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Internet use, depression, and cognitive outcomes among Chinese adolescents

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Abstract

This study provides new evidence on how the growingly significant digital life shapes Chinese adolescents' cognitive and mental health outcomes based on their gender, parental education, and geographical location. Using the China Education Panel Survey, a nationally representative survey following 12–15-year-old students in 2013 and 2014, and individual fixed-effect models, we find that more time spent on the Internet is associated with higher self-reported depression scores. This negative impact on mental health is more substantial for girls, those with less-educated parents, and those living outside the city center. The link between Internet use and cognitive development is almost null. Time spent online negatively affects Chinese young adolescents' subjective well-being but has little impact on their cognitive development. The link between Internet use time and subjective well-being also depends on gender, parental education, and the geographical location of those adolescents. The heterogeneous impacts of Internet use time offer crucial new evidence to the multiple dimensions of the digital divide among adolescents in China.

KEYWORDS

adolescent, China, cognition, depression, digital divide, Internet use, mental health

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1 | INTRODUCTION

Teenagerhood is a critical stage of cognitive and psychological development. Meanwhile, teenagers often adopt digital technology faster than parents, schools, and policymakers, and we are yet to realize the implications of the widespread new technology. With the rapid spread of the Internet and digital devices, parents, schools, and policymakers have begun to ask about the consequences. Is the Internet good or bad for children's cognitive and psychological development, especially among adolescents, who have spent a substantial amount of time online?

In 2019, 93.1% or 175 million of the Chinese population younger than 18 had used the Internet (CNNIC, 2020). The number was 93.9% and 90.3% among children in the urban and rural areas. Chinese students usually access the Internet through smartphones, personal computers, or public computers at the Internet café. 65.6% of Chinese Internet users younger than 18 reported that they had learned to use the Internet without any supervision (CNNIC, 2020). The digital divide, which refers to the "relative level of access to products, services, and benefits of new information and communication technologies between different segments of the population," also reflects social inequality (Sorj, 2008). People have different levels of access to products, services, and benefits of the Internet and computers because they have different motivational access, physical access (first-level divide), digital skills, and usage (second-level divide) (van Dijk, 2006). These differences or the first two levels of the divide are a result of social inequality and recreate or even reinforce inequalities in societies (van Dijk, 2006, 2020). Since 2015, the outcomes of the different levels of access to computers and the Internet have become a heated topic of research on the digital divide. The digital divide is now considered to have developed to the third level, where the unequal digital skills and usage have led to a redistribution of resources and recreation of social inequality (van Dijk, 2020, 2021). In this paper, we follow the literature about the third level of the digital divide and ask whether and how the time spent online is associated with adolescents' subjective well-being and cognitive development, in the context of the high level of physical Internet access among Chinese adolescents.

The relationship between Internet use and cognitive and psychological development among adolescents has attracted many studies but remains hotly debated. Overall, in the literature that concentrates on students in Western, developed societies, Internet use, represented by the time spent on the Internet, is only weakly associated with students' test scores, cognitive outcomes, or subjective well-being (Escueta et al., 2020; Huang, 2010). Among those studies that did find an association, most employed a cross-sectional design. Thus, these findings severely suffer from identifying a spurious relationship due to confounding factors, such as parenting styles or unobserved family social, cultural, and economic backgrounds that are correlated with both problematic Internet use and development outcomes (Cao et al., 2011; Orben, 2020).

This study aims to contribute to the above debate with new evidence from China, where related studies remain rare, restricted to small, nonrepresentative samples, or only employ a cross-sectional design. In this study, we follow the same student over time to document how changes in the adolescents' cognitive and psychological measures are associated with changes in their Internet use time. This methodological improvement would provide more robust evidence on the impact of Internet use. In addition, we further investigate the differentiated effects of Internet use on different groups of young adolescents. We examine whether the associations between Internet use and child development differ between girls and boys, those with parents of different levels of education, and among children living in regions of various levels of socioeconomic development. This analysis will highlight the heterogeneous impacts of Internet use across multiple groups of adolescents and has important implications for our future generation's educational and health inequality.

To achieve the above goals, we use two waves of data from the China Education Panel Survey (CEPS), which interviewed students aged between 12 and 13 years old (equivalent to Grade 7 or the first year of junior high school in the US) in 2013/2014 and then followed up in 2014/2015. We employ linear fixed-effect regressions and interaction models to examine the associations between the students' self-reported depression scores and their cognitive test scores with their time spent on the Internet. This study will provide important contributions to the fast-growing literature on the impact of digital technology.

