement (TAS) data files to examine the effects of social media use by adolescents and young adults on academic achievement, while controlling for their background characteristics and other online time-use activities. The Goldilocks Hypothesis posits that the relationship between the intensity social media use and well-being is curvilinear, meaning that there is an optimal amount of usage, where both too little or too much use is detrimental. We hypothesize that the moderate use of social media, defined as the use of social media a few times a week or once a week, has a positive effect on the educational outcome variables but that the excessive or daily use of social media, might crowd-out time that could have been spent with family, friends, and other life enhancing activities. The results of our study suggest that, compared to those who did not

use it at all, the moderate use of social media had no statistically significant effect on educational achievement, and the frequent or daily use of social media had a negative impact on educational outcomes. These results provide information for educators, parents or caregivers, and policy makers which will help them generate appropriate time-use guidelines for adolescents and young adults that will promote their long-term academic achievement, and even welfare and quality of life.

The scope of this study focuses on American adolescents and their transition into adulthood. In a young person's life, this period marks the transition to adulthood when they enter the labor market, become more financially independent, and take on the roles of worker, parent, and spouse. This period is becoming an increasingly heterogeneous experience in the U.S. and other societies (Benson, 2014). Attitudes towards the transition to adulthood have evolved from the belief that there is a discrete set of experiences common to everyone in the course of life to the idea that this period reflects the adolescent experiences of a person's life and is integral to shaping individuals over their life cycle. For this reason, greater attention to this stage of life is important (Shanahan, 2000).

Young adults' increasing access to technology and social media platforms has significantly increased the screen time of young adults. Nationally representative U.S. surveys found that young adults reported more widespread social media use, internet access, and internet-enabled device access in 2016 (Smith and Anderson, 2018; Villanti et al., 2017) than did previous generations (Vogel, 2019). Young adults spend more time on average using digital technologies than on any other activity (Coyne et al., 2013). Substantial increases in social media usage since 2014 suggest that the use of technology and social media by young adults have changed rapidly, warranting the use of recent data to assess its current impact on individual wellbeing.

The rest of the paper is organized as follows. Section 2 is the literature review. Section 3 is the modeling section. Section 4 is the data description section. Section 5 is the section for model estimation, interpretation, and discussion. Section 6 is robustness check. Finally, section 7 is the conclusion section.

2. Literature Review

Studies on the effects of the use of social media on the academic achievement of young adults have proliferated in recent years. We

reviewed the results reported in the literature which examined how various types of social media use affected academic achievement. At the end of the literature review, we will show how our research adds to the existing literature on the educational effects of social media use.

Studies examining the relationship between the use of social media by young adults and their academic achievement have generated mixed results. Kirschner and Karpinski (2010) conducted a meta-analysis that revealed a small but significant negative correlation between social media use and academic performance which suggested that the increased use of social media was correlated with lower grades. Junco (2012) did a study on college students and discovered a negative correlation between their GPA and time spent on Facebook. This suggested that excessive social media use could distract students from their academic duties. Other studies have found that social media use improved academic performance. Al-Khoury and Daw (2015) found that the use of social media by Lebanese Higher Education students was instrumental in improving their academic performance. Similarly, Skiera, Hinz, and Spann (2015) found that students located in densely connected subnetworks earned better grades. Several other studies found no correlation between social media use and academic performance (Doleck, Lajoie, and Bazelais, 2019; Durak, and Seferoğlu, 2020). Doleck, Lajoie, and Bazelais (2019) conducted a longitudinal study, analyzing both positive and negative paths, which revealed no significant relationship between increased social media use by adolescents and their academic performance. The impact of social media use on academic performance might be dependent to a large degree on its content and purpose. Cheng, Nguyen and Nguyen (2023) found that passive social media use alone did not impact academic performance. However, high levels of passive use combined with active engagement on social media were negatively correlated with academic performance.

