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The impact of Internet use on adolescent learning outcomes: evidence from rural China

Lili Li
China Academy for Rural Development, Zhejiang University – Zijingang Campus, Hangzhou, China
Yue Ma and Dimitris Friesen
Freeman Spogli Institute of International Studies, Stanford University, Stanford, California, USA
Zhonggen Zhang
China Academy for Rural Development, Zhejiang University, Hangzhou, China
Songqing Jin
Agricultural, Food and Resource Economics, Michigan State University, East Lansing, Michigan, USA, and
Scott Rozelle
Freeman Spogli Institute of International Studies, Stanford University, Stanford, California, USA

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Abstract

Purpose – Internet use has become particularly prevalent among adolescents, prompting much thought and concern about both its potential benefits and adverse effects on adolescent learning outcomes. Much of the empirical literature on the impact of Internet use on adolescent learning outcomes is mixed, and few studies examine the causal relationship between the two in rural China. In order to bridge these gaps, we use empirical analysis to investigate the effect of Internet use on the learning outcomes of adolescents in rural China.

Design/methodology/approach – We use fixed effect models with samples drawn from a large nationally representative dataset (the China Family Panel Studies—CFPS) to identify the causal impacts of Internet use on the learning outcomes of three cohorts (Cohort A ($N = 540$), Cohort B ($N = 287$) and Cohort C ($N = 827$)) of adolescents in rural China.

Findings – The results of the descriptive analysis show a continued increase in the number of adolescents accessing the Internet and the amount of time they spend online. The results of the fixed effect models show that Internet use has positive (in many of the analyses), but mostly insignificant impacts, on the learning outcomes of adolescents. In the sets of results that find significant associations between Internet use and learning outcomes, the measured effects are moderate.

Originality/value – This study investigates the causal relationship between Internet use and adolescent learning outcomes in rural China. The findings claim that there is not a great need to worry about adverse effects of Internet use on adolescent learning development. Attention, however, should focus on seeking ways to improve the positive effects of the Internet use on adolescent learning outcomes. The study will provide a reference and experience for the development of education and the Internet in rural areas and promote the integrated development of urban and rural areas in China.

Keywords Internet use, Learning outcomes, Adolescent, Causal effect, Rural China

Paper type Research paper

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1. Introduction

The Internet has grown rapidly in both use and applications worldwide, especially for certain age groups. Internet use has become an increasingly important part of life in modern societies and has changed the way people work, learn, communicate and entertain (Firth *et al.*, 2019). Use of the Internet has become particularly prevalent among adolescents, who are commonly referred to as "digital natives" (Thompson, 2013). Large shares of adolescents spend much of their time online and use internet-connected technologies for social interaction, communication, entertainment, education and information retrieval (Colley and Maltby, 2008; Subrahmanyam and Greenfield, 2008; Kormas *et al.*, 2011; Wang *et al.*, 2011; Reich *et al.*, 2012). Studies show that in Singapore adolescents aged 12 to 18 spend an average of 216.25 min per day on the Internet (Shin and Kang, 2016). Nearly all (94%) of Spanish adolescents with Internet access use instant messaging; 93.5% of Spanish adolescents use social networking sites (Gómez *et al.*, 2017). Similarly, 90% of US teens say they play video games (Anderson and Jiang, 2018). According to Işik and Alkaya (2017), 80.8% of adolescents say they would prefer to browse research websites, and 94.8% of students say they use the Internet for preparing homework in Ankara, Turkey. Trends indicate a continued increase in the number of adolescents accessing the Internet, the amount of time they spend online and the complexity of their online behavior (Livingstone and Helpsper, 2007).

Despite the positive possibilities of Internet use by youth, concerns also have arisen about potentially adverse effects of Internet use on educational development among adolescents (Anderson *et al.*, 2007; Bricolo *et al.*, 2007). Parents, teachers and researchers are concerned that students who spend excessive time on the Internet may have difficulty completing homework assignments, studying and getting sufficient sleep to meet their academic responsibilities (Sinkkonen *et al.*, 2014). Research has shown that the use of the Internet occupies the learning time of adolescents and often can distract them since most adolescents use the Internet to browse websites, listen to music, chat or play games while learning or doing homework (Kirschner and Karpinski, 2010). Moreover, teenagers use the Internet not just for learning, but also for socialization, entertainment and other activities (Qahri-Saremi and Turel, 2016; Chang *et al.*, 2019).

In recent years, a number of research teams have empirically studied the correlations between Internet use and adolescent learning outcomes, but results are mixed. On one hand, some studies found positive relationships between Internet use and academic performance measured via grade point averages and standardized test scores over time (Jackson *et al.*, 2006, 2011; Drain *et al.*, 2012). Using the Internet for accessing information and reading has been demonstrated to positively affect the comprehension capacity and learning of adolescents (Salmerón *et al.*, 2018). Empirical research has also shown that information technology (IT) can provide a highly experiential and interactive learning environment and has potential for assisting adolescent cognitive, psychological and academic development (Straker *et al.*, 2009; Jackson *et al.*, 2011; Fitton *et al.*, 2013; Fonseca *et al.*, 2014; Chang *et al.*, 2019). Students who use the Internet for learning and communicating frequently, or just in general, demonstrate better cognitive capacity than students who do not use the Internet frequently (Johnson, 2008).

On the other hand, there are a number of studies that have found that Internet use can have either no significant relationship or even a negative correlation with adolescent academic development (Sana *et al.*, 2013; Qahri-Saremi and Turel, 2016; Rashid and Asghar., 2016). For instance, the time that children spent online in early childhood has empirically been shown to have a negative and statistically significant impact on their middle childhood academic performance (Hurwitz and Schmitt, 2020). There are uses of the Internet that are thought to have a negative impact on educational development, such as the excessive use of videogames and/or social media (Turel and Serenko, 2012; Sana *et al.*, 2013; Turel, 2015). Mobile phone use also has been found by some research teams to be negatively related to student academic achievement in addition to increasing attention disorders and depression problems (Harman and Sato, 2011; Roberts *et al.*, 2015; Seo *et al.*, 2016; Hsiao *et al.*, 2017). Qahri-Saremi and Turel (2016), however, find that there are no significant effects of utilitarian (school-oriented) Internet use on the educational development outcomes of adolescents.

Although researchers, theoretical and empirical, have focused recently on the issues of the relationship between Internet use and adolescent academic performance, some gaps exist, including some common methodological shortcomings. First, most studies use cross-sectional data and descriptive analysis or relatively simple correlation analysis to study the association between Internet access and its use on student educational development (e.g. Moreno *et al.*, 2011; Moreno *et al.*, 2013; Qahri-Saremi and Turel, 2016). As a consequence, few studies have examined the *causal* impact of Internet use on adolescent academic performance. Hurwitz and Schmitt (2020) use longitudinal survey data to explore the association between Internet use in early childhood and academic performance in middle childhood. Moreover, Li *et al.* (2006) use a randomized experiment to examine the impact of computer use on school readiness and cognitive development. However, these studies have small samples which may not be representative. Second, few research teams have had access to nationally representative data to study issues of Internet use and the ability of adolescents to learn. Most literature uses either small or unrepresentative samples to study this relationship (e.g. Li and Ranieri, 2010; Fitton *et al.*, 2013; Rahardjo *et al.*, 2016; Chang *et al.*, 2019), which may not lead to reliable and general conclusions. Third, to our knowledge, there is relatively little research on the impact of Internet access and use on the academic outcomes of young people in developing countries, both in general and in rural settings in particular. Most studies only examine the relationship between Internet use or social media use and educational development of adolescents in developed countries by using data from urban areas (e.g. Seo *et al.*, 2016). Of greatest relevance to this study, there is little empirical work that has been done in rural China on this issue.