2 | THEORIES AND PREVIOUS EVIDENCE

Surfing on the Internet has become an integral part of children's and teenagers' daily life. The extensive use of the Internet can affect children's well-being through several potential pathways. One important mechanism is that Internet use could crowd out activities that could benefit children's development, such as school work, outdoor activities, or face-to-face interactions with family and friends (Mullan, 2019). For example, sleep loss due to the extended time spent on the Internet is one key explanation to the negative link between Internet use and mental health (Hökby et al., 2016). Second, from the psychological development perspective, Internet use may jeopardize the development and maintenance of social relationships through lowered participation in face-to-face social activities (Amichai-Hamburger & Ben-Artzi, 2003). Moreover, extensive exposure to online information has been argued to be associated with a reduced length of attention span, at least in experimental setups (Firth et al., 2019; Peng et al., 2018). Finally, activities conducted and the content consumed on the Internet could directly affect one's development. For example, the use of social media, video games, and online gambling is considered particularly detrimental to emotional health (Hökby et al., 2016; Kuss & Griffiths, 2012; McDool et al., 2016).

Nonetheless, those pathways could also benefit children's well-being. Internet use may expand social circle and social support, enhancing self-esteem and improving well-being (Morgan & Cotten, 2003). For example, online social media can also improve the scope and intensity of social interactions that could strongly benefit well-being. One study notes that a moderate level of Internet use, such as 1–2 h a day, was associated with slightly higher levels of psychological functioning (Orben & Przybylski, 2020). Another study finds that Internet use was related to better well-being by forming online relationships among college students (Wellman et al., 2001).

In terms of cognitive development, on the one hand, Internet use may interfere with study-related activities. For example, in Brazil, cell phone use is negatively associated with academic performance (Felisoni & Godoi, 2018). On the other hand, the Internet could make many tasks, such as communication and shopping, more efficient, thus freeing up time for other beneficial activities, such as course work. The Internet further enables greater access to high-quality information, which may benefit educational and social development.

Due to the mixed effects of those mechanisms, previous literature, mostly about children from the Western, industrialized countries, generally finds out that the impact of Internet use on children's development outcomes is minimal and often inconsistent. Regarding noncognitive development, reviews on the relationship between Internet use and subjective well-being demonstrate a small detrimental effect on subjective well-being (Huang, 2010; McCrae et al., 2017; Orben & Przybylski, 2019b). However, if the focus is on problematic Internet use, such as Internet addiction or pathological Internet use, the detrimental effect becomes more evident (Cataldo et al., 2021; Li et al., 2014). Notably, most of these studies use cross-sectional surveys. Thus, their results could not exclude confounding effects, such as a dysfunctional family or deficient self-regulation, that are correlated with both problematic Internet use and development outcomes (Orben, 2020). To address this issue, research following the same individual over time does not find strong evidence showing that social media use is associated with adolescents' well-being (Orben et al., 2019; Orben & Przybylski, 2019a). However, opponents suggest that the different use of data and methodology could not undermine the fact that much other research has found a substantial negative impact of Internet use on depression, for example, Twenge et al. (2020).

The documented link between Internet use and children and teenagers' cognitive outcomes in previous work is weak. For example, Internet speed is not associated with British students' online or offline studying time and test scores (Faber et al., 2016). This finding casts doubt on the “crowding out” mechanism discussed above. In an Ohio study, no significant relationship between test scores and the amount of time spent on the Internet was found (Hunley et al., 2005). In Peru, providing home Internet access is not associated with students' cognitive skills or self-esteem (Malamud et al., 2019). A review of the role of the Internet, especially the application of information and communications technology in education on students' test scores, reports that most of the studies have found a null effect (Escueta et al., 2020). Overall, the effects found in cross-sectional studies are more evident than those noted in studies that compare the same group of people before and after a change in Internet use patterns.

The empirical studies in China that we have reviewed so far have all employed a cross-sectional design, where different children who have different levels of Internet use and their development outcomes are compared. Two studies using large-scale survey data have found that Internet use is negatively associated with adolescents' subjective well-being and test scores (Fang & Huang, 2019; Zhang et al., 2019). Many other studies with a much smaller scale of samples focus on pathological Internet use and note the strong link between Internet addiction and adverse mental health outcomes (Cao et al., 2011; Guo et al., 2018; Tan et al., 2016).

Again, the cross-sectional design used in the above studies suffers from selection issues. Internet use, especially those problematic Internet use, often reflects a dysfunctional family or deficient self-regulation (Li et al., 2014; Mougharbel & Goldfield, 2020), which is exposed in the development outcome. Therefore, having unobservable confounders, especially those related to personal ability, personality, or family function and cultural environment, could lead to a spurious relationship between Internet use and development outcomes. Our study will address this issue by employing a fixed-effect regression analysis where the same individual is followed over time. By doing so, our results describe the relationship between the change in the time spent on the Internet and the change in the cognitive and noncognitive outcomes.