Although social media use on one's academic performance seems to have mixed results, current studies are finding that it is positively related to educational attainment. Perrin (2015) found that individuals with higher levels of education were more likely to use social media. 76% of college graduates reported using social media as opposed to 54% of people who had only a High School diploma or less. Koiranen et al. (2020) investigated the change in social media use patterns during the years 2008 and 2016 in

Finland and found that there was on average a 10% difference in the number of social media users between the lowest and highest education groups, with the most educated being the most active users. Similarly, Özgüven and Mucan (2013) found that social media use increased with educational and income levels in Turkey. Addictive social media use has also been found to differ with levels of education. Andreassen, Pallesen, and Griffiths (2017) found that addictive social media use by students was significantly higher among those with less education. However, the same study found that students displayed addictive social media use more than non-students.

Our research adds to the literature by studying the educational effects of social media use on not only adolescents but also young adults in the United States. According to the current literature, few researchers have used PSID data to study the time use of children and emerging adults on social media from a causal perspective. This data will enable us to track the same individuals over time and allow for causal analysis. Furthermore, we will use a relatively new estimation procedure which adjusts for possible endogeneity in the models. This method is useful when there may be some common unobservable factors that affect both our outcome variable, educational attainment, and the social media use the independent variable.

3. Model Specification

Our econometric model provides a framework to test for the significance of key variables, to control for confounding variables, and to quantify the relationship between the intensity of social media use and educational attainment. We use as our starting point the following linear regression model adapted from Dong and Marquis (2025).

$$educHighest = \beta_0 + \boldsymbol{\beta_1} social\ media\ use\ intensity + \boldsymbol{\beta_2}\ use\ intensity\ of\ other\ online\ activities + \boldsymbol{\beta_3}\ control\ variables + u \quad (1)$$

where the dependent variable is a discrete, ordinal variable using an ascending scale to measure the respondents' highest level of education. The independent variables include the intensity of social media use and other types of online activities such as playing video games, checking emails, texting, following interests, researching for schoolwork, and doing job-related internet searches. The control

variables include gender, age, marital status, the educational levels, and marital status of the parents. We hypothesize that the intensity of social media use and educational attainment are inversely related.

Because the dependent variable $educHighest$ is discrete and ordinal in nature, we used a panel data ordered probit (using Stata 18.0) to estimate Equation (1). In ordered probit regressions, the actual values taken on by the dependent variables are irrelevant, except for the fact that the larger values are assumed to correspond to "higher" educational outcomes. In Stata, the xtoprobit likelihood function is calculated by using the Gauss–Hermite quadrature. Specifying vce(robust) causes the Huber/White/sandwich VCE estimator to be calculated for the coefficients estimated in this regression. The dependent variable, the highest level of education, uses an ascending scale from 0 to 17 with 0 not receiving any education and 17 being high school graduate plus law degree. In general, ordered probits generate predictions about the probabilities that a respondent gives response 1, response 2, ..., response κ. It does this by dividing up the domain of an N (0,1) distribution into κ categories defined by $\kappa - 1$ cutpoints, $c_1, c_2, \ldots\ c_{\kappa-1}$. Individual respondents are assumed to have a score such that $score = X\beta + \epsilon$, where $\epsilon \sim N(0,1)$. That score is then used along with the cutpoints to produce probabilities for each respondent producing response $1, 2, \ldots, \kappa$. That is,

$$Prob(educHighest = i|X) = Prob(c_{i-1} < X\beta < c_i)$$

where $c_0 = -\infty$, and $c_\kappa = +\infty$ and where cutpoints, $c_1, c_2, \ldots\ c_{\kappa-1}$ and β are parameters of the model to be estimated. That is, we run our model using the standard panel data regression estimation procedures for our longitudinal data. In doing this, we took into account the ordinal feature of our dependent variable by using an ordered probit method to estimate our panel data model. We then present the results of the average marginal effects obtained from this nonlinear estimation.

Since unobservable factors are not included in the data, the estimated panel data ordered probit regression coefficients could be biased. Hence, we estimate our model using Lewbel's (2012) method, which we will explain in detail in Section 6 Robustness Check. When using the Lewbel (2012) estimation method, we assign the year 2017 as the base omitted year and assign the year 2019 as

an additional and binary independent variable within the context of a typical classical linear regression framework.