As one of the fastest-growing economies in recent years, China has had a steadily increasing rate of Internet penetration. In recent years, almost all individuals, including adolescents, have been able to readily access the Internet in China (Hong, 2017). As of December 2015, the Internet penetration rate of Chinese adolescents was 85.3%, which was 35 percentage points higher than the overall (individuals of all ages) Internet penetration rate (CNNIC, 2016). In 2015, the proportion of total adolescent Internet users was 72.4% urban and 27.6% rural (CNNIC, 2016). As such, China is both in need of a study of these issues on rural youth and is also an appropriate setting for studying the effects of Internet use. Our study focuses on trying to identify the causal relationship between Internet use and learning outcomes of adolescents in rural China. In addition, our study uses a nationwide sample from the China Family Panel Studies (CFPS) survey. Its stratified, multi-stage sampling strategy ensures that the CFPS sample represents 95% of the total Chinese population in 2010 (Xie and Hu, 2014). Compared to other data sources, the large-scale, high quality and nationally representative data from the CFPS can help us better understand the prevalence and trends of Internet use among rural youth in China (Li, 2019). We try to overcome the methodological shortcomings of previous studies, especially in terms of identification. Most studies only use descriptive analysis or relatively simple correlation analysis, while we use fixed-effect models to identify the causal impacts of Internet use on learning.

To bridge the gaps in the literature, the overall goal of our study is to answer the following question: What are the effects of Internet use on the learning outcomes of adolescents in rural China? To help answer this broad question, we pursue four specific objectives. First, we report on the trends of Internet access and usage among adolescents in rural China. Second, we describe the learning outcomes of these adolescents over time. Third, we examine whether Internet access and usage have an impact on the measured learning. Fourth, we investigate whether the impacts of Internet use on learning outcomes change for adolescent of different educational backgrounds and ages.

2. Data and methods

2.1 Sample selection

2.1.1 Sampling. Our study primarily uses data from the CFPS, which is a national and longitudinal survey conducted by the Institute of Social Science Survey (ISSS) at Peking University. The CFPS surveys economic and social development and changes in 25 provinces in China, excluding Tibet, Qinghai, Xinjiang, Ningxia, Inner Mongolia, Hainan, Hong Kong, Macau and Taiwan. The CFPS survey uses a stratified, multi-stage sampling strategy that ensures the sample represents 95% of the total population of China (Xie and Hu, 2014). Therefore, the CFPS sample can be regarded as a nationally representative sample.

The CFPS data set lends two strengths to this study. First, compared to other nationally representative data, such as the Chinese General Social Survey (CGSS) and China's census data, the CFPS is the only existing nationally representative data that contains measures for both adolescent Internet use and learning ability (Li, 2019). Second, since most previous studies on this issue rely on cross-sectional data, they cannot establish a causal relationship between Internet use and adolescent learning outcomes. The longitudinal design of the CFPS follows the same adolescents through multiple years, helping to address the issues of simultaneity and reverse causality.

2.1.2 Follow-up and attrition. The first round of data collection was carried out in 2010, followed by a further four rounds of data collection in 2012, 2014, 2016 and 2018. The CFPS contains an extensive set of measures of Internet access and usage, learning outcomes and sociodemographic characteristics of respondents (Xie and Hu, 2014). Our study primarily uses data from CFPS 2010, CFPS 2014 and CFPS 2018 since the CFPS uses the same set of test questionnaires every four years to measure learning development. As such, this study is based on two cohorts of adolescents: One cohort was made up of adolescents aged 14 to 17 in 2010 who were followed up in 2014 when they were aged 18 to 21. The other cohort was made up of adolescents aged 14 to 17 in 2014 who were followed up in 2018 when they were also aged 18 to 21.

Focusing on these two cohorts allows us to track changes in Internet access and usage by adolescents of the same age group between 2010 and 2014 (henceforth, *Cohort A*), as well as changes in Internet access and usage by adolescents of the same age group between 2014 and 2018 (*Cohort B*). In addition, we can examine the learning development for these two cohorts of adolescents (since the individuals in both cohorts took a test in both years that they participated in the survey). We also combine these two cohorts (which potentially gives the analysis additional statistical power) to study the total impact of the Internet on learning outcomes (*Cohort C*), resulting in three cohorts of adolescents: Cohorts A, B and C.

When tracking the adolescents in the sample over time, the CFPS survey team did encounter substantial attrition. Our original sample in Cohort A in 2010 included 1,368 adolescents aged 14 to 17. CFPS followed up with 653 of these adolescents in 2014. For Cohort B, the original sample in 2014 included 980 adolescents aged 14 to 17, of which CFPS followed up with 441 individuals in 2018. Cohort C was the combination of these two cohorts. Cohort A and B had follow-up rates of 0.48 (=653/1,368) and 0.45 (=441/980), respectively.

We also include one additional adjustment to the final sample sizes of the study. Specifically, we excluded observations that had missing values of the variables that were included in the study. We also excluded cases where the personal information of the respondents was inconsistent between 2010 and 2014 or between 2014 and 2018. After making these adjustments, the final analyzed samples included 540 adolescents in Cohort A and 287 adolescents in Cohort B. The attrition rates due to missing and inconsistent data were 0.173 (= (653–540)/653) in Cohort A and 0.349 (= (441–287)/441) in Cohort B. After all exclusions, a total of 828 adolescents were attrited in Cohort A and a total of 693 adolescents were attrited in Cohort B. Figure 1 shows, in detail, how samples were selected and followed up.

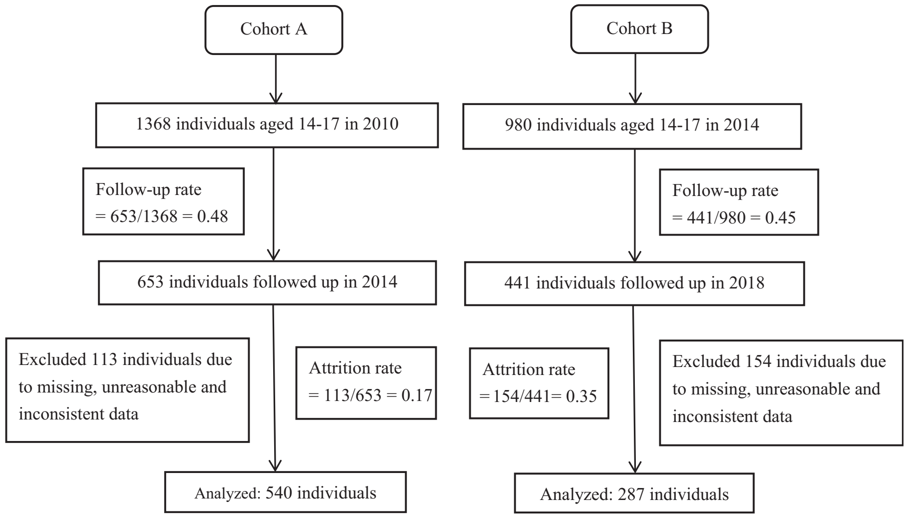

Figure 1.
Sample selection flowchart

As above, we carried out attrition tests for Cohort A and Cohort B to see if the attrition due to various reasons had any impact on the nature of the sample. We regressed attrition status on all variables and found that there were essentially no differences between the final analyzed sample and the attrited sample of both Cohort A and Cohort B, with the exception of one variable that would be expected to change over time. Specifically, we find that the probability of family members migrating for work in the attrited sample and the final analyzed sample is significantly different. For details, please see Table A1 in the appendix.

