

Sociodemographic Digital Divide in Cognitive Function Among Middle-Aged and Older Adults in China: Longitudinal Observational Study

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Abstract

Background: The digital divide has evolved from a simple binary concept of connectivity into a three-level framework encompassing access, usage, and outcomes. In the context of aging populations, this divide may significantly impact cognitive health, yet empirical validation of this framework remains limited.

Objective: This study aimed to document the cascade of influences from digital access to internet use and then to cognitive outcomes and examine how sociodemographic factors affect each element of this pathway over time.

Methods: A longitudinal analysis was conducted using nationally representative data from middle-aged and older adults in China. Parallel Process Latent Growth Curve Modeling (PP-LGCM) was employed to validate the three-level digital divide construct and track its impact on cognitive trajectories.

Results: The γ coefficients of potential influence showed that digital access more strongly influenced internet use ($\gamma=0.53$) than internet use affected cognition ($\gamma=0.19$) at baseline. However, this pattern shifted over time, with the impact of usage growth on cognitive trajectories ($\gamma=0.31$) becoming more pronounced than access growth on usage development ($\gamma=0.25$). Age had a stronger negative effect on the growth of digital usage ($\gamma=-0.41$) than on initial access and cognition, while education was positively associated with baseline digital engagement and showed strong benefits for initial cognition ($\gamma=0.48$). Rural residence was associated with lower initial digital access ($\gamma=-0.30$) and continued to impede the development of digital usage despite positive growth in access.

Conclusions: To address cognitive health disparities in aging populations, interventions must target both immediate and sustained digital engagement following the digital divide pathway over time, with a particular focus on improving digital access and use among older, less educated, and rural populations.

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Original Manuscript

Original Paper

Digital Divide Cascade: Longitudinal Pathways from Access to Usage to Cognitive Health Among Aging Chinese Adults

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Abstract

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trajectories ($\beta=0.31$) becoming more pronounced than access growth on usage development ($\beta=0.25$). Age had a stronger negative effect on the growth of digital usage ($\beta=-0.41$) than on initial access and cognition, while education was positively associated with baseline digital engagement and showed strong benefits for initial cognition ($\beta=0.48$). Rural residence was associated with lower initial digital access ($\beta=-0.30$) and continued to impede the development of digital usage despite positive growth in access.

Conclusions: To address cognitive health disparities in aging populations, interventions must target both immediate and sustained digital engagement following the digital divide pathway over time, with a particular focus on improving digital access and use among older, less educated, and rural populations.

Keywords: Digital divide; Cascade; Cognitive function; Trajectory; PP-LGCM

Introduction

In the digital age, the Internet is central to accessing information, maintaining social connections, and managing everyday tasks¹. Around 2.6 billion people worldwide (roughly 32% of the population) remain offline as of 2024². The benefits of digital innovation are unevenly distributed, resulting in a persistent "digital divide"³. It has evolved from a simple binary notion of connectivity in the 1990s⁴ into a three-level construct from coverage and access, usage, and real-world consequences^{5,6} with significant implications for individual health and societal well-being^{7,8}.

The "Internet Plus" action plan in China, initiated in 2015, aimed to integrate the Internet with various sectors, including healthcare, to enhance service delivery and efficiency⁹. Following its implementation, there has been a significant increase in internet users, which has facilitated greater access to digital use¹⁰. However, age is a key determinant of digital divide¹¹. Older adults face disparities in the utilization of these digital technologies^{11,12}, with many unable to connect with peers through digital networks due to a lack of digital skills¹³. A cohort study in 2024 reported nearly half of participants faced the digital use divide among older adults in Beijing, which was associated with a worse performance in processing speed and general cognitive function¹⁴.

As population age rapidly worldwide, cognitive decline is a major risk factor for disability¹⁵, dementia¹⁶, and death¹⁷. It often begins in individuals aged between 45 and 49 years¹⁸. China

has the largest population of older people in the world¹⁹. Almost 20% of adults over 60 have mild cognitive impairment, with 6% progressing to dementia annually²⁰⁻²².

