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Abstract

The present study examines the reciprocal relationship between Internet use and cognitive function over time among middle-aged and older populations in China. We use data from the first three waves of the China Health and Retirement Longitudinal Study (CHARLS), where participants provided information on Internet use and cognitive function measures at the baseline in 2011 as well as two follow-ups in 2013 and 2015. Cross-lagged panel models were fitted to test the reciprocal association over these four years. Middle-aged and older individuals with higher cognitive function were more likely to be regular Internet users. After controlling for the effects of cognition two years prior, Internet users tended to score higher on cognitive tests than non-users. These findings survived across alternative subsamples and model specifications. Our results suggest that cognitive decline in later life may explain the lower technology adoption rate among older individuals. Meanwhile, Internet use could serve as a protective factor against cognitive decline in mid-life and older adulthood.

Keywords: Internet use; cognitive function; cross-lagged panel; China

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Introduction

The last century has witnessed dramatic technological advances, among which familiarity with the Internet has become a significant determinant of the social connectedness and labor force flexibility of individuals worldwide. As the largest developing country in the world, China's modernization is accompanied by accelerated adoption of the Internet. As reported by the World Development Indicators, with less than 2% Internet users in 2000, the proportion of individuals using the Internet had increased to around 53% by 2016. Despite the marked improvement, China is still left behind by the most developed countries. Japan, for instance, has achieved a usage rate of over 90% from 30% in 2000.

Non-universal Internet use indicates a 'digital divide' in China, where specific segments of the population are excluded from using new technologies to improve the quality of life. Among the characteristics documented to be associated with Internet use, age stands out as a vital factor (Gilleard and Higgs, 2008; Wagner et al., 2010). Calculations from the China Family Panel Studies (CFPS) suggest that about three-quarters of those aged 15 to 44 had used the Internet in 2016, compared to less than one in six people aged 45 and above. Financial constraints due to lower incomes, lack of awareness about the Internet or its benefits, and little prior technology experience are among the many reasons preventing older people from fully adapting to the Internet (Barnard et al., 2013; Carpenter and Buday, 2007; Morris et al., 2007).

Normative health declines impose additional barriers encountered by older adults in using technologies (Hawthorn, 2000; Charness and Boot, 2009; Lee et al., 2011; Matthews et al., 2019). Older adults with physical impairments have more difficulties than do younger people in handling technological devices (Gell et al., 2013; Wright and Hill, 2009). Mental health is also affected by aging. Given the complexity of technologies required to access the Internet, the acquisition of relevant knowledge takes cognitive efforts (Czaja et al., 2006). Cognitive deficits place obstacles to going online, where research has supported the predictive role of declining cognitive abilities in lower rates of Internet use among the elderly (Berner et al., 2013, 2015, 2016, 2019a; Charness and Boot, 2009; Czaja et al., 2006; Elliot et al., 2013; Freese et al., 2006; Gell et al., 2013; Kamin and Lang, 2016, 2018; Umemuro, 2004).

For cognitively disadvantaged people, however, the environment shaped by technological developments can be both challenging and stimulating. Participating in cognitively demanding activities, such as learning new skills or knowledge, is protective against age-related cognitive decline (Bielak, 2010; Chan et al., 2016; Park et al., 2014). Meanwhile, the wide variety of services and activities available through the Internet, such as information seeking and interpersonal interaction, facilitate a mentally engaged lifestyle (Kyriazis and Kiourti, 2018; Myhre et al., 2017; Slegers et al., 2012; Small et al., 2009). Therefore, Internet use could help maintain cognitive health in older adulthood (Almeida et al., 2012; Berner et al., 2019b; d'Orsi et al., 2018; Kamin and Lang, 2018; Klimova, 2016; Slegers et al., 2012; Tun and Lachman, 2010; Xavier et al., 2014).

Both pathways, cognitive ability predicting Internet use and Internet use mitigating the cognitive decline, are plausible. Nevertheless, cross-sectional studies cannot make reliable inferences concerning the direction of this association. A critical earlier longitudinal study of Kamin and Lang (2018) reported both directions of the Internet-cognition association for European older adults. However, the extent to which these effects can be found in other settings remains an unanswered question. In this study, we utilize a longitudinal sample of middle-aged and older Chinese populations to investigate the reciprocal relationship between Internet use and cognitive function over time.

The population aging in China has occurred at a much lower level of Internet penetration than in developed countries. In 2015, around half of the older Europeans were regular Internet users (König et al., 2018), but being online was a minority activity among older people in low and middle-income countries. The purpose of this study is thus to shed additional light on the bidirectional relationship between Internet use and cognition in the Chinese context. Data from a large population-based sample improve the statistical power to detect relatively small effects. We employ cross-lagged panel models to simultaneously estimate the impacts of two variables on each other over time. By incorporating latent variables, we focus more on the within-individual process as an attempt to provide evidence for the causal interpretation.