In order to determine whether adolescents in Cohort A were different from those in Cohort B, we compared the final analyzed samples in Cohort A and Cohort B. We did so because in the midst of China's rapid growth, technological developments and changes in social institutions, it is possible that the cohort of adolescents that were aged 14 to 17 in 2010 had different experiences in Internet/online access than the cohort of adolescents that were aged 14 to 17 in 2014. We found that the adolescents in Cohort A and those in Cohort B indeed showed some differences in their characteristics. For example, the average math test score of adolescents aged 14 to 17 in Cohort B was 12.86, which was 1.45 lower than the average math score of adolescents aged 14 to 17 in Cohort A. Moreover, the percentage of adolescents using the Internet in Cohort B (60%) was higher than the percentage of adolescents in Cohort A (36%). The average household income per capita (8.50) of adolescents in Cohort B was higher than that (8.18) of adolescents in Cohort A. While these results mean that we need to be careful when examining results from Cohort C (which we wish to do, due to the fact that the sample size of the combined cohort is larger, giving the analysis more statistical power), if there are differences (or if there are no differences) in the relationship between Internet access/usage and learning when we use Cohort A or Cohort B, the findings may be meaningful. For details, see Table A2 in the appendix, which compares adolescents of Cohort A and Cohort B.

2.2 Data collection

2.2.1 Outcome measurement. The dependent variables in this study are learning outcomes, as measured by the cognitive ability score of math and language test scales given to a subset of the respondents of the CFPS. Specifically, the CFPS administered comprehensive cognition measures for all survey respondents aged 10 and above in all rounds of surveys

(Xie and Hu, 2014). These measures include two standardized tests–a language test and a math test—that were developed to measure verbal and math abilities of respondents as well as learning performance over time (Huang *et al.*, 2015). The language test had 34 items, and the math test had 24 items, all of which were drawn from the standard primary and secondary school curriculums. For each test, a respondent was scored according to the number of questions that he/she answered correctly. Thus, language test scores ranged from 0 to 34 and math test scores ranged from 0 to 24.

We also aggregated language test scores and math test scores to get a measure of total learning performance. A Cronbach's alpha of 0.79 confirms that combining these variables into a single scale is appropriate (Li, 2019). In addition, using the CFPS cognitive test to measure learning performance can overcome grading inconsistencies across different schools and/or different teachers (Zhang and Xie; 2016; Miao, 2017; Li, 2019). In the analysis, we use the standardized language and math scores.

2.2.2 Internet use measurement. The main set of independent variables that we use in the analysis is Internet use, measured in four different ways: general Internet usage, weekly online time, Internet usage for learning and mobile phone usage. General Internet usage is a binary variable (1 = yes, 0 = no) that asks respondents whether they had access to the Internet (in any capacity and via any means) in the CFPS survey. Weekly online time is a continuous variable (hours) measured by asking respondents how many hours they spend online each week in their spare time. Internet usage for learning was asked as a categorical variable captured by a question in the CFPS that asked how often respondents used the Internet for learning. This was a multiple-choice question with seven answers: An answer of 1 indicates Internet use for learning almost every day; 2 indicates 3 to 4 times per week; 3 indicates 1 to 2 times per week; 4 indicates 2 to 3 times per month; 5 indicates once a month; 6 indicates once every few months; 7 indicates never. In this paper, we transformed these answers into a dummy variable, defining Internet usage for learning with values of 1–3 as "frequent" and assigning these to a new value of 1, and defining Internet using for learning with values of 4–7 as "not frequent" and assigning these to a new value of 0. It should be noted that the CFPS did not collect data on Internet usage for learning until 2014, so this variable could not be used in the analysis of Cohorts A or C. Mobile phone usage is a dummy variable (1 = yes, 0 = no) measured by asking respondents whether they used a mobile phone.

2.2.3 Control variables. The following covariates are used to control potential confounding in the relationship between Internet use and adolescent learning outcomes. First, we control individual characteristics including age, years of education and paid tutor usage (whether adolescents participate in for-pay tutoring). Second, several household characteristics are controlled for, including household income (household log net income per capita), and whether family members migrated out of their home community for work.

2.3 Statistical methods

This subsection describes our analytical approach. To report on the trends of Internet access and usage among adolescents and describe their learning development over time in rural China, we use descriptive analysis. To examine whether Internet access and usage have an impact on learning outcomes of adolescents, we constructed a fixed effect model as follows:

$$Y_{it} = \beta_0 + \beta_1 \text{Internet}_{it} + \beta_2 X_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

Y_{it} is the outcome variable representing standardized math test score, language test score and total score of adolescent i at time t. The independent variables, Internet_{it}, are measured by general Internet usage, weekly online time, Internet usage for learning and mobile phone usage. Except for weekly online time, which is a continuous variable, all other variables contained in Internet_{it} are dummy variables, equal 1 for "yes" and 0 for "no." X_{it} is a vector of covariates that capture the individual characteristics of each adolescent (whether the adolescent belongs to 18–21 age group, years of education and paid tutor usage), as well as household characteristics (household log net income per capita, whether family members migrate for work). μ_i is the individual fixed effect. ε_{it} is an error term. We adjust robust standard errors for clustering at the village level.

In addition, to investigate whether the impacts of Internet use on learning outcomes change for adolescent of different educational backgrounds and ages, we include two interaction items, respectively. One is the interaction of Internet use and education (a dummy variable that is measured by asking whether the adolescent has more than 9 years of education, 1 = yes, 0 = no), the other is the interaction of Internet use and age groups (whether the adolescent belongs to 18–21 age group, 1 = yes, 0 = no). We constructed a fixed effect model as follows:

$$Y_{it} = \beta_0 + \beta_1 \text{Internet}_{it} + \beta_2 \text{Interaction}_{it} + \beta_3 X_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

All variables in model (2) are the same as in model (1), except for Internet$_{it}$, which is the interaction between Internet use and education or the interaction between Internet use and age group. As before, all regressions employ robust standard errors clustered at the village level.

3. Results

3.1 Descriptive analysis

In this initial subsection of the paper, we use descriptive analysis to both provide context for and summarize our data on adolescent Internet use and learning outcomes. The Internet use and learning outcomes of sample adolescents are reported in Table 1. The variables that we use for describing Internet usage, mobile phone usage and weekly online time demonstrate in what ways adolescents are increasing their use of the Internet. General Internet use (row 4, column 3 and column 6) and mobile phone use (row 7, column 3 and column 6) increased significantly by about 40 percentage points in both Cohort A and Cohort B. The same conclusion can be drawn from Cohort C (row 4 and row 7, column 9), which is the combination of cohorts A and B. Weekly online time increased significantly by between 6.64 (row 5, column 3) and 9.56 (row 5, column 6) hours in cohorts A and B, as did Internet usage for learning in Cohort B, which increased by 24 percentage points (row 6, column 6). We also find that, from the comparison of cohorts A and B, Internet use is becoming more popular among adolescents over time.