4. Data and Descriptive Statistics

We use data from the University of Michigan's PSID website. The PSID study began in 1968 with a nationally representative sample of over 18,000 individuals from 5,000 households in the United States. In 1997, the children from those households were included in a study which provided data for the PSID to generate the Child Development Supplement (CDS). These same children were surveyed over several more years enabling the PSID to generate the Transition into Adulthood Supplement (TAS) panel data set which we use for the years 2017 and 2019.

We are interested in how the time spent on social media by adolescents or young adults affects their educational achievement. Sastry et al. (2017) claims that the PSID Child Development Supplement (CDS) has been the leading source of information on children's time use in the U.S. For example, the time use diaries in the CDS – 2014 questionnaires include specific questions about the time spent using media, the timing of media use during the day, the content of media used (e.g., names of television programs, movies, web sites, and electronic games), and the social context of media use (e.g., who was participating with the child). Since we are interested in the long-term effects of social media use over time, we used data from 2017 and 2019 included in the regular PSID core, CDS, and TAS data files. We also focus only on people who are between the ages of 17 and 28 (see Table 1 no. 9). As a result, we have a total of 4,550 observations with 2,399 observations from 2017 and 2,151 from 2019. We have cleaned our data by removing the observations where respondents refused to provide a valid answer. Detailed descriptive information on the variables is provided in Table 1. The variables in Table 1 are all discrete and/or ordinal in nature. For example, our key independent variable, no. 4 in Table 1, describes how often the respondent interacts with social media by choosing from the following 5 responses: (1) Everyday; (2) A few times a week; (3) Once a week; (4) Less than once a week; and (5) Never. 57.21% of people in our sample used social media every day, 24.99% used it a few times a week, 6.04% used it once a week, 5.82% used it less than once a week, and 5.93% never used social media.

5. Estimation, Interpretation, and Discussion

Table 2 reports the estimated ordered probit regression model coefficients, $\hat{\beta}$s, in Equation (1). We find from Table 2 column (1) that the highest educational attainment is positively correlated with being female (row 1), being older (row 2), using social media for email (rows 21 – 24), to follow interests online (rows 29 – 32), for job-related activities (row 38), and with having a head of the household who is better educated (row 7) or single (row 9). The independent variables that are negatively correlated with educational attainments include young people who are divorced (row 5), separated (row 6), never married (row 3), who use social media every day (row 13), who play video games every day or a few times a week (rows 17 and 18), who research online for schoolwork every day or once a week (rows 33 and 35), and who were not working in past 30 days at the interview time (row 42).

Because the $\hat{\beta}$s generated by our ordered probit model cannot be interpreted as the marginal effect of independent variables on the dependent variable, as in a linear regression model, we focus our attention on the average marginal effects of social media use on the dependent variable for our respondents. For example, Table 3 reports the average marginal effects of the intensity of social media use by the respondents on their level of educational attainment (columns 1 – 4). We find in column (1) row (13) that respondents who use social media everyday decrease the probability of achieving a GED plus law degree by an average of 2%. Row (14) indicates that respondents who use social media everyday decrease the probability of achieving a high school plus law degree by an average of 1.2%. They are individually and statistically significant at the 5% level.

This result is consistent with some of the literature. For example, according to Nguyen (2024), Uzun and Kilis (2019) provided more context on the impact of media and technology engagement on academic performance. They conducted a cross-sectional survey study to explore how the use of media and technology by university students is related to their academic performance, while controlling for the influence of multitasking and self-regulation, as well as demographic variables such as gender, age, and year of study. The descriptive and inferential statistics and hierarchical multiple linear regression model results showed the most common utilization of technology among students included e-mailing, social media use, media sharing, and internet browsing.