Methods

Data

We use data from the first three waves of the China Health and Retirement Longitudinal Study (CHARLS). CHARLS is a nationally representative panel survey of Chinese community-residents aged 45 years or older, along with their spouses. As part of the international network of longitudinal aging studies, it was designed to provide demographic, health, and socio-economic information for a better understanding of the aging process in China (Zhao et al., 2012). In 2011, the national baseline survey was fielded using a stratified multistage sampling design, which included 10,257 households and 17,708 individuals in 150 counties/districts and 450 villages/resident committees (Zhao et al., 2013). Survey participants would be followed every two years with a computer-aided personal interview (CAPI) in face-to-face visits. If possible, we obtain variables from the Harmonized CHARLS data, which contain cleaned and processed variables with generally consistent meanings across waves.

Variables

Internet Use

Survey participants answered the question of whether they had ever used the Internet in the last month (0 for no, 1 for yes). The relatively short recall window produces a measure of regular Internet usage behavior (König et al., 2018; Kamin and Lang, 2018), which might thus indicate a lower usage rate. In the CHARLS baseline survey, for instance, 1.1% of the participants aged no less than 60 years identified themselves as Internet users. By extending the recall window to the last six months, however, a report by the China Internet Network Information Center (2012) in the same year suggested a usage rate of 2.0% among the same segment of the population. The following results need to be interpreted with this measurement issue in mind.

Cognitive Function

A set of cognitive assessments was administered during the baseline survey, as well as two follow-up visits. Following previous literature (Lei et al., 2012; Jin et al., 2019), we calculate a cognition score to proxy two domains of adult cognition: episodic memory and intact mental status.

A word recall test measures episodic memory. A list of ten Chinese nouns was read to participants. They were asked to recall as many of the words as possible in any order immediately. About five minutes later, after the participants had finished modules on depression, numeracy, and drawing, they were asked to recall the same word list. We count the number of correct answers to construct a single memory score ranging from 0 to 20.

Intact mental status is based on components of the Telephone Interview of Cognitive Status (TICS) battery, which include numeracy, time orientation, and figure drawing. Numerical literacy was tested by successively subtracting seven from 100 up to five times. Time orientation was measured by naming the date, month, year, and day of the week of the interview day. Participants were also asked to replicate as similarly as possible a picture of two overlapping pentagons, as was shown by the interviewers. We construct a single score of mental intactness ranging from 0 to 10 by counting the number of successfully performed tasks.

For an overall measure of cognitive function, scores from both domains are aggregated to represent an individual's cognition as a whole, ranging from 0 to 30. When used in the regression analysis, cognitive variables are standardized into z-scores for ease of interpretation.

Covariates

Several covariates identified in the literature as being relevant to both Internet use and cognitive function are used as controls. Among the demographic factors, we include age (classified into 10-year groups: 45-54 years, 55-64 years, 65-74 years, and 75 years or above), gender (1 for male, 0 for female), and marital status (1 for married or partnered, 0 for otherwise).

Among socio-economic factors, we include the highest educational level (below elementary school, elementary school, middle school, and high school or above) and annual household expenditure per capita (divided into quartiles within each year). Household expenditure is a robust indicator of resources available to the household in a low-income context as China (Strauss et al., 2010).

Among health factors, we include functional impairment as having difficulties in performing any activities of daily living (ADL: dressing, bathing, eating, getting in and out of bed, using the toilet, and controlling urination and defecation) or any instrumental activities of daily living (IADL: managing money, taking medications, shopping for groceries, preparing hot meals, and household chores). We assess the severity of depression using the short ten question version of the Centre for Epidemiologic Studies Depression (CES-D) scale. A cutoff of 10 or more out of 30 is used to identify depressive symptoms (Boey, 1999).

The final set of covariates relates to one's living environment. We include living with children, urban residence, and geographic areas (coastal, central, and western China). In the regression analysis, all covariates are measured two years before the associated dependent variable.

Analysis Sample

For the analysis sample, we first include 17,220 individuals aged 45 and older at the baseline. Limiting the analysis to participants with no missing information on variables used drops the sample size to 14,788. In this way, we exclude people who were too frail to make their responses since data on cognition were not allowed to be collected from proxy respondents in CHARLS. If these people were less likely to use the Internet and had more cognitive impairments, our findings could be biased towards the null of no effects.

The sample size is further reduced to 13,160 as a result of attrition between the baseline and the follow-ups. Contrary to our speculation, those exiting the survey were more likely to be Internet users and perform better on cognitive tests at the baseline. Since we only include people who participated in at least two successive waves, we might arrive at an underestimation.