Looking at learning outcomes from Table 1, indicators measured by math test scores, language test scores and total scores show that adolescent learning outcomes have increased over time in all cohorts showing that adolescents perform better as they grow. In Cohort A, math test scores rose from 14.31 (row 1, column 1) to 15.40 (row 1, column 2) between 2010 and 2014 and language test scores rose from 25.08 (row 2, column 1) to 26.02 (row 2, column 2). In Cohort B, math tests scores rose from 12.86 (row 1, column 4) to 17.70 (row 1, column 5), and language test scores rose from 25.50 (row 2, column 4) to 27.74 (row 2, column 5). In all cohorts, math test scores increase more than language test scores do, and we find that for all score measurements, growth over time is the largest in Cohort B, indicating that the learning outcomes of the adolescents in Cohort B have increased the most. A possible reason for this is that, compared with Cohort A, more adolescents in Cohort B choose to stay at home for education and take part in for-pay tutoring instead of going out to work, although these differences are not significant. Adolescents in Cohort B also have higher rates of Internet use. In addition, between 2014 and 2018, the Ministry of Education of China issued several plans on education informatization, such as the “Thirteenth Five-Year Plan for Educational Informatization” in 2016 and the “Action Plan for Educational Informatization 2.0” in 2018.

Table 1. Descriptive analysis of Internet use and learning outcomes for sample of adolescent from rural China, ages 14 to 21 from three cohorts

Variables	Cohort A Mean (SD) 14–17 (1)	18–21 (2)	Differ: (2)–(1) (3)	Cohort B Mean (SD) 14–17 (4)	18–21 (5)	Differ (5)–(4) (6)	Cohort C Mean (SD) 14–17 (7)	18–21 (8)	Differ (8)–(7) (9)
Measures of learning outcomes									
(1) Math test raw score	14.31 (4.32)	15.40 (5.96)	1.09*** (0.32)	12.86 (5.27)	17.70 (5.51)	4.84*** (0.45)	13.81 (4.72)	16.20 (5.91)	2.39*** (0.26)
(2) Language test raw score	25.08 (6.82)	26.02 (7.91)	0.94* (0.45)	25.50 (7.40)	27.74 (6.42)	2.24*** (0.58)	25.23 (7.03)	26.62 (7.47)	1.39*** (0.36)
(3) Total score (Math + Language test raw score)	39.39 (10.08)	41.42 (12.71)	2.03*** (0.70)	38.36 (11.50)	45.44 (10.98)	7.08*** (0.94)	39.04 (10.60)	42.81 (12.28)	3.78*** (0.56)
Measures of Internet use									
(4) General Internet usage (1 = yes, 0 = no)	0.36 (0.48)	0.77 (0.42)	0.42*** (0.03)	0.60 (0.49)	1.00 (0.00)	0.40*** (0.03)	0.44 (0.50)	0.85 (0.35)	0.41*** (0.02)
(5) Weekly online time (hours)	2.92 (7.06)	9.56 (12.80)	6.64*** (0.63)	5.36 (9.53)	14.92 (15.45)	9.56*** (1.07)	3.77 (8.08)	11.42 (14.00)	7.65*** (0.56)
(6) Internet usage for learning (1 = yes, 0 = no)[a]	–	0.43 (0.50)	–	0.30 (0.46)	0.54 (0.50)	0.24*** (0.04)	–	0.47 (0.50)	–
(7) Mobile phone usage (1 = yes, 0 = no)	0.48 (0.50)	0.90 (0.30)	0.42*** (0.03)	0.52 (0.50)	0.95 (0.22)	0.43*** (0.03)	0.50 (0.50)	0.92 (0.27)	0.42*** (0.02)
(8) Observations	540	540	540	287	287	287	827	827	827

Note(s): Data drawn from the China Family Panel Studies (CFPS). Data are presented as mean and SD in columns 1, 2, 4, 5, 7 and 8. SD is shown in parentheses. Columns 3, 6 and 9 present the difference between columns 1 and 2, 4 and 5, and 7 and 8 and their SE, respectively. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed test). [a] CFPS 2010 did not collect data to measure the variable of Internet use for learning

These plans are both aimed at promoting education modernization by promoting the integration of information technology and education. In all, we find that adolescents with more education and Internet use perform better academically, as can be seen in Appendix Table A2. Thus, it is hypothesized that Internet use may be related to learning outcomes.

3.2 The impacts of Internet use

Results for the impact of general Internet use on math and language scores for all cohorts are found in Table 2 and are reported in standard deviations. Focusing on Cohort A (that is the adolescents that were 14–17 years old in 2010 and 18–21 years old in 2014—$n_A = 540$), we see no significant effects of general Internet usage on learning outcomes. The coefficient for math score (0.07—row 1, column 1) is positive, but insignificant (standard error = 0.06). The coefficient for language score, while positive and larger (0.14—row 1, column 2), is also insignificant (standard error = 0.08).

The results are slightly different for Cohort B ($n_B = 287$), the cohort that was 14–17 in 2014, especially for language. As in the case of Cohort A, we find a positive but insignificant effect of general Internet use on math scores (coefficient = 0.01; standard error = 0.11—row 1, column 3). However, for the impact of general Internet use on language scores, we do see a positive and significant coefficient. The coefficient (0.27) is significant at the 0.05 level of significance. Despite being positive and significant, this effect is still moderate. A coefficient of this size implies that if a student from Cohort B uses the Internet, their language score increases by 0.27 standard deviations.

In Cohort C, the combination of cohorts A and B (so $n_C = 827$), we see results that roughly fall between those in columns 1 to 4. There is no effect of general Internet use on math scores (row 1, column 5). The impact of general Internet use on language scores, however, is positive and significant (row 1, column 6). As in the case of the impact of general Internet use on learning outcomes when we only use Cohort B, the magnitude of the coefficient (coefficient = 0.17; standard error = 0.07) is moderate (and is smaller than the measured effect using just Cohort B as shown in the previous paragraph).

In Table 3, the analysis examines the impact of the other three measures of Internet use, Weekly online time, Internet usage for learning and Mobile phone usage. We first look at the results for both Cohorts A and B of the impact of weekly online time on learning outcomes [1]. In the case of the weekly online time [2] regressions (row 1), we find few significant impacts, and for those we do find, the magnitudes of the measured effects are relatively small. In Cohort A in the language score regression (row 1; column 2) and in Cohort B in the math and language score regressions (row 1; columns 3 and 4), none of the coefficients are statistically significant from zero. In the case of math scores for students in Cohort A, however, we find the measured impact is negative and significant. In other words, like a number of authors in the literature predict (Hurwitz and Schmitt, 2020; Junco and Cotten, 2012; Lepp *et al.*, 2015), when students are online for more time each week, their learning outcomes (in this case math score) suffer. However, it is important to note that, although negative, the magnitude of the coefficient is small. In fact, the magnitude (in absolute value) is more than 50 times smaller than the effect of general Internet usage that we found above (Table 2, row 1, column 4). This means that if the average student in Cohort A increased their weekly online time by one hour, their math score would only fall by 0.004 standard deviations.

In the analysis of the impacts of Internet usage for learning on the learning outcomes of adolescents we only run regressions using data from Cohort B. The more restricted analysis was necessary as Internet usage for learning was not measured until 2014 (Table 3, row 5). According to the findings, the coefficients for math and language scores are both positive. Despite this, these coefficients are also not significantly different from zero.