The results indicated a negative relationship between academic performance and the use of social media. Uzun and Kilis (2019)

asserts that heavy media use is associated with increased multitasking and decreased academic performance. Additionally, an increased utilization of social media was linked to higher levels of multitasking behaviors. Notably, certain media and technology use, like smartphones, social media, e-mailing, media sharing and social media, were found to have more of a significant and negative impact on academic performance; while internet browsing, and video gaming were not significantly linked to academic performance. Therefore, the study by Uzun and Kilis (2019) reveals that certain utilization of technology can pose negative effects on academic performance. Gender, age, and year of study were found to be significant predictors of students' GPA, indicating demographic factors' influence on technology usage habits as well. Nguyen (2024) investigated the multifaceted influences of technology use, race, gender, and cognitive skills on the academic GPA outcomes of 9th grade high school students. Through regression analysis of 15 independent variables, including time spent online, race/ethnicity, gender, and cognitive skills, the study revealed significant correlations with GPA. Findings indicate a negative correlation between extensive online activity and GPA, emphasizing the importance of responsible internet habits. On the other hand, Alshalawi (2022) found a positive relationship between the academic performance and intensity of social network use of students in Saudi Arabia after controlling for gender and high school GPA.

Our results listed in Table 3 columns (2) through (4) show that the moderate or absence of social media use by respondents had no statistically significant impact on the highest educational level achieved. Huang (2018) conducted a meta-analysis to estimate the relationship between academic achievement and the use of social network sites (SNS) and found the mean correlation to be very small and negative. The mean correlation was close to zero for studies assessing the use of Facebook, was small for studies measuring use of all SNSs, was small for studies assessing the time spent on social media, and was about zero for studies measuring the frequency of social media use.

6. Robustness Check

We did not estimate our panel data model by using Two Stage Least Squares (2SLS) estimation processes to adjust for possible endogeneity in the models resulting from missing or improperly measured independent variables. Since it is hardly possible to find

a good (external) instrumental variable to be correlated with the suspected endogenous variable, i.e., social media use (the relevance assumption) but not to be correlated with the outcome variable, i.e., the dependent variable (the exclusion assumption). However, Lewbel (2012) developed an estimation procedure which uses the independent variables within the model to construct instrumental variables that satisfy the "new" exclusion and relevance assumptions required for good instrumental variables. To our knowledge, only one study by Courtemanche, Pinkston, and Stewart (2021) has used the Lewbel estimator to adjust for possible bias in the OLS or 2SLS estimation processes due to unmeasured or poorly measured independent variables. In Stata, ivreg2h can estimate an instrumental variables regression model by providing the option to generate instruments using Lewbel's method. This technique allows the identification of structural parameters in regression models with endogenous or mismeasured regressors or in the absence of traditional identifying information, such as external instruments or repeated measurements. Identification in Lewbel's method is achieved in this context by having regressors that are uncorrelated with the product of heteroskedastic errors. This is often a feature of models in which error correlations are due to an unobserved common factor. The greater the degree of scale heteroskedasticity in the error process, the higher will be the correlation of the generated instruments with the included endogenous variables which are the regressands in the auxiliary (first stage) regressions. Using this form of Lewbel's method, instruments may be constructed as simple functions of the model's data. This approach may be applied when no external instruments are available, or, alternatively, used to supplement external instruments to improve the efficiency of the IV estimator.

We applied this method by assuming there were no adequate instruments available. The estimation results are shown in Table 4. We can see from the test of endogeneity, found in row (19) in Table 4, that the frequency of interaction using social media (socmedia) is not an endogenous variable in the regression for educational attainment (column 1) because the p-value is 14.8% higher than the 5% level of significance. We find that the frequent use of social media has no significant effect on respondents' educational attainment (row 1 and column 1). This result from Lewbel's estimation method is not exactly consistent with our average marginal effects result estimated by the nonlinear panel data ordered probit estimation method reported in the earlier table (see

Table 2). Because endogeneity did not seem to be an issue, we focus on our former ordered probit estimation results presented in Table 3.

7. Conclusion

This paper used the Child Development Supplement (CDS) and Transition into Adulthood Supplement (TAS) data from the Panel Study of Income Dynamics (PSID) for 2017 and 2019, to generate a longitudinal dataset which enabled us to study the effects of social media use on young-adult educational outcomes. In particular, we examined how the use of social media affected their highest degree achieved, while controlling their background characteristics such as gender, age, marital status, as well as the educational level and marital status of their parents. We initially hypothesized that the excessive use of social media by respondents would negatively impact their educational achievement. Surprisingly, our hypotheses did not stand up to our empirical analysis completely which generated mixed results consistent with some of the studies in the literature review. In particular, we found from the panel data ordered probit model estimation that the daily use of social media was negatively related to their highest educational attainment. This may imply that time spent on social media may crowd out time that could be spent with family, friends, and other activities which promote individual education, health and wellbeing. In addition, we think that factors such as age, gender, race, and socioeconomic status further complicate this dynamic, with disparities in technology access widening the educational gap.