The digital divide as a determinant of health²³ is strongly linked to the cognitive disparities^{14,24}. For digital access, digital device ownership has been independently associated with slower cognitive decline²⁵. For digital usage, Internet and email use are strong predictors of improved performance in delayed recall²⁶. Different types of digital activities uniquely contribute to mitigating cognitive decline²⁷, and an increased likelihood of cognitive maintenance²⁸. Moreover, emerging evidence indicates that internet use appears optimal for preserving intrinsic capacity²⁹, and regular digital engagement may lead to persistent improvements in global cognitive functions^{30,31}. Collectively, these findings suggest that increasing digital access and encouraging regular, diverse digital engagement could serve as an effective, non-pharmacological intervention to reduce cognitive decline in later life²⁷. Based on the three-level digital divide theoretical framework and empirical evidence linking broadband subscription and internet use to cognitive functions. This study proposes that internet use may serve as a key intermediary between broadband subscription and cognitive outcomes as Figure 1. This hypothesis suggests a cascade effect where digital inequalities progressively impact cognitive health. Although evidence supports the evolving nature of the digital gap among older adults, longitudinal research is essential to fully understand the developmental spectrum of the digital divide and its enduring implications for cognitive resilience and decline. Concurrently, China is experiencing population aging and digital infrastructure development rapidly, which offers a critical natural context for investigating the digital divide phenomenon among middle-aged and older adults.

Current studies mainly focus on either digital access or digital use in isolation, neglecting an integrated three-level digital divide framework that captures the cascade effect from access to use and ultimately to cognitive trajectories. Moreover, few studies have explored the full spectrum of older adults' digital technology experience over time³². Building on this framework, the parallel process latent growth curve model (PP-LGCM)³³ approach could examine how digital access disparities not only predict initial differences in digital use and cognitive functions (intercept factors) but also shape trajectories of use and cognitive functions (slope factors) over time. By simultaneously examining the differential impact of sociodemographic variables at each stage of the digital cascade and their diffusion through the

pathway, our analysis offers insights for evidence-based policies to reduce the digital divide.