Statistical Analysis

To examine the longitudinal interplay between Internet use and cognitive function, we formulate a cross-lagged model with a structural equation modeling approach over the three-wave data period (McArdle and Nesselroade, 2014). For individual i observed at both wave t and $t-1$ ($t = 2, 3$), the model is denoted as follows.

$$I_{i,t} = \mathbb{1}(\mu_t + \beta_{1,t} C_{i,t-1} + \gamma_{1,t} I_{i,t-1} + \delta_{1,t} Z_{i,t-1} + \phi_{1,t} \alpha_i + \varepsilon_{i,t} > 0) \quad (1)$$

$$C_{i,t} = \tau_t + \beta_{2,t} I_{i,t-1} + \gamma_{2,t} C_{i,t-1} + \delta_{2,t} Z_{i,t-1} + \phi_{2,t} \alpha_i + \upsilon_{i,t} \quad (2)$$

Equation (1) denoted by the indicator function $\mathbb{1}(\cdot)$ specifies the path from cognition ($C_{i,t-1}$) to Internet use ($I_{i,t}$). Given that Internet use is a dichotomous variable, probit regressions are used. The path from Internet use ($I_{i,t-1}$) to cognition ($C_{i,t}$) is specified in Equation (2). To establish a temporal relation between predictors and the corresponding outcome, predictors (including covariates $Z_{i,t-1}$) measured at the preceding wave are modeled against the outcome at the subsequent wave. Individual error terms, $\varepsilon_{i,t}$ and $\upsilon_{i,t}$, are assumed to be independent and normally distributed. The dependence of an individual's Internet use or cognition over time is captured by autoregressive parameters, γ. Cross-lagged parameters, β, describe the lagged reciprocal Internet-cognition relationship, which is of central interest in the present study.

Both Internet use and cognitive function are complex issues influenced by numerous factors. Although a rich set of covariates are included, they are by no means exhaustive. Following the suggestion of Hamaker et al. (2015), an individual-level latent variable, α_i, is controlled for in each equation with coefficients denoted by $\phi_{1,t}$ and $\phi_{2,t}$. It accounts for unobserved time-invariant (at least for the duration of the study) individual traits. The lagged relationship pertains to the within-individual process. The latent variable also captures the likely correlation between equations. Its distribution was restricted to be a standard normal for identification. All coefficients, as well as the variance of $\upsilon_{i,t}$, are allowed to vary with time.

Three waves of data generate a system of four equations, which are estimated simultaneously by the maximum likelihood method using STATA/SE 14.2 ‘gsem’ package. Because of missing observations, the sample size will differ across equations depending on the measures used. The hierarchical sampling structure of CHARLS might result in dependent observations in the same community (either rural villages or urban resident committees). To account for such a dependency and violations of distributional assumptions, we compute robust standard errors allowing for clustering at the community level. Given the large sample size, we choose a p-value of 0.05 or less to indicate significance.

We estimate cross-lagged models for the overall measure of cognition as well as two separate domains to examine whether different cognitive dimensions were differentially associated with Internet use. Since our sample consists of quite a diverse group of middle-aged and older adults, we also conduct stratified analysis by gender, age, and education. We then carry out two sensitivity analyses to provide supportive evidence for the causal interpretation.

Firstly, communities in China are highly relevant (Hong et al., 2017; Strauss et al., 2010). Unmeasured factors related to the place of residence, such as culture and infrastructure, might affect the adoption of new technologies. Also, the environment one lives in could have significant impacts on health outcomes. Taking a multilevel perspective in that individuals belong to communities, we extend the benchmark model in Equation (1) and (2) by including an additional latent variable for community effects.

Secondly, to improve the internal validity, we restrict the analysis to a more homogeneous group of participants who resided in households where the broadband Internet was available at least once during the study period. Presumably, these people were less constrained by financial resources so that we could obtain greater control over potential confounders.

Results

Descriptive Statistics

A descriptive analysis is presented in Table 1 for an overview of the data. We list distributions of the baseline characteristics in the first column, where the cognitive score is dichotomized at its median (13 out of 30). Most participants were younger than 64 years old, married, and living in rural areas. Educational attainments of the survey respondents were generally low, with about 45% not finishing the elementary school. Roughly 25% suffered from functional impairments, and 35% had depressive symptoms above the threshold.

The next three columns depict the profile of Internet users. For middle-aged and older participants during the study period, those using the Internet were quite a minority group. Throughout the 4-year follow-up, there was an increase in Internet use from about 2.3% in 2011 to 3.9% in 2015, with a larger increment occurring between 2011 and 2013. Prior use of the Internet was a strong predictor of the later utilization, although some people started, and some people stopped using it. As a first hint of the Internet-cognition correlation, there were few Internet users among those who scored lower than the median in the baseline cognitive tests.

In accordance with previous literature, Internet use was highly stratified by many of the covariates. Even within the middle-aged and older population, there was a steep decline with age in the percentage of people reporting Internet use. Over the data period, Internet use was generally increasing for all age groups, with the highest rate of increase among the youngest cohort. Females were less likely to use the Internet than males. A higher proportion of single persons reported using the Internet compared with married ones.

There were noteworthy differences across each additional level of education. Since the Internet is mainly text-based, it was not surprising to see so few Internet users without elementary education. Internet use was much more prominent for high school graduates, probably because they had more opportunities to expose themselves to new technologies (Kämpfen and Maurer, 2018). Increasing financial resources were also associated with a higher likelihood of Internet use. The speed of technology adoption was faster among people living in households with higher per capita expenditure.