2.1 | Differential links by gender, socioeconomic backgrounds, and geographical location

Offline social inequality is the root cause of the first two levels of the digital divide, which, in turn, has different effects on different social groups. The empirical research partially supports the above argument. An interesting and consistent finding from the previous literature is that girls' well-being tends to be more negatively linked to Internet use. For example, social media usage negatively affects girls' life satisfaction more strongly (Orben et al., 2019). McDool et al. (2020) also report that the detrimental effect of Internet speed on mental health is more substantial for girls, and the strongest link is between Internet use and appearance among girls. Among Irish children, early mobile phone ownership is only negatively associated with girls' (between 9 and 13 years old) intellectual self-concept scores (Dempsey et al., 2020). In a cross-sectional study using the same CEPS data, the association between the time spent on the Internet and the higher depression scores is stronger among girls (aged between 12 and 17 years old) in China (Zhang et al., 2019). Different patterns of Internet use are one reason. Girls use social media more frequently than boys, whereas boys spend substantially more time on video games than girls (Ahn, 2011; Shaw, 2012; Twenge et al., 2018). The body image populated on social media, which is usually the idealized thin female body image, is one of the key reasons why women are more likely to experience a contrast between themselves and the models. And this leads to lower body satisfaction and self-esteem (Kleemans et al., 2018). Girls also have more pressure to develop and maintain their online presence than boys (Booker et al., 2018), are more likely to post “cute” photos (Peluchette & Karl, 2008), and display friendship ties (Herring & Kapidzic, 2015). These self-presentation strategies enhance cultural gender stereotypes and masculine fantasy, where women are sexually available and men are strong and powerful (Gorbacheva et al., 2019; Siibak, 2009). These gender differences in Internet use behaviors, motivations, and exposure to the gender-stereotyped online content imply different impacts of the Internet for boys and girls even if they spend the same time online.

Children's socioeconomic status (SES) could also moderate the relationship between Internet use and development outcomes. More educated parents are more engaged in interacting with their children through talking, reading, and organizing structured activities (Hertog & Zhou, 2021; Lareau, 2011). Those parents also have the skills and knowledge to utilize new technology for the benefit and guide their children to navigate online to enhance their capital (Zillien & Hargittai, 2009). Accordingly, children with disadvantaged socioeconomic backgrounds are more likely to go online without proper supervision and guidance and be affected by negative information on the Internet. Research has shown that adolescents with greater socioeconomic and cognitive resources use the Internet more frequently for information and less for entertainment than their peers with fewer socioeconomic and cognitive resources (Peter & Valkenburg, 2006). In the US, the diffusion of residential broadband is associated with better PSAT and SAT scores, but only among high-SES students (Dettling et al., 2018). In China, the negative association between Internet use and students' test scores is larger among those living in rural areas and poverty (Fang & Huang, 2019). In conclusion, students of low socioeconomic backgrounds are less likely to enjoy the benefits brought by the Internet and more likely to be negatively affected.

Regional development gaps could also affect how adolescents spend their time on the Internet. One study found that the benefit of classroom computer use is stronger for students with higher SES and mostly confined to developed societies (Falck et al., 2018). In China, regional development is predominantly led by the government, and the distribution of educational resources is highly uneven across regions. Structural factors, such as residence, are an important source of social inequality. One of the most important contributors to educational inequality in China is a residence (Liu et al., 2020), especially in recent decades (Hannum & Wang, 2006). Urban schools have more access to high-quality and quantity of teachers, books, computers, and other facilities to assist teaching and learning. For example, the teacher-to-student ratio in Beijing is approximately 10, whereas, in the less developed Guangxi Province, this number is 17 (Liu et al., 2020, fig. 1). Those who live in better-developed areas, such as the city center, attend schools that are able to work together with parents to provide better supervision and guidance to Internet use. This could explain why students who live in more affluent areas are more likely to grasp most of the benefits brought by the Internet and minimize the negative impact of which. Accordingly, those who live in the more affluent areas, such as the city center, are more likely to reap the benefits brought by the Internet.

Our analysis will examine these potential differentiated impacts of Internet use and advance our understanding of the third level of the digital divide in China.

3 | DATA AND SAMPLE

We use data from the CEPS, where the baseline survey was conducted in the fall of 2013 and spring of 2014 (Wave 1) for students in Grade 7 (10,279 students, usually aged between 12 and 13) and Grade 9 (9208 students, usually aged between 14 and 15) by the Renmin University of China and the National Survey Research Center. In the fall of 2014 and spring of 2015, the Wave 2 survey followed up these Grade 7 students interviewed in Wave 1. This survey is a national representative sample of all middle schools in China. The sample is based on randomly selected 112 schools from randomly selected 28 counties in 2013–2014.

This survey contains detailed information about the students' socioeconomic backgrounds, their time use during typical school and nonschool days, measures of their cognitive and noncognitive ability, their performance at schools, their perception of the family financial conditions, parental relationship, and feelings towards their classmates. This survey also interviewed the class teachers, school headteachers, the students' parents with information that could be linked to the students.

Among the 9449 Grade 7 students who were followed up for 2 years, 8262 (87%) of them have no missing values in all the variables in both waves and are used in this analysis.

4 | VARIABLE SELECTION AND MEASURES

4.1 | Depression score

This variable measures the level of depression, with the highest value representing the strongest depressive symptoms. Students were asked to answer how frequently ("Never," "Seldom," "Sometimes," "Often," "Always") they have the following five feelings in the last seven days. These feelings are "Feeling blue," "Depressed," "Unhappy," "Not enjoying life," and "Sad." The raw score adds up these answers towards the five feelings to have a range of 5–25 with a standard deviation of 4.29. We standardized this score, and the standardized depression score has a range of −1.32 to 3.55 with a standard deviation of 1.