Although the daily use of social media does not capture the daily screen time of these respondents, the negative relationship between the intensity of social media use and academic achievement could provide information to educators, parents or caregivers, and policy makers, which will help them generate appropriate guidelines for the time use of young people to promote their long-term academic benefit, or even better welfare and quality of life.

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Table 1 Descriptive Information and Summary Statistics

	Variable	Renamed Label	Original Label in PSID	Range	Description	Descriptive statistics		
						Freq.	Percent	Cum.
	Dependent variables							
	Highest level of education	educHighest	TA171990 & TA192191	0 -- 17	0 Not receiving any education	368	8.09	8.09
					5 High school graduate plus some college	1	0.02	8.11
					6 GED plus Associate's degree	1	0.02	8.13
					7 High school graduate plus Associate's degree	5	0.11	8.24
					8 GED plus Bachelor's degree	16	0.35	8.59
					9 High school graduate plus Bachelor's degree	43	0.95	9.54
					10 GED plus Master's degree	172	3.78	13.32
					11 High school graduate plus Master's degree	474	10.42	23.74
					12 GED plus Doctoral degree	1402	30.81	54.55
					13 High school graduate plus Doctoral degree	580	12.75	67.3
					14 GED plus Medical degree	499	10.97	78.27
					15 High school graduate plus Medical degree	245	5.38	83.65
					16 GED plus Law degree	512	11.25	94.9
					17 High school graduate plus Law degree	232	5.1	100
	Independent variables							
1	A23A HOW OFTEN PLAY GAMES ON COMPUTER	freqplaygamesInst30days	TA170045 & TA190050	1 -- 5	1 Every day	1569	34.48	34.48
	In the past 30 days, how often have you used a computer or other electronic device (such as a tablet, smartphone or gaming console) to play games? Higher scores are indicative of less frequent use of technology.				2 A few times a week	1059	23.27	57.75
	'this variable is a component of a Technology Use Scale. The scale includes these 5 items scored 1-5 for a total score of 35 where higher scores are indicative of less frequent use of technology. (1) TA190050 A23a How Often Play Games on Computer (2) TA190051 A23b How Often Send/Receive Email (3) TA190052 A23c How Often Send/Receive Texts (4) TA190053 A23d How Often Interact on Social Media (5) TA190054 A23e How Often Follow Interests				3 Once a week	396	8.7	66.45
					4 Less than once a week	723	15.89	82.34
					5 Never	803	17.65	99.99
2	A23B HOW OFTEN SEND/RECEIVE EMAIL	frequendreceiveemail	TA170046 & TA190051	1 -- 5	1 Every day	2601	57.23	57.23
	In the past 30 days how often have you… Sent or received email? higher scores are indicative of less frequent use of technology.				2 A few times a week	1017	22.35	79.58
					3 Once a week	375	8.24	87.82
					4 Less than once a week	371	8.15	95.97
					5 Never	183	4.02	99.99
3	A23C HOW OFTEN SEND/RECEIVE TEXTS	frequendreceivetext	TA170047 & TA190052	1 -- 5	1 Every day	4051	89.03	89.03
	(In the past 30 days how often have you…) Sent or received text messages?				2 A few times a week	355	7.8	96.83