Table 2. The impact of general Internet usage on learning outcomes (standardized math and language test scores) of adolescent from rural China, ages 14 to 21, in three cohorts

	Cohort A		Cohort B		Cohort C	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Math	Language	Math	Language	Math	Language
(1) General Internet usage (1 = yes, 0 = no)	0.07 (0.06)	0.14 (0.08)	0.01 (0.11)	0.27* (0.13)	0.04 (0.06)	0.17* (0.07)
(2) 18–21 age group (1 = yes, 0 = no)	−0.15* (0.07)	−0.06 (0.11)	0.57*** (0.11)	0.05 (0.11)	0.12 (0.07)	−0.01 (0.08)
(3) Years of education (years)	0.10*** (0.02)	0.03 (0.03)	0.06** (0.02)	0.04 (0.02)	0.09*** (0.02)	0.03* (0.02)
(4) Paid tutor usage (1 = yes, 0 = no)	−0.19 (0.18)	0.05 (0.17)	0.32** (0.12)	0.20 (0.15)	0.27* (0.12)	0.17 (0.11)
(5) Household log net income per capita (Yuan)	−0.01 (0.03)	−0.01 (0.04)	0.01 (0.01)	−0.02 (0.02)	−0.01 (0.01)	−0.03 (0.02)
(6) Whether family members migrate for work (1 = yes, 0 = no)	0.01 (0.07)	0.10 (0.07)	0.06 (0.08)	0.16 (0.12)	−0.03 (0.06)	0.10 (0.06)
(7) Constant	−0.73* (0.30)	−0.32 (0.40)	−1.02*** (0.22)	−0.48* (0.23)	−0.78*** (0.18)	−0.26 (0.20)
(8) Fixed effects[a]	Yes	Yes	Yes	Yes	Yes	Yes
(9) Observations	540	540	287	287	827	827
(10) R^2	0.39	0.20	0.31	0.14	0.32	0.17

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed test)

[a] All regressions control for individual fixed effects

Table 3. The impact of weekly online time, Internet usage for learning and mobile phone usage on learning outcomes (standardized math and language test scores) of adolescent from rural China, ages 14 to 21, in two cohorts

Variables	Cohort A (1) Math	(2) Language	Cohort B (3) Math	(4) Language
(1) Weekly online time (hours)	−0.004* (0.002)	0.002 (0.003)	0.001 (0.004)	0.002 (0.003)
(2) Controls	Yes	Yes	Yes	Yes
(3) Fixed effects[a]	Yes	Yes	Yes	Yes
(4) R^2	0.39	0.20	0.31	0.11
(5) Internet usage for learning (1 = yes, 0 = no)			0.09 (0.07)	0.05 (0.08)
(6) Controls			Yes	Yes
(7) Fixed effects[a]			Yes	Yes
(8) R^2			0.32	0.12
(9) Mobile phone usage (1 = yes, 0 = no)	0.01 (0.09)	−0.10 (0.09)	0.16 (0.12)	0.22 (0.12)
(10) Controls	Yes	Yes	Yes	Yes
(11) Fixed effects[a]	Yes	Yes	Yes	Yes
(12) R^2	0.39	0.19	0.31	0.10
(13) Observations	540	540	287	287

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we only study Cohort B for the impact of Internet usage for learning on adolescent learning outcomes
[a]All regressions control for individual fixed effects

Finally, we examine the impact of mobile phone usage on the learning outcomes of adolescents in both Cohorts A and B. Here we can see that in Cohort A, the sign on the coefficient for math score is positive while the sign on the coefficient for language score is negative (Table 3, row 9). In Cohort B both coefficients are positive. As with Internet usage for learning, however, these coefficients are not significant for either cohort.

3.3 Heterogeneous effects

To further draw out important effects of Internet use on academic achievement, we now examine important adolescent subgroups, specifically educational background and age. Education is the most important contributing factor to the level of Internet skills of students, which positively affect adolescent academic performance and intellectual capacity (van Deursen and van Dijk, 2011; van Deursen and van Diepen, 2013). Students with higher levels of education draw more benefit from using social media for learning, interaction and collaboration (Chai-Lee, 2013). As children grow older, their cognitive processes and abilities (language, perception, memory and metacognition) improve substantially in response to genetic and environmental forces (Spiess *et al.*, 2016), thus Internet as an environmental stimulus may have a greater impact on learning development of older adolescents.

Results for the impact of general Internet use on math and language scores for adolescents of different educational backgrounds are found in Table 4. Looking at Cohort A, we find that, while the signs on the point estimates of the coefficients are mixed for the poorly educated and positive for the highly educated, only the effect on the language score of highly educated adolescents is significant (row 10, column 2). The coefficient (0.28) is significant at the 0.01 level and moderate in size. In Cohort B, the signs of the coefficients are mixed for the poorly educated and negative for the highly educated, but none of these effects are statistically different from zero.

The effect of other measures of Internet use (Weekly online time, Internet usage for learning and Mobile phone usage) on adolescents of different educational backgrounds

Variables	Cohort A (1) Math	(2) Language	Cohort B (3) Math	(4) Language
(1) General Internet usage (1 = yes, 0 = no)	−0.03 (0.08)	0.02 (0.10)	−0.04 (0.12)	0.28 (0.16)
(2) General Internet usage × Education level	0.18 (0.12)	0.26* (0.12)	−0.09 (0.25)	−0.41 (0.29)
(3) Education level[a]	0.37** (0.11)	0.09 (0.11)	0.58** (0.20)	0.53* (0.22)
(4) 18–21 age group (1 = yes, 0 = no)	−0.09 (0.07)	−0.09 (0.10)	0.50*** (0.10)	0.12 (0.10)
(5) Paid tutor usage (1 = yes, 0 = no)	−0.24 (0.18)	0.05 (0.17)	0.23 (0.12)	0.17 (0.15)
(6) Household log net income per capita (Yuan)	0.01 (0.03)	0.01 (0.04)	0.01 (0.02)	−0.03 (0.02)
(7) Whether family members migrate for work (1 = yes, 0 = no)	0.01 (0.07)	0.10 (0.07)	0.09 (0.07)	0.16 (0.11)
(8) Constant	−0.27 (0.25)	−0.21 (0.36)	−0.60*** (0.17)	−0.25 (0.20)
(9) Treatment Effect for the poorly educated[bc]	−0.03 (0.08)	0.02 (0.10)	−0.04 (0.12)	0.28 (0.16)
(10) Treatment Effect for the highly educated[bc]	0.15 (0.09)	0.28** (0.09)	−0.13 (0.20)	−0.13 (0.21)
(11) Fixed effects[d]	Yes	Yes	Yes	Yes
(12) Observations	540	540	287	287
(13) R^2	0.23	0.13	0.34	0.10

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed test)

[a]Education level (1 = yes, 0 = no) is a dummy variable that is measured by asking whether the adolescent has more than 9 years of education

[b]In this table, we take "poorly educated" as a value of 0 from the education level dummy variable (lower than 9 years of education) and we take "highly educated" as a value of 1 from the education level dummy variable (higher than or equal to 9 years of education)

[c]In this table, we wish to illustrate separate effects between poorly educated individuals and highly educated individuals. To do so, we take Row 9 as Row 1 and Row 10 as Row 1 plus Row 2

[d]All regressions control for individual fixed effects

Table 4. The impact of general Internet usage on learning outcomes of adolescent with different educational backgrounds in two cohorts

largely follow those of the analysis with no interaction and are presented in Table 5. We first examine the effects of weekly online time on the learning outcomes of adolescents of different educational backgrounds. We find few significant impacts of weekly online time on learning outcomes, and the ones that we do find are relatively small. We see that, for Cohort A, weekly online time affects the math scores of the poorly educated (coefficient = −0.006; row 1, column 1) and the language scores of the highly educated (coefficient = 0.007; row 2, column 2), both at a significance level of p = 0.05. This means that if the average poorly educated adolescent in Cohort A increased their weekly online time by one hour, their math score would fall by 0.006 standard deviations, and that if the average highly educated adolescent did the same, their language score would rise by 0.007 standard deviations. The other coefficients for Cohort A, math scores of the highly educated and language scores of the poorly educated are not statistically different from zero. In Cohort B, while coefficients for the math and language scores of both the poorly and highly educated are all positive, they are also all small and not statistically different form zero.