Poor health was associated with a reduced likelihood of Internet use. Those with functional impairments or depressive symptoms were less likely to use the Internet. Living with children facilitated the adoption of new technologies, possibly because children could teach and encourage their older parents to use the Internet. As expected, Internet users were less likely to live in rural areas or the western region of China, where less developed infrastructure might restrict access to the Internet.

We summarize mean cognitive scores in the last three columns. Cognitive scores decreased across waves, where the decline mainly took place among non-users of the Internet. Age was a strong predictor of cognitive abilities. With each 10-year increment in age, cognitive function decreased monotonically. When following specific cohorts over time, cognition dropped the fastest among the oldest adults. Consistent with Lei et al. (2012, 2014), older females performed worse on cognitive tests than older males in China.

Cognitive function was also associated with socio-economic and health status. Educational attainment was predictive of cognition (Huang and Zhou, 2013). There were large increases in average cognitive scores as schooling levels rose. Over time, better-educated people suffered less from cognitive decline. Those with more financial resources, living in urban areas, or living in the coastal region performed better cognitively. As a measure of mental health, cognition was also positively associated with other health measures, no functional limitation, and fewer mood problems.

Regression Results

Table 2 reports estimations from the cross-lagged model specified in Equation (1) and (2). Dependent variables are having ever used the Internet in the last month and the overall measure of cognition. For each probit equation of Internet use, we give estimated coefficients as well as population-averaged average marginal effects to make the results more interpretable.

Panel A summarizes the results obtained by restricting the effects of the individual latent variable to be zero. Estimating a system of four equations without a common latent variable is equivalent to estimating separate probit and linear regressions. There was a significant lagged reciprocal relationship between regular Internet use and cognitive function among middle-aged and older Chinese adults. Prior cognitive performance predicted subsequent Internet use, which in turn protected individuals from cognitive decline.

Panel B of Table 2 adds the individual latent variable so that we could focus more on the influences over time within individuals. We also present a graphical representation in Figure 1 and detailed results on all the other covariates in Table A1. In this specification, the estimated cross-lagged coefficients remained positive and statistically significant.

Cognitive function exerted stronger impacts on Internet use with unobserved individual traits controlled for, although these effects varied across waves. On average, a one-standard-deviation increase of the cognitive score in 2011 (2013) was associated with a higher rate of Internet use in 2013 (2015) by 0.77 (3.27) percentage points. Given the small proportion of Internet users in our sample, these effects were also substantively significant. Using the Internet two years prior would also increase the likelihood of subsequent use.

Consistent with descriptive evidence, Internet users were more likely to be younger, better-

Table 1: Descriptive statistics by year and covariates

	Internet use: %			Cognitive score		
Covariates: %	2011	2013	2015	2011	2013	2015
Total	2.33	3.60	3.89	13.5 (5.3)	13.1 (5.7)	12.3 (5.8)
Internet use						
No: 97.7		2.06	2.52	13.4	12.9	12.2
Yes: 2.3		67.3	67.5	19.1	19.5	18.9
Cognitive score						
Below median: 48.0	0.38	0.70	0.69	9.02	10.2	9.53
Above median: 52.0	4.40	6.46	6.95	17.7	16.0	15.3
Age						
45 - 54: 34.7	4.29	6.64	7.44	15.0	14.9	14.3
55 - 64: 39.6	1.64	2.52	2.44	13.5	13.1	12.3
65 - 74: 19.5	0.88	1.25	1.27	12.2	11.3	10.2
75 +: 6.3	0.49	0.85	0.97	9.66	8.22	6.79
Gender						
Female: 52.4	2.02	2.96	2.98	12.7	12.1	11.5
Male: 47.6	2.67	4.29	4.89	14.5	14.1	13.3
Marital status						
Single: 13.8	2.44	3.85	4.21	12.1	11.1	10.4
Married or partnered: 86.2	2.31	3.55	3.84	13.8	13.4	12.6
Educational level						
Below elementary school: 45.5	0.09	0.15	0.17	10.7	10.0	9.12
Elementary school: 21.9	0.54	0.90	1.22	14.3	14.0	13.3
Middle school: 20.9	2.79	5.21	6.63	16.2	16.1	15.6
High school or above: 11.8	13.6	19.1	19.3	17.7	18.0	17.3
Expenditure per capita						
First quartile: 21.4	0.22	0.57	0.92	12.1	11.6	10.9
Second quartile: 22.0	0.43	1.17	1.93	13.0	12.6	11.8
Third quartile: 21.5	1.57	3.01	3.59	13.9	13.6	12.9
Fourth quartile: 19.6	7.02	9.85	9.74	15.3	15.0	14.1
Information missing: 15.5	3.03	4.13	4.19	13.2	12.8	12.0
Functional impairment						
No: 74.5	3.01	4.54	4.81	14.3	13.9	13.1
Yes: 25.5	0.40	0.83	1.19	11.2	10.8	10.1
Depressive symptom						
No: 64.8	3.16	4.72	5.19	14.5	13.9	13.1
Yes: 35.2	0.89	1.51	1.45	11.8	11.5	10.8
Living with children						
No: 40.1	1.88	2.59	2.92	13.1	12.6	11.8
Yes: 59.9	2.63	4.27	4.53	13.8	13.4	12.7
Residence						
Rural: 62.6	0.32	0.86	1.45	12.7	12.1	11.5
Urban: 37.4	5.66	8.18	8.29	14.8	14.7	13.9
Region						
Coastal: 34.5	2.95	4.38	4.63	14.2	13.6	12.9
Central: 32.7	2.66	4.28	4.64	13.5	13.3	12.5
Western: 32.8	1.33	2.08	2.36	12.8	12.3	11.5