4.2 | Cognitive scores

The dataset provides standardized cognitive test scores of the students calculated based on the item response theory (IRT) model (Lord, 1980; Sijtsma & Molenaar, 2002). The IRT approach is the main approach to measure latent cognitive ability based on item response profiles. This score measures general logic and analytical skills. The test design follows the questions used in the Taiwan Education Panel Survey (Tam, 2016; Yang et al., 2004) and has 20 questions for students to finish within 15 min. IRT has been widely applied to generate psychometrically sound estimates of cognitive ability based on a battery of aptitude test items, including literacy, shape and space, and calculation and logic. This variable is provided in the original dataset and ranges from −3.13 to 2.33. For more details, please refer to the psychometric report for the CEPS baseline survey (in Chinese) (Wang & Li, 2015).

4.3 | Internet use time

Weekly hours spent on the Internet is the combination of the usual hours spent on the Internet during school days multiply by five plus the hours spent during nonschool days multiply by two. The question asked in both waves is "How much time ON AVERAGE did you spend on the following extra-curricular activities from Monday to Friday last week/LAST WEEKEND?" Students in Wave 1 need to fill in the number of hours for the item "Surfing on the Internet or playing video games." In Wave 2, the students were asked to select an answer out of six categories —"0 hour," "Less than 1 hour" (0.5 h), "About 1-2 hours" (1.5 h), "About 2-3 hours" (2.5 h), "About 3-4 hours" (3.5 h), and "More than 4 hours" (5 h).

We first convert the exact hours reported in Wave 1 to the same six categories in Wave 2 to have consistent measures for both waves. We then take the midpoints of these categories to generate a numeric answer following the bracket above.

4.4 | Moderators

Gender (female = 1), parental education, which is the higher level of education of the parents ("<senior high school" [reference], "senior high school," and "tertiary"), and school location ("city center" [reference], "outskirts," "town/rural areas") are used to examine whether they would moderate the relationship between time spent on the Internet and the cognitive and depression scores. These variables are constant for the same individual, and fixed-effect regressions will only provide estimates on the interaction terms where these variables interact with the weekly Internet use hours.

4.5 | Other variables

We control several variables that may correlate with both the Internet use pattern and the outcome variables. The first group is the family structure: not living together with mother, not living together with father, and living with grandparents. The second group is the students' self-evaluated health condition ("Not good" [reference], "Average," "Good," and "Very good") and their evaluation of the family's financial condition ("Poor" [reference], "Average," "Rich," "Very rich"). The final control is the wave indicator with the value of 1 denoting the second wave while the first wave is the reference. The inclusion of this variable is necessary because the students' depression and cognitive scores as well as their time spent on the internet change with time.

5 | ANALYTICAL METHODS

The key outcomes include students' depression scores (psychological measure) and cognitive scores (cognitive measures). We conduct a fixed-effect regression analysis to investigate whether the change in Internet use pattern is associated with the change in the two outcome variables. This method considers the time-constant individual characteristics correlated with both the outcomes and the Internet use.

The baseline model represented by Equation (1) relates the depression score and cognitive score to students of different Internet use patterns:**

$$\text{Outcome}_{it} = \beta \text{InternetTime}_{it} + \lambda C_{it} + \pi Z_i + \vartheta_i + \varepsilon_{it}, \tag{1}$$

where index *it* denotes person *i* at time point *t*, and Outcome_{it} is the two outcomes for the person *i* at time point *t*. InternetTime_{it} is the weekly hours spent on the Internet for a given person-wave record with β as its coefficient. C_{it} includes the wave dummies, family demographic variables, the self-reported health condition, and the student's evaluation of the family's financial condition. Z_i includes the time-constant variables such as gender, school location, and parental education, which have the same association with the outcome across waves. ϑ_i and ε_{it} are the two error terms: ϑ_i represents the person-specific fixed effect, simultaneously capturing the time-invariant characteristics associated with the dependent and independent variables; and ε_{it} is the random variation for each person-wave.

The fixed-effect model calculates within-individual variations by demeaning the dependent and independent variables from person-specific means, thus deleting πZ_i and ϑ_i. This approach substantially lowers the risk of deriving a spurious relationship due to the unobserved variables that are correlated with both Internet use and development outcomes. Therefore, the estimated coefficients indicate that conditional on the same student, whether the change in the key independent variable, which is the time spent on the Internet, could predict the change in the depression and cognitive scores. In this fixed-effect regression approach, the time-constant variables are allowed to be correlated with all the predictors (Allison, 2009).