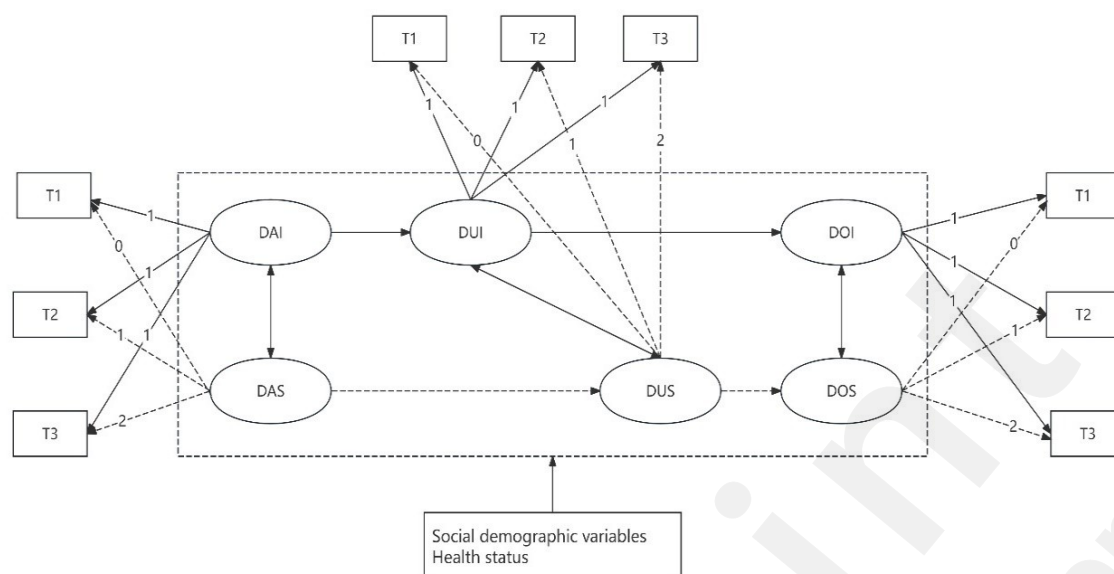


Figure 1. The hypothesized model of the digital divide across three waves. T1: Time 1 (2015), T2: Time 2 (2018), T3: Time 3 (2020). In this model, intercept factors—digital access (DAI), digital use (DUI), and digital outcomes (DOI)—capture baseline levels of outcomes, such as household bandwidth, internet use, and cognitive functions, respectively. Slope factors—digital access slope (DAS), digital use slope (DUS), and digital outcomes slope (DOS)—represent the rates of change in these outcomes over time. This configuration allows for an integrated longitudinal analysis of how initial levels in digital resources and practices influence future trajectories and digital outcomes, thereby providing a comprehensive view of the evolving digital divide.