Notes: Covariates are measured at the baseline. Means and standard deviations in parentheses are reported for cognitive scores.

educated, less financially constrained, and living in urban areas. Internet use in 2013 was also strongly related to gender, marital status, living with children, and living in the western region of China. Nevertheless, we find no significant coefficients of functional impairments or depressive symptoms on Internet use in either year.

After accounting for the initial cognitive performance, individuals who used the Internet in 2011 (2013) scored 0.15 (0.12) standard deviations higher than non-users on cognitive tests in 2013 (2015). The effects of Internet use on cognitive function seemed to be smaller in magnitude than the other way around. It was not unexpected, however, since we have measured the general Internet use without specifying activities engaged in online. The raw correlation between cognitive score 2011 (2013) and 2013 (2015) was 0.61 (0.67). Nevertheless, accounting for the individual latent variable made cognition 2013 much more predictive of cognition 2015 than was cognition 2011 of 2013.

Cognitive ability was lower among people from older cohorts as well as those with functional limitations. Marital status, educational attainment, household economic resources, depressive symptoms, and urban residence were also significant predictors of cognition 2013, but their effects on cognition 2015 appeared to be fully mediated. Conditional on cognitive function two years prior, males performed slightly better in 2013 cognitive tests, while the impact of gender was somehow reversed in 2015.

Coefficients of the latent variable turned out to be highly significant, which justified its inclusion. Latent variables always have indeterminate meanings a priori. For the current estimation, the individual latent variable captured traits that would negatively predict Internet use (cognition) in 2013 conditional on that in 2011. In the meanwhile, these same traits were positively associated with the change between 2013 and 2015, once Internet use (cognition) in 2013 was kept constant. Individuals who tended to be Internet users also scored higher on cognitive tests in the same year.

Table 3 gives results for separate cognitive domains using the same specification as that in Panel B of Table 2. Better cognitive performance in either dimension was correlated with an increased

Table 2: Results of the cross-lagged model

	Internet use (2013)		Internet use (2015)		Cognition	Cognition
	Coef.	AME: %	Coef.	AME: %	(2013)	(2015)
Panel A. Individual latent variable excluded						
Internet use	1.64**	19.6**	1.75**	23.4**	0.15**	0.13**
	(0.10)	(2.24)	(0.09)	(2.16)	(0.04)	(0.03)
Cognitive score	0.15**	0.69**	0.30**	1.47**	0.41**	0.50**
	(0.04)	(0.17)	(0.04)	(0.22)	(0.01)	(0.01)
Number of observations	11,592		11,793		11,497	10,148
Panel B. Individual latent variable included						
Internet use	1.66**	19.3**	1.81**	23.5**	0.15**	0.12**
	(0.10)	(2.21)	(0.09)	(2.11)	(0.04)	(0.04)
Cognitive score	0.17**	0.77**	0.62**	3.27**	0.42**	0.99**
	(0.04)	(0.17)	(0.07)	(0.45)	(0.01)	(0.02)
Individual latent variable	-0.20**		0.37**		-0.57**	0.55**
	(0.04)		(0.06)		(0.04)	(0.04)
Number of observations	11,592		11,793		11,497	10,148

Notes: Both estimated coefficients and population-averaged average marginal effects (AME) are reported for each probit equation of Internet use. Robust standard errors clustered at the community level are given in parentheses. Covariates are included in all equations. ** $p < 0.01$, * $p < 0.05$.