We have also conducted a random-effect regression analysis to compare to two models. We add gender, parental education, and school location in the random-effect models. The random-effect models assume that the unobserved time-constant variables ϑ_i are not correlated with all the predictors (Allison, 2009), thus providing a less relaxed assumption than the fixed-effect models. Hausman's test does not show that the estimates of the two models are similar. The random-effect regression substantially overestimates the effect of the Internet use time. These differences highlight the unobserved time-constant variables correlated with both the Internet use time and the depression and cognitive scores. Therefore, we present the results from the fixed-effect regressions, which enable us to draw a more robust conclusion. Please refer to Appendix Table A1 for the estimates from both models.

6 | DESCRIPTIVE RESULTS

Table 1 provides an overview of the sample statistics. From Wave 1 to Wave 2, there is a clear increase in weekly Internet hours from 6 to 7.3 h, cognitive ability score, and depression score. These differences between the two waves are significantly different from zero ($p < 0.001$ based on paired T-test). Therefore, Internet use time is positively correlated with cognitive ability scores and the level of depression.

TABLE 1 Sample statistics

	Wave 1		Wave 2	
	Mean/%	SD	Mean/%	SD
Weekly Internet hours	5.99	(7.78)	7.28	(8.40)
Cognitive ability score	0.07	(0.86)	0.36	(0.80)
Depression score	−0.15	(0.92)	0.06	(1.06)
Mother not in HH	0.19		0.12	
Father not in HH	0.13		0.16	
Grandparents in HH	0.33		0.33	
Self-reported health				
Not good health	0.04		0.06	
Average health	0.21		0.29	
Good health	0.35		0.35	
Very good health	0.41		0.30	
Self-reported family financial condition				
Poor	0.10		0.15	
Average income	0.72		0.73	
Rich	0.13		0.12	
Very rich	0.05		0.00	
Personal fixed characteristics				
	Mean/%			
Women	0.48			
Parental education				
Lower than senior high school	0.56			
Senior high school	0.24			
Tertiary education	0.20			
School location				
City center	0.40			
Outskirts	0.26			
Town/rural	0.34			
Number of students	8262			

Note: Data: China Education Panel Survey.
Abbreviations: HH, household; SD, standard deviation.

Approximately, 20% of the children do not have their mothers in the household in Wave 1. This percentage is 12% in Wave 2. Thirteen percent of the children do not have their fathers in the household in Wave 1, and this percentage increases to 16% in Wave 2. Thirty-three percent of the children are living together with their grandparents. Most of the students report that they are in good or very good health condition, and most of them report that their family financial condition should be average.

Forty-eight percent of the students are females. Fifty-six percent of the students have their parents having lower than senior high school level of education. Twenty-four percent of the students have parents with senior high school level of education, and 20% have parents with tertiary education levels. School location shows that 40% of them are located in the city center, 26% in the outskirts of the cities, and 34% are in small towns or rural areas.

7 | REGRESSION RESULTS

The linear fixed-effect regressions predicting how changes in the depression and cognitive test scores are associated with changes in the time spent on the Internet are presented in Tables 2 and 3.

In Table 2, the fixed effects models attribute approximately 53.7% of the variance in the depression score to the fixed effects, which are the combined effect of all time-constant variables. That is, students' depression score is mostly stable over time; however, a substantial part of the variation in depression score is associated with variables that change over time. In Table 3, this number is 61.7%. Students' cognitive score is slightly more stable over time than that of depression score, but there is still a substantial variation in the cognitive score that is associated with time-varying predictors.

The values of the three different types of R^2 are relatively small because the calculation of all the three R^2 does not use the coefficients for the fixed effects dummy variables, which is the student ID. One is the within-R^2, which is of key interest in fixed-effect regressions. It is just the usual R^2 calculated for the regression using the mean deviation variables. The values of 0.068 and 0.113 when predicting changes in depression and cognitive scores indicate the amount of variation of the dependent variable within one student that can be explained by the selected independent variables. The between R^2 is the squared correlation between the student-specific mean of the dependent variable and the predicted person-specific mean of the dependent variable. Finally, the overall R^2 is the squared correlation between the dependent variable itself and the predicted value of the dependent variable.

In Table 2, the positive link between depression and Internet use is evident. The baseline model shows that for 1 h increase in Internet use time per week, there is an increase of 0.008 standard deviations of the depression score (standard error = 0.002). The gender and Internet use time interaction model shows that for boys (the reference group), the association is estimated to be 0.006 (standard error = 0.002), but for girls, the association becomes much larger, reaching a level of 0.012 (0.006 + 0.006) (standard error = 0.003).

The association differs for children with parents of different educational levels. Among those whose parents have lower than senior high school education (reference group), 1 h increase in weekly Internet use time is associated with an increase of 0.009 standard deviations of depression scores (standard error = 0.002), but this estimate becomes almost zero or even negative (=0.009–0.013) among those whose parents have a tertiary level of education (standard error = 0.004). This finding supports our expectation that children of higher SES are more likely to minimize the negative impact of the Internet.

Following this line, regional differences are also noted. Compared with students whose schools are located in the city center, those attending schools located in the town/rural areas show a stronger association (0.004 + 0.006 = 0.010, standard error = 0.003) between depression and Internet use time.