Similar to the regressions with no interaction, Internet usage for learning and mobile phone usage have almost no significant impacts on the learning outcomes of adolescents of different educational backgrounds, with one exception. In Cohort B, we find that, for the poorly educated, mobile phone usage has a positive and significant impact on language scores. This impact (coefficient = 0.26) is significant at the p = 0.05 level [3]. In the case of all other regressions (the heterogeneous impacts of Internet use for learning on the math and

Variables	Cohort A (1) Math	Cohort A (2) Language	Cohort B (3) Math	Cohort B (4) Language
Independent variable: Weekly online time (hours)				
(1) Treatment Effect for the poorly educated[a]	−0.006* (0.003)	−0.002 (0.004)	0.003 (0.01)	0.004 (0.004)
(2) Treatment Effect for the highly educated[a]	−0.002 (0.003)	0.007* (0.003)	0.002 (0.004)	0.002 (0.004)
(3) Controls	Yes	Yes	Yes	Yes
(4) Fixed effects[b]	Yes	Yes	Yes	Yes
(5) R^2	0.22	0.13	0.34	0.10
Independent variable: Internet usage for learning (1 = yes, 0 = no)				
(6) Treatment Effect for the poorly educated[a]			0.05 (0.10)	0.09 (0.14)
(7) Treatment Effect for the highly educated[a]			0.09 (0.09)	0.02 (0.10)
(8) Controls			Yes	Yes
(9) Fixed effects[b]			Yes	Yes
(10) R^2			0.35	0.10
Independent variable: Mobile Phone Usage (1 = yes, 0 = no)				
(11) Treatment Effect for the poorly educated[a]	−0.06 (0.10)	−0.14 (0.10)	0.11 (0.12)	0.26* (0.13)
(12) Treatment Effect for the highly educated[a]	0.11 (0.16)	−0.07 (0.13)	0.19 (0.16)	0.05 (0.23)
(13) Controls	Yes	Yes	Yes	Yes
(14) Fixed effects[b]	Yes	Yes	Yes	Yes
(15) R^2	0.23	0.11	0.33	0.08
(16) Observations	540	540	287	287

Note(s)*:* Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we only study Cohort B for the impact of Internet usage for learning on adolescent learning outcomes
[a]In this table, we take "poorly educated" as a value of 0 from the education level dummy variable (lower than 9 years of education) and we take "highly educated" as a value of 1 from the education level dummy variable (higher than or equal to 9 years of education)
[b]All regressions control for individual fixed effects

Table 5. The impact of weekly online time, Internet usage for learning and mobile phone usage on learning outcomes of adolescent with different educational backgrounds in two cohorts

language scores of adolescents with different educational backgrounds for Cohort B; and the same heterogeneous effects of mobile phone usage on math scores for Cohorts A and B and on language scores for Cohort A) the measured effects are all statistically insignificant from zero.

Turning to the impact of general Internet use on the learning outcomes of adolescents of different age groups, shown in Table 6, we also find similar results to our previous interaction comparison (in Table 4). For adolescents in the 18–21 age group in Cohort A, we see that general Internet use has a positive effect (coefficient = 0.29; row 10, column 2) on language scores [4]. Although this effect is significant at the $p = 0.05$ level, this is the only significant effect we see in this analysis.

In Table 7, which presents the impact of other measures of Internet use (Weekly online time, Internet usage for learning and Mobile phone usage) on the learning outcomes of adolescents of different age groups, we find only one significant effect, which was in Cohort B. We found that mobile phone usage affected the language scores of adolescents in the 14–17 age group (coefficient = 0.30; row 11, column 4) at a significant level of $p = 0.05$. All other measured effects in this analysis are insignificant. Again, the magnitude of this effect is

Table 6. The impact of general Internet usage on learning outcomes of adolescent in different age groups in Cohort A

Variables	Cohort A[a] (1) Math	(2) Language
(1) General Internet usage (1 = yes, 0 = no)	0.07 (0.08)	0.03 (0.09)
(2) General Internet usage × 18–21 age group	0.00 (0.12)	0.25 (0.16)
(3) 18–21 age group (1 = yes, 0 = no)	−0.15 (0.11)	−0.21 (0.17)
(4) Years of education (years)	0.10*** (0.02)	0.03 (0.03)
(5) Paid tutor usage (1 = yes, 0 = no)	−0.19 (0.18)	0.08 (0.17)
(6) Household log net income per capita (yuan)	−0.01 (0.03)	−0.01 (0.04)
(7) Whether family members migrate for work (1 = yes, 0 = no)	0.01 (0.07)	0.11 (0.07)
(8) Constant	−0.73* (0.29)	−0.26 (0.39)
(9) Treatment Effect for the 14–17 age group[b]	0.07 (0.08)	0.03 (0.09)
(10) Treatment Effect for the 18–21 age group[b]	0.07 (0.10)	0.29* (0.14)
(11) Fixed effects[c]	Yes	Yes
(12) Observations	540	540
(13) R^2	0.39	0.21

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$ (two-tailed test)
[a]In this table, we only use data from Cohort A, as all adolescents went online in 2018. This resulted in multicollinearity between general Internet usage and 18–21 age group of Cohort B
[b]In this table, we wish to illustrate separate effects between younger and older individuals. To do so, we take Row 9 as Row 1 and Row 10 as Row 1 plus Row 2
[c]All regressions control for individual fixed effects

moderate. Specifically, a coefficient of 0.30 for 14–17 age group in Cohort B is equivalent to a 2.22 point increase in test score (0.30 × 7.40 = 2.22), relative to a mean test score of 25.50.

4. Conclusion

Although previous studies have investigated the impact of Internet use on adolescent academic performance, the causal relationship between the two is not yet fully understood. Most of the studies on this topic only use cross-sectional data and descriptive analysis to study this relationship in developed countries. To bridge these gaps in the literature, we have examined the causal relationship between Internet use and adolescent learning outcomes using in two different cohorts, using fixed-effect models and longitudinal data from three waves of a nationally representative survey in rural China. We also investigated the heterogeneous effects of Internet use on adolescents of different educational backgrounds and ages.

The findings of this study are consistent with research which shows that Internet use as measured by a comprehensive set of items (General Internet usage, Weekly online time, Internet usage for learning and Mobile phone usage) largely has no significant impact on adolescent academic performance (Qahri-Saremi and Turel, 2016; Rashid and Asghar, 2016; Hsiao *et al.*, 2017). We found that most coefficients were insignificant, but of those that were not, the analysis showed that there were moderate positive effects, which were partially in line with the results of some studies that demonstrate a positive relationship between Internet use and academic performance (Bawaneh, 2011; Jackson *et al.*, 2011; Fonseca *et al.*, 2014). The findings show that Internet use causes no harm to adolescent learning development and there is no need to worry about the potentially adverse effects of the Internet.