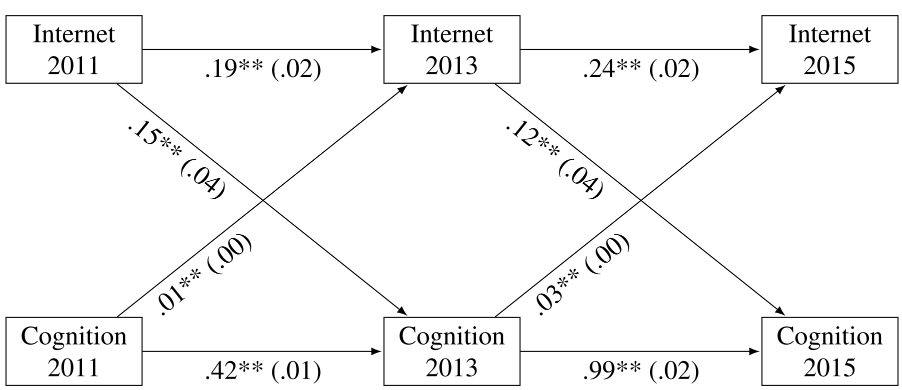

Figure 1: Cross-lagged panel model of Internet use and cognition. The effects on Internet use are average marginal effects. Robust standard errors are given in parentheses. Covariates and the individual latent variable are included in the estimation but not reported. ** $p < 0.01$, * $p < 0.05$.

likelihood of using the Internet. Memory seemed to derive more benefit from Internet use than mental intactness, while the differences were not large enough to generate non-overlapping confidence intervals. We discuss results with the overall cognitive score in the following analysis.

Table 3: Separate cognitive domains

	Internet use (2013)		Internet use (2015)		Cognition (2013)		Cognition (2015)	
	AME: %		AME: %					
Panel A. Episodic memory								
Internet use	19.6**	(2.24)	24.2**	(2.21)	0.19**	(0.05)	0.12*	(0.05)
Cognitive score	0.53**	(0.14)	2.42**	(0.41)	0.30**	(0.01)	1.00**	(0.03)
Number of observations	11,592		11,793		11,497		10,148	
Panel B. Intact mental status								
Internet use	20.1**	(2.27)	24.3**	(2.11)	0.10**	(0.03)	0.10*	(0.04)
Cognitive score	0.49**	(0.19)	2.73**	(0.44)	0.42**	(0.01)	1.01**	(0.02)
Number of observations	11,592		11,793		11,497		10,148	

Notes: Population-averaged average marginal effects (AME) are reported for each probit equation of Internet use. Robust standard errors clustered at the community level are given in parentheses. Covariates and the individual latent variable are included in all equations. ** $p < 0.01$, * $p < 0.05$.

Stratified Analysis

Demographic variables have been included as covariates in the previous estimations, but they might also influence the reciprocal Internet-cognition relationship discovered above. Three sets of stratified analyses are thus conducted to determine whether the estimated associations would differ according to gender, age, and education. We find that the significant bidirectional relationship generally survived across alternative subsamples.

Separate results for females and males are listed in Panel A and B of Table 4, respectively. Cognition in 2013 appeared to differentiate Internet users from non-users in 2015 to a greater extent for males than for females. Cognitive benefits from using the Internet were more robust for men than for women. These findings are in line with previous studies (Freese et al., 2006; Tun and Lachman, 2010). There might exist differences between genders in the types of Internet use (Morris et al., 2007).

We next split the sample by age at the baseline survey. Since the proportion of Internet users in older age groups was small, we distinguish between middle-aged (aged 45 to 54) and older adults (aged no less than 55). For the older subsample, the more modest marginal effects of cognition on the likelihood of Internet adoption probably came from a much lower rate of Internet use. The Internet seemed to be more mentally stimulating if it was introduced in one's midlife when the cognitive decline was already evident (Singh-Manoux et al., 2012).

Panel E and F report stratified results by educational attainment. The cognitive function had stronger effects on Internet use for the better-educated group. For people with more opportunities for exposure to the Internet, cognitive incompetence might be a major barrier that discouraged some of them from using new technologies. Better-educated adults seemed to reap more persistent benefits from using the Internet. It might imply an enlarging education-cognition gradient since education was positively associated with both Internet use and cognition (Huang and Zhou, 2013; Kämpfen and Maurer, 2018).

Sensitivity Analysis

Table 5, Panel A presents results with the latent variable for community effects included. Compared with the benchmark results shown in Table 3, the lagged impacts of Internet use and cognition on each other remained mostly similar. The reciprocal Internet-cognition relationship found above was not driven by some unmeasured community influences.

To arrive closer to causal inferences, Panel B reports results on a subsample of participants who had broadband Internet access at home. Having access was far from sufficient for middle-aged and older Chinese adults to utilize the Internet. In this subsample, the proportion of Internet users was 5.9%, 9.0%, and 10.7% in 2011, 2013, and 2015, respectively.