The associations between the cognitive test outcomes and the time spent on the Internet are weak (baseline model, Table 3). The baseline model shows that an increase in 1 h spent on the Internet per week is not associated with a change in the cognitive ability score. When we interact gender with the Internet use time, no evidence shows that there is a gender-specific association. Considering the paternal education and Internet use time interaction model, this null association is similar across parents of different educational levels. The same null association is also found across students located in schools in different areas. Overall, we find that the association between Internet use time and cognitive scores is very weak across different groups based on their gender, parental education, and school location.

TABLE 2 Linear fixed-effect regressions to predict changes in depression score

	Baseline	Gender	Parental education	School location
Weekly Internet hours	0.008***	0.006*	0.009***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Females #		0.006*		
Weekly Internet hours		(0.003)		
Senior high sch #			0.002	
Weekly Internet hours			(0.004)	
Tertiary #			−0.013**	
Weekly Internet hours			(0.004)	
Outskirts #				0.005
Weekly Internet hours				(0.005)
Town/rural #				0.006+
Weekly Internet hours				(0.003)
Mother not in HH	−0.052+	−0.052+	−0.051+	−0.052+
	(0.029)	(0.029)	(0.029)	(0.029)
Father not in HH	0.043	0.042	0.042	0.043
	(0.027)	(0.026)	(0.027)	(0.027)
Grandparents in HH	−0.015	−0.016	−0.013	−0.015
	(0.025)	(0.025)	(0.025)	(0.025)
Average health (ref: Not good)	−0.289***	−0.288***	−0.289***	−0.290***
	(0.049)	(0.049)	(0.049)	(0.049)
Good health	−0.454***	−0.452***	−0.453***	−0.454***
	(0.053)	(0.052)	(0.053)	(0.053)
Very good health	−0.590***	−0.588***	−0.591***	−0.590***
	(0.054)	(0.054)	(0.054)	(0.054)
Wave 2 (ref: Wave 1)	0.149***	0.148***	0.148***	0.149***
	(0.019)	(0.019)	(0.020)	(0.019)
Average income (ref: Poor)	−0.088**	−0.087**	−0.089**	−0.088**
	(0.032)	(0.032)	(0.033)	(0.032)
Rich	−0.111*	−0.112*	−0.108*	−0.110*
	(0.047)	(0.047)	(0.047)	(0.047)
Very rich	−0.142*	−0.144*	−0.144*	−0.141*
	(0.057)	(0.057)	(0.057)	(0.057)
Constant	0.204**	0.202**	0.207**	0.206**
	(0.067)	(0.067)	(0.068)	(0.067)

(Continues)

TABLE 2 (Continued)

	Baseline	Gender	Parental education	School location
The standard deviation of the time-invariant individual-specific term u_i	0.798	0.797	0.799	0.798
Standard deviation of the error term e_it	0.741	0.741	0.740	0.741
Variance in the dependent variable due to u_i	0.537	0.536	0.538	0.537
Within R^2	0.068	0.068	0.069	0.068
Between R^2	0.140	0.141	0.123	0.133
Overall R^2	0.104	0.106	0.098	0.102
Number of individuals	8262	8262	8262	8262
Number of person-years	16,524	16,524	16,524	16,524

Note: Data: CEPS. Standard errors are in parentheses and clustered at the individual level.
Abbreviation: HH, household.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
$^{+}p < 0.10$.

8 | ROBUSTNESS CHECK

Although fixed-effect regression approach substantially lowers the selection based on personal-fixed time-constant variables, such as family background, students' personality, and so forth. Other time-varying variables could be correlated with both the outcome and the Internet time use pattern. For example, students may experience bullying at schools and then feel depressed and seek the online world as a path to escape. There could be a sudden change in family circumstances. For example, the parents may not be in a good relationship, which will also cause high levels of depression and probably longer time spent on the Internet. Therefore, we further include several variables to capture those changes in the students' family and school experiences. These variables are whether your parents often quarrel, whether your parents are in a good relationship, and how do you feel about your classmates. The results remain unchanged when adding those variables, but the sample size is reduced due to missing values in those additional variables. Please refer to Tables A2 and A3 for the detailed results. In summary, these additional checks support our main result reported above.

We have also tested whether there is a nonlinear relationship between the time spent online and the outcomes. We further included a squared term of the Internet use time in the above models. We do not find a nonlinear relationship between the change in the Internet use time and that of the outcomes. Therefore, in our sample, the change in the Internet use time is linearly correlated with the change in the outcome variables.