Methods

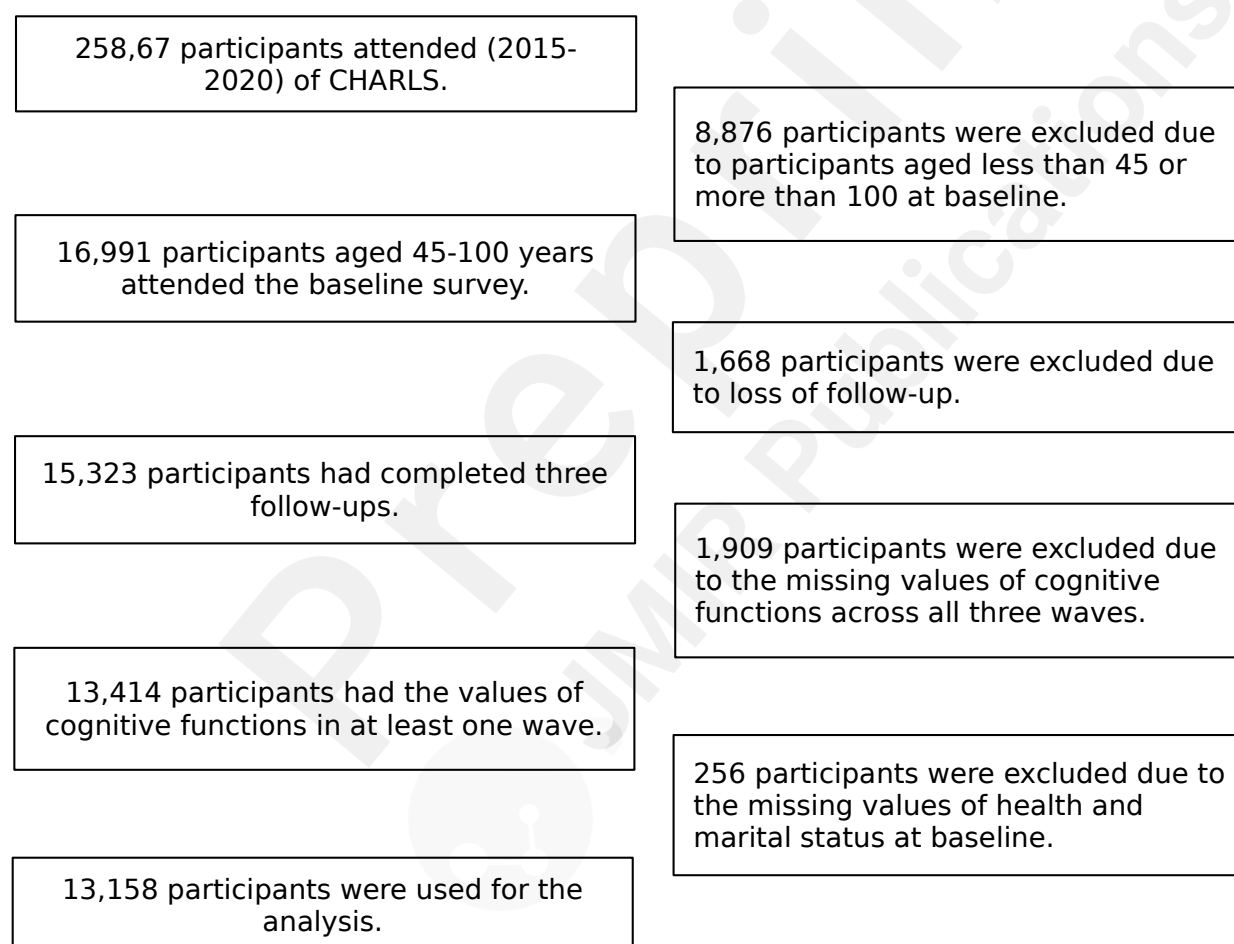
Participants

Participants were enrolled in three follow-ups of the China Health and Retirement Longitudinal Study (CHARLS) from 2015 to 2020. It is a nationally representative sample of the middle-aged and elderly population (45+ years) in China, which is a community-based longitudinal study, conducted by China Center for Economic Research at Peking University³⁴. The CHARLS utilized a multi-stage stratified probability-proportional-to-size sampling technique to select participants. The primary sampling units were administrative villages in rural residences and neighborhoods in urban areas. The CHARLS data can be accessed through its official website (charls.ccer.edu.cn/en). It is designed to better understand the socioeconomic determinants and consequences of aging.

This study used CHARLS data to do analysis and research. A final sample of 13,158 respondents

resulted from an initial pool of 25,867. This study focused on adults aged 45 to 100 years old in 2015. We used data from Wave 3 (2015) as a baseline, with follow-up data from Wave 4 (2018) and Wave 5 (2020), representing a 5-year longitudinal period. Household broadband ownership, internet use, and cognitive function were assessed using consistent measures across all three waves. We applied the following exclusion criteria: (1) respondents aged below 45 or above 100 years at baseline ($n=8,876$), (2) participants lost to follow-up after matching across the three waves ($n=1,668$), (3) missing information on cognitive function ($n=1,909$), and (4) missing data for independent variables ($n=256$). Missing internet use data was recorded as 0. Figure 2 illustrates the participant screening process and final sample derivation.

Figure 2. Flowchart of participant selection.



Measurements

Dependent variables

Cognitive function assessment tools used an adapted Chinese version of the Mini-Mental State

Examination (MMSE)³⁵. Four specific dimensions were assessed at each wave, including orientation, episodic memory, calculation ability, and constructability. Orientation was measured by naming the date (day, month, and year), and day of the week (score range: 0 - 4). For episodic memory, participants were first asked to immediately repeat as many as possible of 10 Chinese nouns that were just read to them and then to recall the same list 5 minutes later (score range: 0 - 20). Calculation ability was evaluated using the Serial 7 subtraction task, which required participants to subtract 7 from 100 and continue subtracting 7 from each subsequent number 5 times (score range: 0 - 5). Constructability was evaluated through a drawing task that assesses visuospatial skills and motor coordination (score range: 0 - 1). General cognition was the sum of cognitive scores (score range: 0 - 30)³⁶, which was considered to be the digital outcome.

Mediators

The digital divides were measured by the ownership of a household broadband connection, and the usage of the internet. Respectively, digital access and use were measured by followed questions: "Does your residence have a broadband internet connection?", "Have you accessed the Internet in the past month?". All measures were dichotomized into yes-no answers.

Independent variables

Demographic characteristics included age, gender, education, area of residence, and marital status, self-reported health status. In this study, the ages were ranged from 45 to 100. Gender was coded dichotomously (Male=0, Female=1). Education was categorized into 4 groups (No education, Primary and Secondary education, High School and Vocational School=3, College and above). Rural residence was a dummy variable (No=0, Yes =1), and Marital status was categorized into two groups (Single=0, Couple=1). Self-reported health status was measured at each wave using a single item asking participants to rate their overall health on a 5-point scale (1 = excellent, 5 = poor).