	Variable	Renamed Label	Original Label in PSID	Range	Description	Descriptive statistics		
	higher scores are indicative of less frequent use of technology.				3 Once a week	58	1.27	98.1
					4 Less than once a week	46	1.01	99.11
					5 Never	40	0.88	99.99
4	A23D HOW OFTEN INTERACT ON SOCIAL MEDIA	freqinteractonsocialme	TA170048 & TA190053	1 -- 5	1 Every day	2603	57.21	57.21
	(In the past 30 days how often have you...) Interacted with friends or family on a social media site (like Facebook, Instagram, or Twitter)?				2 A few times a week	1137	24.99	82.2
	higher scores are indicative of less frequent use of technology				3 Once a week	275	6.04	88.24
					4 Less than once a week	265	5.82	94.06
					5 Never	270	5.93	99.99
5	A23E HOW OFTEN FOLLOW INTERESTS	freqfollowinterests	TA170049 & TA190054	1 -- 5	1 Every day	1599	35.14	35.14
	(In the past 30 days, how often have you...) Followed topics or people that interest you on websites, blogs, or social media sites (like Facebook, Instagram, or Twitter), not including following or interacting with friends or family online?				2 A few times a week	1312	29.49	64.63
	higher scores are indicative of less frequent use of technology.				3 Once a week	563	12.37	77
					4 Less than once a week	578	12.7	89.7
					5 Never	468	10.29	99.99
6	A23F HOW OFTEN RESEARCH SCHOOL WORK	freqresearchschlwk	TA170050 & TA190055	1 -- 5	1 Every day	985	21.65	21.65
	(In the past 30 days, how often have you...) Used the Internet for research for school work done at school or at home?				2 A few times a week	962	21.14	42.79
	higher scores are indicative of less frequent use of technology.				3 Once a week	335	7.36	50.15
					4 Less than once a week	381	8.37	58.52
					5 Never	1126	24.75	83.27
					6 Not in school in past 30 days	761	16.73	100
7	A23G HOW OFTEN JOB-RELATED INTERNET USE	freqjobrelainternetuse	TA170051 & TA190056	1 -- 5	1 Every day	1494	32.84	32.84
	(In the past 30 days, how often have you...) Used the Internet for job-related activities and duties?				2 A few times a week	1211	26.62	59.46
	higher scores are indicative of less frequent use of technology.				3 Once a week	495	10.88	70.34
					4 Less than once a week	572	12.57	82.91
					5 Never	598	13.14	96.05
					6 Not working in past 30 days	180	3.96	100.01
	Control variables							
8	Sex of Individual	gender	ER32000	1 -- 2	1 Male	2160	47.47	47.47
					2 Female	2390	52.53	100
9	Age at the Time of the Interview	age	ER34501 & ER34704	17 -- 28	17	223	4.9	4.9
					18	425	9.34	14.24
					19	380	8.35	22.59

	Variable	Renamed Label	Original Label in PSID	Range	Description	Descriptive statistics		
					20	393	8.64	31.23
					21	372	8.18	39.41
					22	407	8.95	48.36
					23	437	9.6	57.96
					24	442	9.71	67.67
					25	424	9.32	76.99
					26	424	9.32	86.31
					27	435	9.56	95.87
					28	188	4.13	100
10	CI CURRENT MARITAL STATUS	maritalstatus	TA170093 & TA190132	1 -- 5	1 Married	475	10.44	10.44
	What is your current marital status? Are you married, widowed, divorced, separated or have you never been married?				2 Never married	3966	87.16	97.6
					3 Widowed	1	0.02	97.62
					4 Divorced, annulled	71	1.56	99.18
					5 Separated	37	0.81	99.99
11	Reference Person's Completed Education Level	educhead	ER71538 & ER77599	0 -- 17	0	14	0.31	0.31
	Values in the range 1-16 represent the actual grade of school completed; e.g., a value of 8 indicates that the Reference Person completed the eighth grade.				2	9	0.2	0.51
					3	10	0.22	0.73
					4	18	0.4	1.13
					5	5	0.11	1.24
					6	46	1.01	2.25
					7	15	0.33	2.58
					8	28	0.62	3.2
					9	68	1.49	4.69
					10	149	3.27	7.96
					11	352	7.74	15.7
					12	1295	28.42	44.12
					13	474	10.42	54.54
					14	622	13.67	68.21
					15	235	5.16	73.37
					16	759	16.68	90.05
					17	453	9.96	100.01
12	Spouse's/Partner's Completed Education Level	educwife	ER71539 & ER77600	0 -- 17	0	2494	54.81	54.81
	Values in the range 1-16 represent the actual grade of school completed; e.g., a value of 8 indicates that the Spouse/Partner completed the eighth grade.				2	2	0.04	51.85
					3	6	0.13	54.98
					4	5	0.11	55.09
					5	2	0.04	55.13
					6	46	1.01	56.14