9 | CONCLUSION AND DISCUSSION

The popularity of Internet access and use among young people has led to an urgent need to understand its potential impact on youth development. However, empirical results are still highly inconsistent and are often limited by a cross-sectional design that suffers from selection bias. The heterogeneous impact of Internet use across different social groups is also inadequately addressed. Our analysis documents how Internet use time is associated with two development outcomes—depression and cognitive ability among Chinese adolescents aged between 12 and 15. We

TABLE 3 Linear fixed-effect regressions to predict change in a cognitive ability score

	Baseline	Gender	Parental education	School location
Weekly Internet hours	−0.000	0.000	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Females #		−0.002		
Weekly Internet hours		(0.002)		
Senior high school #			0.001	
Weekly Internet hours			(0.002)	
Tertiary #			0.003	
Weekly Internet hours			(0.003)	
Outskirts #				−0.003
Weekly Internet hours				(0.003)
Town/rural #				−0.001
Weekly Internet hours				(0.003)
Mother not in HH	−0.054*	−0.053*	−0.054*	−0.053*
	(0.021)	(0.021)	(0.022)	(0.021)
Father not in HH	−0.039	−0.038	−0.039	−0.039
	(0.024)	(0.024)	(0.024)	(0.024)
Grandparents in HH	0.026	0.026	0.025	0.026
	(0.021)	(0.021)	(0.021)	(0.021)
Average health (ref: Not good)	0.047	0.047	0.047	0.047
	(0.038)	(0.038)	(0.038)	(0.038)
Good health	0.024	0.024	0.024	0.024
	(0.041)	(0.041)	(0.040)	(0.041)
Very good health	0.030	0.029	0.030	0.030
	(0.039)	(0.039)	(0.039)	(0.039)
Wave 2 (ref: Wave 1)	0.282***	0.282***	0.282***	0.282***
	(0.024)	(0.024)	(0.024)	(0.024)
Average income (ref: Poor)	0.013	0.013	0.013	0.013
	(0.024)	(0.024)	(0.024)	(0.024)
Rich	0.035	0.035	0.034	0.035
	(0.041)	(0.041)	(0.041)	(0.041)
Very rich	0.031	0.031	0.031	0.031
	(0.044)	(0.044)	(0.044)	(0.044)
Constant	−0.246***	−0.245***	−0.246***	−0.246***
	(0.062)	(0.062)	(0.062)	(0.062)

(Continues)

TABLE 3 (Continued)

	Baseline	Gender	Parental education	School location
The standard deviation of the time-invariant individual-specific term u_i	0.720	0.720	0.718	0.719
The standard deviation of the error term e_it	0.566	0.566	0.566	0.566
Variance in the dependent variable due to u_i	0.617	0.618	0.616	0.617
Within R^2	0.113	0.113	0.113	0.113
Between R^2	0.027	0.021	0.043	0.035
Overall R^2	0.038	0.037	0.042	0.040
Number of individuals	8262	8262	8262	8262
Number of person-years	16,524	16,524	16,524	16,524

Note: Data: China Education Panel Survey. Standard errors are in parentheses and clustered at the individual level.
Abbreviation: HH, household.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

use a more rigorous approach, which follows the same student over 1 year to conduct within-individual analysis. We find that Internet use time is not linked to cognitive ability, but an increase in Internet use time is associated with a higher level of depression scores among Chinese junior middle school students. This study fills an important gap in our knowledge about the link between Internet use and mental and cognitive development outcomes in early adolescents in China.

Beyond the overall modest link between Internet use and cognitive development, the group differences in this association are also small. This finding is consistent with many previous studies (Escueta et al., 2020; Faber et al., 2016; Hunley et al., 2005). These findings cast doubt over the claim that time spent on the Internet is detrimental to junior middle school students' cognitive development.

Consistent with what we have known from the work on youths in the Western, industrialized societies, the link between Internet use and depression is more evident than that between Internet use and cognitive scores. The result supports that the longer time spent on the Internet is associated with an increased level of depression. This association is stronger among girls, those with less-educated parents, and those who live in less developed areas. This finding again highlights the potential of enlarged inequality in adolescents' mental health in a digital society. Those socioeconomically disadvantaged are more vulnerable to the spread of the Internet. The content spread on the Internet, the different motivations and skills to surf on the Internet, and the unequal educational resources owned by the students all explain the differentiated impacts of the Internet use time.

Our study is not without limitations. First, the fixed-effect regression analysis cannot solve the direction of the causality. Students may feel depressed and then spend more time on the Internet. Another possibility is that they do not perform well at school and feel discouraged from studying hard on schoolwork, thus spending more time on the Internet. In this paper, we have conducted additional robustness checks to include several other factors, such as parental relationships or feelings about classmates, that may lead to the potential change in depression or cognitive scores. Nonetheless, there could be other omitted factors that could lead to changes in the outcomes. Moreover, due to data limitations, information on the activities conducted and the content consumed on the Internet are not available. For example, we do not know whether the larger negative effects of internet use time on girls than boys are due to girls' longer time spent on social media. This limitation prevents us from exploring the mechanisms that could explain those links between Internet use and depression outcomes. Certain online activities, such as social media, video games, and gambling, are particularly detrimental to emotional health (Hökby et al., 2016; Kuss & Griffiths, 2012). We call for more detailed data collection work on Internet use and further research to address these limitations. Our findings show that given the online activities of those adolescents back in 2013/2014, how the time spent on the Internet is linked to the selected cognitive and noncognitive outcomes. Changes in adolescents' online behaviors, such as the popularity of e-shopping and new Apps including Tiktok and the widely adopted online education induced by COVID-19 in more recent years, may alter the conclusion of this paper.