Statistical Analysis

Analysis was performed using R (version 4.1.0) for descriptive, correlational analyses. Descriptive statistics were used to summarize the characteristics of the clients, namely frequency with percentage for categorical variables and median with IQR) for continuous variables. The "lavaan" R package was used to examine structural equation modeling. We

employed parallel process Latent Growth Curve Modeling (PP-LGCM) to examine the cascade effects of digital access to digital use on trajectories in cognitive functions. For each domain, we modeled the baseline level (intercept) and rate of change over time (slope)³⁷. The cascade effects framework posits that digital access influences digital use, which in turn affects the intercepts and slopes of the cognitive. Full Information Maximum Likelihood (FIML) was used for handling missing data by utilizing all available information from each participant. The following four model fit indices were examined: the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of Approximation (RMSEA), and standardized root mean square residual (SRMR). According to standard conventions, CFI and TLI indices above .90 are thought to be acceptable, and values above .95 indicate a good fit. For RMSEA and SRMR, values below .05 indicate a good fit, and values between .05 and .08 indicate an acceptable fit³⁸. In conditional LGCM and PP-LGCM, demographic variables were included as predictor variables.

Results

Descriptive Statistics

A total of N = 13,158 Chinese middle-aged and older adults were included in this study, Table 1 showed significant sociodemographic disparities in digital access and use. Participants with broadband access (30.2%) and those using the internet (6.8%) were notably younger, with median ages of 54 and 51 years, respectively, compared to 60 and 59 years among those without broadband or internet. While the gender distribution remained relatively balanced for broadband access, internet users comprised a higher proportion of males (62.1% male vs. 37.9% female). Educational attainment markedly distinguished the groups. Among non-broadband users, 21.7% were illiterate, and only 0.6% attained college education, whereas broadband users had lower illiteracy (8.7%) and higher college education rates (4.3%). This disparity was even more pronounced among internet users, where illiteracy was almost negligible (0.1%) and 14.5% had college-level education. Rural-urban disparities were also evident. Rural residents represented 70.1% of those without broadband and 63.9% among non-internet users, contrasting with 41.6% and 27.3% for broadband and internet users, respectively. Marital status, while less variable, showed a slightly higher proportion of coupled individuals among those with digital access. For health status, the proportion of participants reporting excellent or very good health was higher among those with broadband (30.7%) and internet access (40.2%) compared to their non-digital counterparts (22.3% for non-broadband

and 23.8% for non-internet users). Additionally, sociodemographic digital divide and cognitive function disparities at different waves were significant as detailed in Multimedia Appendix 2 and Multimedia Appendix 3, respectively.

Table 1. Baseline characteristics of participants by digital divide status

	No broadband	Broadband	P value	No internet	Internet	P value	Total
Total	9178	3980		12267	891		13158
Age(year)			< 0.001			< 0.001	
median (IQR)	60 (52,66)	54 (49,61)		59 (52,65)	51 (47,57)		58 (51,65)
Gender			0.772			< 0.001	
Male	4639 (50.5)	2000 (50.3)		6086 (49.6)	553 (62.1)		6639 (50.5)
Female	4539 (49.5)	1980 (49.7)		6181 (50.4)	338 (37.9)		6519 (49.5)
Education			< 0.001			< 0.001	
Illiterate	1988 (21.7)	347 (8.7)		2334 (19)	1 (0.1)		2335 (17.7)
Primary	4566 (49.7)	1466 (36.8)		5919 (48.3)	113 (12.7)		6032 (45.8)
Secondary	2565 (27.9)	1994 (50.1)		3911 (31.9)	648 (72.7)		4559 (34.6)
College and above	59 (0.6)	173 (4.3)		103 (0.8)	129 (14.5)		232 (1.8)
Rural Residence			< 0.001			< 0.001	
Yes	6433 (70.1)	1654 (41.6)		7844 (63.9)	243 (27.3)		8087 (61.5)
No	2745 (29.9)	2326 (58.4)		4423 (36.1)	648 (72.7)		5071 (38.5)
Marriage			< 0.001			< 0.001	
Single	1049 (11.4)	288 (7.2)		1278 (10.4)	59 (6.6)		1337 (10.2)
Couple	8129 (88.6)	3692 (92.8)		10989 (89.6)	832 (93.4)		11821 (89.8)
Health status			< 0.001			< 0.001	
Excellent	1060 (11.5)	577 (14.5)		1480 (12.1)	157 (17.6)		1637 (12.4)
Very Good	994 (10.8)	646 (16.2)		1439 (11.7)	201 (22.6)		1640 (12.5)
Good	5001 (54.5)	2196 (55.2)		6736 (54.9)	461 (51.7)		7197 (54.7)
Fair	1671 (18.2)	470 (11.8)		2081 (17)	60 (6.7)		2141 (16.3)
Poor	452 (4.9)	91 (2.3)		531 (4.3)	12 (1.3)		543 (4.1)

Note. Rank sum test for age, and chi-square test for others.