In addition, our results showed that Internet use had almost no heterogeneous effects on the learning outcomes of adolescents of different educational backgrounds and age groups. In the regressions that did show impact, the results demonstrated that the effects on

Variables	Cohort A (1) Math	(2) Language	Cohort B (3) Math	(4) Language
Independent variable: Weekly online time (hours)				
(1) Treatment Effect for the 14–17 age group	−0.004 (0.004)	0.001 (0.005)	0.004 (0.01)	0.007 (0.01)
(2) Treatment Effect for the 18–21 age group	−0.005 (0.003)	0.003 (0.003)	0.001 (0.004)	0.001 (0.004)
(3) Controls	Yes	Yes	Yes	Yes
(4) Fixed effects[a]	Yes	Yes	Yes	Yes
(5) R^2	0.39	0.20	0.31	0.11
Independent variable: Internet usage for learning (1 = yes, 0 = no)				
(6) Treatment Effect for the 14–17 age group			−0.04 (0.11)	0.09 (0.12)
(7) Treatment Effect for the 18–21 age group			0.20 (0.11)	0.02 (0.12)
(8) Controls			Yes	Yes
(9) Fixed effects[a]			Yes	Yes
(10) R^2			0.32	0.12
Independent variable: Mobile Phone Usage (1 = yes, 0 = no)				
(11) Treatment Effect for the 14–17 age group	0.03 (0.09)	−0.10 (0.10)	0.12 (0.11)	0.30* (0.12)
(12) Treatment Effect for the 18–21 age group	−0.05 (0.15)	−0.09 (0.19)	0.42 (0.31)	−0.39 (0.41)
(13) Controls	Yes	Yes	Yes	Yes
(14) Fixed effects[a]	Yes	Yes	Yes	Yes
(15) R^2	0.39	0.19	0.31	0.09
(16) Observations	540	540	287	287

Note(s)*:* Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we only study Cohort B for the impact of Internet usage for learning on adolescent learning outcomes
[a]All regressions control for individual fixed effects

Table 7. The impact of weekly online time, Internet usage for learning and mobile phone usage on learning outcomes of adolescent in different age groups in two cohorts

standardized math and language scores in Cohorts A and B were significant but moderate among these groups. Specifically, the language scores of highly educated adolescents in Cohort A would increase if they had a general Internet use. In Cohort B, the significant and positive effect was the effect of mobile phone usage on the language scores of the poorly educated. For adolescents of different age groups, we found that adolescents in the older group in Cohort A would increase their language scores if they had a general Internet use. Mobile phone usage had a positive impact on language scores of adolescents in the younger group in Cohort B.

The fact that we find few significant impacts can likely be attributed to digital divides, which refers to gaps in not only Internet access but also digital skills (or Internet skills, digital competences). Since the Internet is increasingly widespread in developing countries, the lack of digital skills is becoming a key problem (van Deursen and van Dijk, 2009). Although existing research has different definitions of digital skills, they all believe that digital skills should involve the abilities to use a digital device and the Internet efficiently and effectively (Hargittai, 2003; Pagani *et al.*, 2016). In addition, digital skills play a significant role in student learning (van Deursen and van Diepen, 2013; Hurwitz and Schmitt, 2020). However, digital divide usually occur between rural and urban settings (Philip *et al.*, 2017), since rural adolescents are in low socioeconomic status and they lack chances and guidance to practice their digital skills, such as school information communication technology (ICT) facilities, teaching resources. Moreover, lower-income parents are less likely to offer help and expertise for ICT use (Zhong, 2011). Although adolescents have high Internet access in rural China, Internet access does not necessarily guarantee that individuals will have the necessary skills to enjoy the benefits brought by ICTs (Ono and Zavodny, 2007; Zhong, 2011). As we did not explore this, we include it as a limitation of our study.

Further attention should also be paid to distinct patterns of Internet use, as each pattern is likely to have different impacts on adolescent development. In particular, it seems likely that social activities such as text messaging, email and social media use have different impacts than playing video games or browsing the web (Wilmer *et al.*, 2017). For instance, using social media requires expressive and receptive written language competencies, which involve successive cognitive processing and help to improve language achievement (Johnson, 2006; Abrahim *et al.*, 2019). Video game usage has been found to be related to the visual and spatial skills of children (Green and Bavelier, 2007), which are believed to contribute to math achievement (Anobile *et al.*, 2013). Moreover, using the Internet for accessing information, mostly for learning, can have positive impacts on adolescent educational development (Willoughby, 2008). Considering the potential impacts of different patterns of Internet use on specific learning developments among adolescents, further research is required to study how these patterns affect adolescent development.

Unfortunately, we are unable to address potential mechanisms of the effects of Internet use on adolescent learning outcomes as they are outside the scope of our analysis. When looking to the literature, to our knowledge, no studies have been able to address the mechanisms by which Internet use affects adolescent learning outcomes, revealing a larger gap in the literature as a whole. This limitation presents an opportunity for future research to address these potential mechanisms.

Despite limitations, our study has important implications. Information technology has developed rapidly and brought significant changes to personal life in recent years. This is especially significant, as the Internet is increasingly viewed as an environmental stimulus with a potential impact on adolescent growth and development (Young, 2007; Johnson and Puplampu, 2008; Fuhrmann *et al.*, 2015). Our study finds that Internet access and usage cause no harm to adolescent learning development, and even have some positive but moderate impacts on learning outcomes, although most impacts are statistically insignificant. Future research should focus on ways to improve these positive effects.

Notes

1. Please note, in the rest of the paper, we do not include the results from cohort C, as they are similar to those for cohorts A and B. For the interested user, however, please see the online appendix with these results—<Appendix>.
2. To draw out and examine potential nonlinear relationships between weekly online time and test scores, we initially included the squared term in the regression. We found that the results were essentially unchanged, and thus we omit it from the analysis.
3. As Internet use for learning was not measured until 2014, we only study Cohort B for this regression.
4. In this table, we only use data from Cohort A, as Cohort B exhibits multicollinearity between general Internet usage and 18–21 age group.

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Further reading

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Corresponding author
Lili Li can be contacted at: 11620059@zju.edu.cn

Appendix

Table A1. Attrition analysis for samples of adolescent from rural China, ages 14 to 17 from Cohorts A and B at baseline

Variables	Attrition (1 = yes, 0 = no) Cohort A (1)	Cohort B (2)
Individual characteristics		
(1) Age (years)	0.01 (0.02)	0.03 (0.02)
(2) Gender (1 = male, 0 = female)	0.00 (0.03)	0.02 (0.03)
(3) Years of education (years)	−0.00 (0.01)	0.01 (0.01)
(4) Paid tutor usage (1 = yes, 0 = no)	0.04 (0.08)	0.01 (0.07)
Household characteristics		
(5) Household log net income per capita (Yuan)	−0.02 (0.02)	−0.01 (0.01)
(6) Whether family members migrate for work (1 = yes, 0 = no)	0.12** (0.03)	0.08* (0.04)
Measures of learning outcomes		
(7) Standardized math test score	0.00 (0.02)	0.00 (0.02)
(8) Standardized language test score	−0.03 (0.02)	−0.04 (0.02)
Measures of Internet use		
(9) General Internet usage (1 = yes, 0 = no)	−0.04 (0.04)	−0.01 (0.05)
(10) Weekly online time (hours)	−0.00 (0.00)	0.00 (0.00)
(11) Internet usage for learning (1 = yes, 0 = no)	–	−0.04 (0.04)
(12) Mobile phone usage (1 = yes, 0 = no)	0.01 (0.04)	0.05 (0.04)
(13) Constant	0.51 (0.27)	0.16 (0.28)
(14) R^2	0.02	0.03
(15) Observations	1,248	844

Note(s): Data drawn from the China Family Panel Studies (CFPS). *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed test). Robust standard errors in parentheses are clustered at village level