Variable	Renamed Label	Original Label in PSID	Range	Description	Descriptive statistics		
				7	5	0.11	56.25
				8	14	0.31	56.56
				9	30	0.66	57.22
				10	48	1.05	58.27
				11	78	1.71	59.98
				12	451	9.91	69.89
				13	158	3.47	73.36
				14	302	6.64	80
				15	147	3.23	83.23
				16	418	9.19	92.42
				17	344	7.56	99.98
13 REFERENCE PERSON MARITAL STATUS	maritalstatus_head	ER66024 & ER72024	1 -- 5	1 Married	1709	37.56	37.56
Are (you/Reference Person) married, widowed, divorced, separated, or have you never been married?				2 Never married	2005	44.07	81.63
				3 Widowed	104	2.29	83.92
				4 Divorced, annulled	549	12.07	95.99
				5 Separated	183	4.02	100.01

Table 2 Effect of Social Media Use on Educational Attainment

VARIABLES	(1) educHighest
1 SEX OF INDIVIDUAL = 2, Female	0.212***
	(0.050)
2 age	0.173***
	(0.009)
3 maritalstatus = 2, Never married	-0.593***
	(0.090)
4 maritalstatus = 3, Widowed	0.051
	(0.155)
5 maritalstatus = 4, Divorced, annulled	-0.688***
	(0.179)
6 maritalstatus = 5, Separated	-0.597***
	(0.174)
7 educhead	0.181***
	(0.015)
8 educwife	-0.003
	(0.005)
9 maritalstatus_head = 2, Never married	0.321***
	(0.090)
10 maritalstatus_head = 3, Widowed	-0.162
	(0.191)
11 maritalstatus_head = 4, Divorced, annulled	-0.001
	(0.110)
12 maritalstatus_head = 5, Separated	-0.168
	(0.131)
13 freqinteractonsocialmc = 1, Every day	-0.214**

VARIABLES	(1) educHighest
	(0.091)
14 freqinteractonsocialme = 2, A few times a week	-0.149
	(0.094)
15 freqinteractonsocialme = 3, Once a week	-0.068
	(0.118)
16 freqinteractonsocialme = 4, Less than once a week	-0.063
	(0.116)
17 freqplaygameslast30days = 1, Every day	-0.142**
	(0.064)
18 freqplaygameslast30days = 2, A few times a week	-0.121*
	(0.067)
19 freqplaygameslast30days = 3, Once a week	-0.008
	(0.079)
20 freqplaygameslast30days = 4, Less than once a week	-0.049
	(0.075)
21 freqsendreceiveemail = 1, Every day	0.618***
	(0.085)
22 freqsendreceiveemail = 2, A few times a week	0.419***
	(0.088)
23 freqsendreceiveemail = 3, Once a week	0.454***
	(0.094)
24 freqsendreceiveemail = 4, Less than once a week	0.390***
	(0.095)
25 freqsendreceivetext = 1, Every day	-0.072
	(0.133)
26 freqsendreceivetext = 2, A few times a week	-0.091
	(0.143)

VARIABLES	(1) educHighest
27 freqsendreceivetext = 3, Once a week	0.107
	(0.181)
28 freqsendreceivetext = 4, Less than once a week	-0.260
	(0.226)
29 freqfollowinterests = 1, Every day	0.196***
	(0.075)
30 freqfollowinterests = 2, A few times a week	0.315***
	(0.071)
31 freqfollowinterests = 3, Once a week	0.241***
	(0.082)
32 freqfollowinterests = 4, Less than once a week	0.179**
	(0.082)
33 freqresearchschlwk = 1, Every day	-0.137**
	(0.062)
34 freqresearchschlwk = 2, A few times a week	-0.061
	(0.061)
35 freqresearchschlwk = 3, Once a week	-0.126*
	(0.073)
36 freqresearchschlwk = 4, Less than once a week	-0.049
	(0.073)
37 freqresearchschlwk = 6, Not in school in past 30 day	0.054
	(0.054)
38 freqjobrelainternetuse = 1, Every day	0.347***
	(0.068)
39 freqjobrelainternetuse = 2, A few times a week	0.093
	(0.064)
40 freqjobrelainternetuse = 3, Once a week	0.067