Bivariate correlations

Results from Table 2 revealed moderate stability in household broadband access (DA) across time points ($r = 0.33$ - 0.46), with similar patterns observed for internet use (DU, $r = 0.30$ - 0.44)

and stronger consistency in cognitive function (DO, $r = 0.52-0.58$). Cross-domain correlations indicated that household broadband access was positively associated with internet use ($r = 0.19-0.36$) and modestly related to cognitive function ($r = 0.19-0.24$). Internet use showed slightly stronger relationships with cognitive outcomes ($r = 0.21-0.32$). These patterns suggested relationships between digital access, internet engagement, and cognitive functioning over time.

Table 2 Bivariate correlations (Spearman r and 2-tailed P value)

	DA			DU			DO		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
DA at T1	1.00								
DA at T2	0.45	1.00							
DA at T3	0.33	0.46	1.00						
DU at T1	0.34	0.24	0.19	1.00					
DU at T2	0.28	0.29	0.22	0.44	1.00				
DU at T3	0.30	0.35	0.36	0.30	0.39	1.00			
DO at T1	0.20	0.21	0.19	0.25	0.26	0.30	1.00		
DO at T2	0.22	0.24	0.23	0.23	0.26	0.32	0.52	1.00	
DO at T3	0.20	0.20	0.20	0.21	0.23	0.30	0.53	0.58	1.00

Note. Correlations above were all significant at $p < .001$. DA= household broadband subscription, DU= internet use, DO = general cognitive. T1 to T3 = assessment Waves 1 to 3. a: Mean (SD).

Conditional LGCMs for each element of digital divide

Table 3. Model Fit Indices for Conditional Latent Growth Curve Models

Variable	$\chi^2(df)$	CFI	TLI	RMSEA A	RMSEA 90% CI	SRMR
DA	40.808(7)	0.997	0.990	0.019	[0.014,0.025]	0.006
DU	13.996(6)	0.999	0.998	0.010	[0.003,0.017]	0.004
DO	315.436 (7)	0.980	0.941	0.058	[0.053,0.063]	0.029

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; SRMR = Standardized Root Mean Square Residual.

The model fit indices in Table 3 provided strong support for the measurement models underlying each domain. Household broadband access exhibited excellent fit with $\chi^2 (7) = 40.808$, CFI = 0.997, TLI = 0.990, RMSEA = 0.019 [90% CI: 0.014, 0.025], and SRMR = 0.006. Similarly, the internet use model (DU) demonstrated outstanding fit ($\chi^2 (6) = 13.996$, CFI = 0.999, TLI = 0.998, RMSEA = 0.010 [90% CI: 0.003, 0.017], SRMR = 0.004). The cognitive function (DO) model also provided acceptable fit with $\chi^2 (7) = 315.436$, CFI = 0.980, TLI =

0.941, RMSEA = 0.058 [90% CI: 0.053, 0.063], and SRMR = 0.029, indicating that while slightly lower, the indices remained within acceptable thresholds. Overall, these results supported the adequacy of the latent construct representations across time, supporting the validity of the developmental trajectories examined.