Variables	Cohort A Mean (SD) (1)	Cohort B Mean (SD) (2)	Difference (2)–(1) (3)
Individual characteristics			
(1) Age (years)	15.37 (1.08)	15.24 (1.10)	−0.13* (0.08)
(2) Gender (1 = male, 0 = female)	0.49 (0.50)	0.49 (0.50)	0.00 (0.04)
(3) Years of education (years)	7.41 (2.44)	7.68 (2.03)	0.27 (0.17)
(4) Paid tutor usage (1 = yes, 0 = no)	0.04 (0.20)	0.06 (0.23)	0.02 (0.02)
Household characteristics			
(5) Household log net income per capita (Yuan)	8.18 (0.84)	8.50 (1.18)	0.32*** (0.07)
(6) Whether family members migrate for work (1 = yes, 0 = no)	0.31 (0.46)	0.54 (0.50)	0.23*** (0.03)
Measures of learning outcomes			
(7) Math test raw score	14.31 (4.32)	12.86 (5.27)	−1.45*** (0.34)
(8) Language test raw score	25.08 (6.82)	25.50 (7.40)	0.41 (0.51)
(9) Total score (Math + Language test raw score)	39.39 (10.08)	38.36 (11.50)	−1.03 (0.77)
Measures of Internet use			
(10) General Internet usage (1 = yes, 0 = no)	0.36 (0.48)	0.60 (0.49)	0.24*** (0.04)
(11) Weekly online time (hours)	2.92 (7.06)	5.36 (9.53)	2.44*** (0.58)
(12) Internet usage for learning (1 = yes, 0 = no)	–	0.30 (0.46)	–
(13) Mobile phone usage (1 = yes, 0 = no)	0.48 (0.50)	0.52 (0.50)	0.04 (0.04)
(14) Observations	540	287	–

Note(s): Data drawn from the China Family Panel Studies (CFPS). Data are presented as mean and SD in columns 1 and 2. SD is shown in parentheses. Column 3 presents the difference between columns 1 and 2, and its SE. SE is shown in parentheses. **p* < 0.05, ***p* < 0.01, ****p* < 0.001 (two-tailed test)

Table A2.
Descriptive statistics of adolescent from rural China, ages 14 to 17, in two cohorts

Variables	Cohort C (1) Math	(2) Language
(1) Weekly online time (hours)	0.000 (0.002)	0.003 (0.002)
(2) Controls	Yes	Yes
(3) Fixed effects[a]	Yes	Yes
(4) R^2	0.32	0.15
(5) Mobile phone usage (1 = yes, 0 = no)	0.07 (0.07)	−0.003 (0.07)
(6) Controls	Yes	Yes
(7) Fixed effects[a]	Yes	Yes
(8) R^2	0.32	0.15
(9) Observations	827	827

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. **p* < 0.05, ***p* < 0.01, ****p* < 0.001 (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we could not study Cohort C for the impact of Internet usage for learning on adolescent learning outcomes
[a]All regressions control for individual fixed effects

Table A3.
The impact of weekly online time, and mobile phone usage on learning outcomes (standardized math and language test scores) of adolescent from rural China, ages 14 to 21, in Cohort C

Variables	Cohort C (1) Math	(2) Language
Independent variable: General Internet usage (1 = yes, 0 = no)		
(1) Treatment Effect for the poorly educated	−0.11 (0.07)	0.10 (0.08)
(2) Treatment Effect for the highly educated	0.26** (0.08)	0.27** (0.09)
(3) Controls	Yes	Yes
(4) Fixed effects[a]	Yes	Yes
(5) R^2	0.24	0.13
Independent variable: Weekly online time (hours)		
(6) Treatment Effect for the poorly educated	−0.004 (0.003)	0.001 (0.003)
(7) Treatment Effect for the highly educated	0.004 (0.003)	0.005 (0.003)
(8) Controls	Yes	Yes
(9) Fixed effects[a]	Yes	Yes
(10) R^2	0.24	0.11
Independent variable: Mobile phone usage (1 = yes, 0 = no)		
(11) Treatment Effect for the poorly educated	−0.02 (0.08)	−0.02 (0.08)
(12) Treatment Effect for the highly educated	0.23* (0.11)	−0.02 (0.11)
(13) Controls	Yes	Yes
(14) Fixed effects[a]	Yes	Yes
(15) R^2	0.25	0.10
(16) Observations	827	827

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. **p* < 0.05, ***p* < 0.01, ****p* < 0.001 (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we could not study Cohort C for the impact of Internet usage for learning on adolescent learning outcomes
[a]All regressions control for individual fixed effects

Table A4. The impact of general Internet usage, weekly online time and mobile phone usage on learning outcomes of adolescent with different educational backgrounds in Cohort C

Variables	Cohort C (1) Math	(2) Language
Independent variable: Weekly online time (hours)		
(1) Treatment Effect for the 14–17 age group	−0.004 (0.01)	0.003 (0.004)
(2) Treatment Effect for the 18–21 age group	0.001 (0.002)	0.003 (0.003)
(3) Controls	Yes	Yes
(4) Fixed effects[a]	Yes	Yes
(5) R^2	0.32	0.15
Independent variable: Mobile phone usage (1 = yes, 0 = no)		
(6) Treatment Effect for the 14–17 age group	0.04 (0.07)	0.03 (0.08)
(7) Treatment Effect for the 18–21 age group	0.18 (0.14)	−0.13 (0.17)
(8) Controls	Yes	Yes
(9) Fixed effects[a]	Yes	Yes
(10) R^2	0.32	0.15
(11) Observations	827	827

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. **p* < 0.05, ***p* < 0.01, ****p* < 0.001 (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we could not study Cohort C for the impact of Internet usage for learning on adolescent learning outcomes
Since there was multicollinearity between general Internet usage and 18–21 age group of Cohort B, there would also be multicollinearity in Cohort C, and we could not study the effect of general Internet usage of Cohort C here
[a]All regressions control for individual fixed effects

Table A5. The impact of weekly online time, and mobile phone usage on learning outcomes of adolescent in different age groups in Cohort C

Table A6.
The impact of general Internet usage, weekly online time, Internet usage for learning and mobile phone usage on standardized total scores of adolescent from rural China, ages 14 to 21, in three cohorts

Variables	Cohort A (1)	Cohort B (2)	Cohort C (3)
(1) General Internet usage (1 = yes, 0 = no)	0.12(0.06)	0.16 (0.11)	0.13* (0.06)
(2) Controls	Yes	Yes	Yes
(3) Fixed effects[a]	Yes	Yes	Yes
(4) R^2	0.36	0.24	0.29
(5) Weekly online time (hours)	−0.000 (0.002)	0.002 (0.003)	0.002 (0.002)
(6) Controls	Yes	Yes	Yes
(7) Fixed effects[a]	Yes	Yes	Yes
(8) R^2	0.36	0.22	0.27
(9) Internet usage for learning (1 = yes, 0 = no)		0.08 (0.06)	
(10) Controls		Yes	
(11) Fixed effects[a]		Yes	
(12) R^2		0.24	
(13) Mobile phone usage (1 = yes, 0 = no)	−0.06 (0.08)	0.21* (0.10)	0.03 (0.07)
(14) Controls	Yes	Yes	Yes
(15) Fixed effects[a]	Yes	Yes	Yes
(16) R^2	0.36	0.21	0.27
(17) Observations	540	287	827

Note(s): Data drawn from the China Family Panel Studies (CFPS). Robust standard errors in parentheses are clustered at village level. *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed test)
As CFPS 2010 did not collect data to measure the variable of Internet use for learning, we only study Cohort B for the impact of Internet usage for learning on adolescent learning outcomes
[a] All regressions control for individual fixed effects