VARIABLES	(1) educHighest
	(0.073)
41 freqjobrelainternetuse = 4, Less than once a week	0.120
	(0.075)
42 freqjobrelainternetuse = 6, Not working in past 30 d.	-0.256**
	(0.117)
43 maritalstatus = 3, omitted	
44 lnsig2u	
45 Constant	4.285***
	(0.321)
Observations	4,550
Number of id	3,083

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 Average Marginal Effects of Social Media Use on Educational Attainment

VARIABLES	(1) educHighest	(2) educHighest	(3) educHighest	(4) educHighest
	ise social media=Everyday	ise social media=A few times a week	ise social media=Once a week	use social media=Less than once a week
1._predict: Pr(0.educHighest), predict(pr outcome(0))	0.020**	0.014	0.006	0.006
	(0.008)	(0.008)	(0.011)	(0.010)
2._predict: Pr(5.educHighest), predict(pr outcome(5))	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
3._predict: Pr(6.educHighest), predict(pr outcome(6))	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
4._predict: Pr(7.educHighest), predict(pr outcome(7))	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
5._predict: Pr(8.educHighest), predict(pr outcome(8))	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
6._predict: Pr(9.educHighest), predict(pr outcome(9))	0.001**	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
7._predict: Pr(10.educHighest), predict(pr outcome(10))	0.005**	0.003	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
8._predict: Pr(11.educHighest), predict(pr outcome(11))	0.011**	0.007	0.003	0.003
	(0.005)	(0.005)	(0.006)	(0.006)
9._predict: Pr(12.educHighest), predict(pr outcome(12))	0.013**	0.010	0.005	0.004
	(0.006)	(0.007)	(0.008)	(0.008)
10._predict: Pr(13.educHighest), predict(pr outcome(13))	-0.004***	-0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
11._predict: Pr(14.educHighest), predict(pr outcome(14))	-0.009**	-0.006	-0.003	-0.002
	(0.004)	(0.004)	(0.005)	(0.005)
12._predict: Pr(15.educHighest), predict(pr outcome(15))	-0.007**	-0.005	-0.002	-0.002
	(0.003)	(0.003)	(0.004)	(0.004)
13._predict: Pr(16.educHighest), predict(pr outcome(16))	-0.020**	-0.014	-0.006	-0.006
	(0.009)	(0.009)	(0.011)	(0.011)
14._predict: Pr(17.educHighest), predict(pr outcome(17))	-0.012**	-0.008	-0.004	-0.004
	(0.005)	(0.006)	(0.007)	(0.007)
Observations	4,550	4,550	4,550	4,550

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Effect of Social Media Use on Educational Attainment: ivreg2h

VARIABLES	(1) educ
1 RECODE of interactionsocialme	0.040
	(0.112)
2 female	0.362***
	(0.120)
3 age	0.264***
	(0.020)
4 married	1.789***
	(0.208)
5 educhead	0.113***
	(0.023)
6 educwife	-0.011
	(0.014)
7 married_head	-0.978***
	(0.214)
8 RECODE of playgamesdast30days	-0.039
	(0.039)
9 RECODE of sendreceiveemail	0.145***
	(0.055)
10 RECODE of sendreceivetext	-0.055
	(0.108)
11 RECODE of followinterests	0.021
	(0.059)
12 RECODE of researchachlwk	-0.094***
	(0.036)
13 RECODE of jobrelatinternetuse	0.008
	(0.041)
14 year2019	0.033
	(0.129)
15 Constant	4.416***
	(0.749)
16 Observations	4,550
17 R-squared	0.110
18 Adjusted R-squared	0.108
19 endog test p-value	0.148

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1