This study provides new evidence to the impact of Internet use time on adolescents in China and highlights how Internet use time could bring in distinct consequences to different groups of adolescents. The school-based intervention effectively promoted time management skills and improved emotional, cognitive, and behavioral symptoms (Du et al., 2010). Policies targeting the vulnerable groups—providing more educational resources, helping less-educated parents, and monitoring those content spread on the Internet will be essential to prevent the enlarged gender and social inequality that emerged from adolescents at the time of a digital society.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Chinese National Survey Data Archive at http://cnsda.ruc.edu.cn/index.php?r=projects/view%26id=72810330, Reference Number 72810330.

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PEER REVIEW

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APPENDIX

See Tables A1, A2, and A3.

TABLE A1 Comparison of the shared estimated coefficients of fixed-effect and random-effect regressions of the baseline models

	Depression score		Cognitive score	
	Fixed-effect	Random-effect	Fixed-effect	Random-effect
Weekly Internet hours	0.008	0.012	0.000	−0.009
Mother not in HH	−0.052	0.032	−0.054	−0.074
Father not in HH	0.043	0.111	−0.039	−0.066
Grandparents in HH	−0.015	−0.036	0.026	0.103
Health: Average versus not good	−0.289	−0.393	0.047	0.019
Health: Good versus not good	−0.454	−0.658	0.024	0.051
Health: Very good health versus not good	−0.590	−0.905	0.030	0.014
Second year	0.149	0.117	0.282	0.298
Income: Average versus poor	−0.088	−0.223	0.013	0.165
Income: Rich versus poor	−0.111	−0.250	0.035	0.211
Income: Very rich versus poor	−0.142	−0.244	0.031	0.123

Note: Data: China Education Panel Survey. Gender, parental education, and school location are further included in the random-effect regressions.

Abbreviation: HH, household.

TABLE A2 Robustness check: Linear fixed-effect regressions to predict change in depression score

	Baseline
Weekly Internet hours	0.008***
	(0.001)
Mother not in HH	−0.064*
	(0.029)
Father not in HH	0.020
	(0.030)
Grandparents in HH	−0.024
	(0.028)
Average health (ref: Not good)	−0.270***
	(0.044)
Good health	−0.438***
	(0.044)

TABLE A2 (Continued)

	Baseline
Very good health	−0.560***
	(0.046)
Wave 2 (ref: Wave 1)	0.153***
	(0.013)
Average income (ref: Poor)	−0.097**
	(0.034)
Rich	−0.113*
	(0.047)
Very rich	−0.149*
	(0.061)
Parents often quarrel	0.182***
	(0.039)
Parents in good relationship	−0.094**
	(0.033)
Somewhat disagree (ref: Strongly disagree)	−0.036
	(0.053)
Somewhat agree	−0.148**
	(0.049)
Strongly agree	−0.233***
	(0.049)
Constant	0.425***
	(0.076)
The standard deviation of the time-invariant individual-specific term u_i	0.790
The standard deviation of the error term e_it	0.731
Variance in the dependent variable due to u_i	0.539
Within R^2	0.081
Between R^2	0.180
Overall R^2	0.143
Number of individuals	8245
Number of person-years	16,087

Note: Data: China Education Panel Survey. Standard errors are in parentheses and clustered at the individual level. Abbreviation: HH, household.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE A3 Robustness check: Linear fixed-effect regressions to predict change in cognitive score

	Baseline
Weekly Internet hours	−0.000
	(0.001)
Mother not in HH	−0.039+
	(0.022)
Father not in HH	−0.049*
	(0.023)
Grandparents in HH	0.022
	(0.022)
Average health (ref: Not good)	0.048
	(0.034)
Good health	0.023
	(0.034)
Very good health	0.030
	(0.036)
Wave 2 (ref: Wave 1)	0.289***
	(0.010)
Average income (ref: Poor)	0.019
	(0.027)
Rich	0.047
	(0.037)
Very rich	0.034
	(0.047)
Parents often quarrel	−0.014
	(0.030)
Parents in a good relationship	−0.029
	(0.025)
Somewhat disagree (ref: Strongly disagree)	−0.000
	(0.041)
Somewhat agree	0.011
	(0.038)
Strongly agree	0.017
	(0.038)
Constant	−0.242***
	(0.059)

TABLE A3 (Continued)

	Baseline
The standard deviation of the time-invariant individual-specific term u_i	0.724
The standard deviation of the error term e_it	0.565
Variance in the dependent variable due to u_i	0.621
Within R^2	0.116
Between R^2	0.012
Overall R^2	0.038
Number of individuals	8245
Number of person-years	16087

Note: Data: China Education Panel Survey. Standard errors are in parentheses and clustered at the individual level.

Abbreviation: HH, household.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

$^{+}p < 0.10$.