Restricting the analysis to people with similar socio-economic backgrounds could not eliminate the positive bidirectional association between Internet use and cognition. Individuals with lower cognitive abilities were less apt to make use of the Internet, even if they had access. The declining

Table 4: Subsamples by gender, age, or education

	Internet use (2013)		Internet use (2015)		Cognition (2013)		Cognition (2015)	
	AME: %		AME: %					
Panel A. Female								
Internet use	6.19**	(0.47)	7.55**	(0.61)	0.15**	(0.05)	0.06	(0.07)
Cognitive score	0.85**	(0.22)	2.17**	(0.50)	0.44**	(0.01)	1.00**	(0.03)
Number of observations	6,069		6,174		6,016		5,304	
Panel B. Male								
Internet use	8.81**	(0.74)	11.5**	(0.78)	0.15**	(0.04)	0.16**	(0.05)
Cognitive score	0.64*	(0.27)	4.35**	(0.74)	0.38**	(0.01)	0.98**	(0.03)
Number of observations	5,523		5,619		5,481		4,844	
Panel C. Age: 45 - 54								
Internet use	11.8**	(0.93)	16.0**	(1.04)	0.16**	(0.04)	0.18**	(0.05)
Cognitive score	0.93*	(0.42)	5.95**	(0.99)	0.37**	(0.02)	0.98**	(0.04)
Number of observations	4,023		4,132		3,999		3,573	
Panel D. Age: 55 +								
Internet use	16.8**	(3.31)	19.3**	(2.95)	0.17**	(0.06)	0.04	(0.06)
Cognitive score	0.72**	(0.16)	2.19**	(0.47)	0.44**	(0.01)	1.00**	(0.03)
Number of observations	7,569		7,661		7,498		6,575	
Panel E. Education: elementary school or below								
Internet use	29.0**	(10.7)	22.7**	(6.04)	0.26*	(0.12)	0.04	(0.12)
Cognitive score	0.06	(0.06)	0.71**	(0.24)	0.43**	(0.01)	1.01**	(0.03)
Number of observations	7,734		8,000		7,662		6,795	
Panel F. Education: middle school or above								
Internet use	36.6**	(3.09)	41.6**	(3.03)	0.17**	(0.04)	0.16**	(0.05)
Cognitive score	2.19**	(0.52)	9.17**	(1.42)	0.36**	(0.02)	0.91**	(0.04)
Number of observations	3,858		3,793		3,835		3,353	

Notes: See notes following Table 3. ** $p < 0.01$, * $p < 0.05$.

cognitive function might make it challenging to use and operate new technologies successfully.

To our knowledge, only one study has examined the cognitive benefits of involvement with computer technology in China. Jin et al. (2019) found a positive effect of household desktop ownership on the cognitive function of its older members using the same CHARLS data. However, the possession of technology can be different from the use of technology, especially in households with multiple members (Kamin and Lang, 2016). Focusing on actual Internet use, we provide evidence suggesting that it was the mental stimulation offered by Internet activities that helped maintain cognitive function.

Table 5: Sensitivity checks

	Internet use (2013)		Internet use (2015)		Cognition (2013)		Cognition (2015)	
	AME: %		AME: %					
Panel A. Community latent variable included								
Internet use	19.0**	(2.25)	23.1**	(2.21)	0.13**	(0.04)	0.10*	(0.04)
Cognitive score	0.81**	(0.17)	3.15**	(0.45)	0.43**	(0.01)	0.98**	(0.02)
Number of observations	11,592		11,793		11,497		10,148	
Panel B. Households with broadband Internet access								
Internet use	28.2**	(2.87)	31.2**	(2.62)	0.14**	(0.04)	0.10*	(0.04)
Cognitive score	1.56**	(0.41)	7.27**	(1.24)	0.40**	(0.02)	1.00**	(0.04)
Number of observations	4,546		3,883		4,490		3,369	

Notes: See notes following Table 3. ** $p < 0.01$, * $p < 0.05$.

Conclusion

Although improvements in the quality of life depend increasingly on technological developments, there were very few middle-aged and older Chinese using the Internet in our study period. As a fast-growing population group, older adults have become the focal point of many social policies but seem not to catch the attention of technology markets as consumers of great potential yet. The current study extends the empirical evidence regarding the reciprocal association between Internet use and cognition to a developing country context.

Our findings highlight the role of cognitive function as a significant predictor of Internet use among middle-aged and older adults. Since more and more services are delivered through information technologies, the Internet should be made available and usable, especially to older people with declining cognitive abilities. The design of digital products and training programs needs to accommodate more for the capabilities of aging adults, such as by reducing the complexity of the operation and offloading cognitive requirements (Hawthorn, 2000).

Cognitive skills are essential for making better decisions and living independently (Salthouse, 2012). We observe that prior Internet use reduced cognitive decline over time, which could provide further motivation to start and keep using new technologies. Although the estimated protective effects of the general use of the Internet were relatively small in magnitude, we are expecting more substantial benefits from specific online stimulating activities. Using the Internet might provide a cost-effective way to prevent age-related cognitive decline.

The reciprocal, dynamic relationship between Internet use and cognition is also of policy interest. The cognitive inequalities as people age could widen the existing digital divide, which might, in turn, breed new inequalities in cognitive skills. Furthermore, our stratified analysis suggests that the already advantaged groups, males, younger cohorts, and better-educated adults, could derive more persistent benefits from being online. To help reduce disparities, the promotion of Internet use and healthy cognitive aging should put more emphasis on disadvantaged segments of the population.

The current study has been limited by its time frame when the Internet popularization was still in an early phase in China. The low usage rate among middle-aged and older adults made specific facets of Internet use less informative, such as activities engaged in online, frequency of use, and duration of use. There has been a trend towards going online via mobile devices, such as tablet computers and smartphones, which might involve more older adults with new technologies in the future. Research with further follow-ups is needed for a better understanding of the long-term Internet-cognition relationship.

Demonstrating causality in an observational study is difficult. We are thus cautious about making causal inferences. The same cognitive tests were given to the same individuals multiple times. It is not clear whether Internet use could help maintain general cognitive function or make people more adapting to repeated tests. Future research using alternative designs, such as randomized trials, is required to understand the underlying causal mechanisms.

Appendix

Table A1: Results of the cross-lagged model

	Internet use (2013)		Internet use (2015)		Cognition	Cognition
	Coef.	AME: %	Coef.	AME: %	(2013)	(2015)
Internet use	1.66** (0.10)	19.3** (2.21)	1.81** (0.09)	23.5** (2.11)	0.15** (0.04)	0.12** (0.04)
Cognitive score	0.17** (0.04)	0.77** (0.17)	0.62** (0.07)	3.27** (0.45)	0.42** (0.01)	0.99** (0.02)
Age						
55 - 64	-0.16* (0.08)	-0.76* (0.37)	-0.31** (0.07)	-1.74** (0.43)	-0.04* (0.02)	-0.03 (0.02)
65 - 74	-0.42** (0.11)	-1.74** (0.42)	-0.41** (0.11)	-2.20** (0.54)	-0.21** (0.02)	-0.08** (0.02)
75 +	-0.56* (0.23)	-2.15** (0.66)	-0.78** (0.20)	-3.52** (0.68)	-0.46** (0.03)	-0.16** (0.04)
Male	0.13* (0.06)	0.59* (0.28)	0.10 (0.07)	0.51 (0.36)	0.04** (0.01)	-0.05** (0.02)
Married or partnered	-0.25* (0.11)	-1.25* (0.61)	-0.06 (0.10)	-0.34 (0.56)	0.05** (0.02)	0.01 (0.02)
Educational level						
Elementary school	0.37* (0.16)	0.79* (0.33)	0.28 (0.14)	1.02* (0.49)	0.34** (0.02)	0.05 (0.03)
Middle school	0.87** (0.14)	2.81** (0.40)	0.63** (0.14)	2.86** (0.51)	0.50** (0.02)	0.05 (0.03)
High school or above	1.27** (0.14)	5.78** (0.63)	0.81** (0.15)	4.13** (0.62)	0.65** (0.03)	0.02 (0.04)
Expenditure per capita						
Second quartile	0.10 (0.16)	0.30 (0.48)	0.20 (0.14)	0.88 (0.62)	0.03 (0.02)	0.01 (0.02)
Third quartile	0.45** (0.14)	1.67** (0.48)	0.22 (0.13)	0.98 (0.57)	0.09** (0.02)	0.03 (0.02)
Fourth quartile	0.61** (0.14)	2.57** (0.50)	0.39** (0.14)	1.93** (0.69)	0.09** (0.02)	0.01 (0.02)
Information missing	0.44** (0.15)	1.64** (0.51)	0.32* (0.13)	1.54** (0.59)	0.07** (0.02)	0.01 (0.02)
Functional impairment	-0.15 (0.10)	-0.63 (0.39)	-0.12 (0.10)	-0.59 (0.48)	-0.04* (0.02)	-0.04* (0.02)
Depressive symptom	-0.12 (0.07)	-0.52 (0.31)	-0.03 (0.08)	-0.15 (0.39)	-0.06** (0.01)	0.00 (0.02)
Living with children	0.22** (0.07)	0.95** (0.29)	-0.06 (0.07)	-0.34 (0.37)	-0.02 (0.01)	-0.01 (0.01)
Urban residence	0.53** (0.09)	2.34** (0.36)	0.30** (0.08)	1.58** (0.41)	0.13** (0.02)	-0.02 (0.02)
Region						
Central	0.04 (0.08)	0.21 (0.40)	0.01 (0.08)	0.04 (0.44)	0.00 (0.02)	-0.04 (0.02)
Western	-0.21* (0.11)	-0.90* (0.42)	-0.13 (0.10)	-0.67 (0.50)	-0.04 (0.03)	-0.04 (0.02)
Individual latent variable	-0.20** (0.04)		0.37** (0.06)		-0.57** (0.04)	0.55** (0.04)
Number of observations	11,592		11,793		11,497	10,148

Notes: Both estimated coefficients and population-averaged average marginal effects (AME) are reported for each probit equation of Internet use. Robust standard errors clustered at the community level are given in parentheses. Omitted categories are '45-54' for age, 'below elementary school' for educational level, 'first quartile' for expenditure per capita, and 'coastal' for region. ** $p < 0.01$, * $p < 0.05$.

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