Table 4. Conditional latent growth curve models

Variable	DA			DU			DO		
	β	SE	P value	β	SE	P value	β	SE	P value
Fixed effects									
Intercept	2.050	0.041	< .001	0.999	0.022	< .001	3.940	0.399	< .001
Slope	1.364	0.027	< .001	2.945	0.011	< .001	1.248	0.233	< .001
Variance									
Intercept	0.736	0.003	< .001	0.783	0.001	< .001	0.509	0.350	< .001
Slope	0.966	0.002	< .001	0.743	0.001	< .001	0.985	0.171	< .001
Intercept-slope correlation	-0.449	0.002	< .001	-0.209	0.001	< .001	0.082	0.193	0.358
Intercept									
Log (Age)	-0.223	0.000	< .001	-0.152	0.001	< .001	-0.252	0.004	< .001
Gender	0.061	0.008	< .001	-0.008	0.004	0.467	0.013	0.074	0.169
Education	0.239	0.005	< .001	0.317	0.003	< .001	0.535	0.053	< .001
Rural residence	-0.292	0.008	< .001	-0.183	0.004	< .001	-0.125	0.074	< .001
Marital status	0.008	0.012	0.466	-0.035	0.007	0.001	0.056	0.121	< .001
Health status	-0.091	0.004	< .001	-0.079	0.002	< .001	-0.070	0.037	< .001
Slope									
Log (Age)	-0.119	0.000	< .001	-0.412	0.001	< .001	-0.117	0.003	< .001
Gender	0.003	0.005	0.857	0.017	0.002	0.121	0.003	0.043	0.909
Education	-0.002	0.004	0.917	0.201	0.001	< .001	-0.016	0.031	0.599
Rural residence	0.133	0.005	< .001	-0.033	0.002	0.002	0.027	0.042	0.304
Marital status	0.006	0.008	0.676	0.007	0.002	0.487	-0.018	0.073	0.527
Health status	0.038	0.002	0.006	-0.001	0.001	0.916	0.042	0.021	0.114

Note. β =standardized coefficients; SE= standardized error.

PP-LGCM in digital divide

The conditional latent growth curve analysis revealed significant patterns in the development of digital access, usage, and cognitive outcomes as shown in table 4. Household broadband access (DA), internet use (DU), and cognitive function (DO) all demonstrated positive growth trajectories over time (β = 1.364, 2.945, and 1.248 respectively, all p < .001). To accommodate potential non-linear growth patterns in internet usage, we specified a piecewise latent growth curve model with a freely estimated slope parameter at wave 3, capturing the accelerated adoption trajectory that emerged in later waves. Education emerged as the most consistent positive predictor of baseline levels across all three domains (β ranging from 0.239 to 0.535), with its strongest effect on cognitive function. Conversely, age (log-transformed) consistently demonstrated negative associations with initial levels (β = -0.223 to -0.252) and growth rates (β = -0.119 to -0.412) across all domains, suggesting that older individuals start lower and

progress more slowly in digital engagement and cognitive performance. Rural residence similarly showed negative effects on baseline levels ($\beta = -0.125$ to -0.292), though interestingly, it positively influenced growth in broadband access ($\beta = 0.133$), potentially indicating catch-up development in previously underserved areas. The significant negative intercept-slope correlations for broadband access (-0.449) and internet use (-0.209) suggested ceiling effects where those with higher initial levels experience slower growth. Health status demonstrated modest negative effects on initial performance across all domains, while gender and marital status showed minimal or inconsistent influences. A statistically significant negative covariances were observed between DAI and DAS ($= -0.39$), DUI and DUS ($\beta = -0.23$) as well, indicating an inverse relationship. However, covariance between DOI and DOS was not significant, suggesting limited empirical support for systematic covariation between these latent variables.

Table 5. Parallel process latent grow curve model

Link	β	SE	95% CI	P value
DUI~DAI	0.53	0.01	[0.50, 0.56]	< .001
DOI~DUI	0.19	0.01	[0.16, 0.21]	< .001
DUS~DAS	0.25	0.02	[0.22, 0.29]	< .001
DOS~DUS	0.31	0.06	[0.20, 0.42]	< .001
DAI ~ Log (Age)	-0.23	0.01	[-0.25, -0.21]	< .001
DAI ~ Gender	0.06	0.01	[0.04, 0.09]	< .001
DAI ~ Education	0.25	0.01	[0.23, 0.27]	< .001
DAI ~ Rural residence	-0.30	0.01	[-0.32, -0.28]	< .001
DAI ~ Marital status	0.01	0.01	[-0.01, 0.03]	0.45
DAI ~ Health status	-0.10	0.01	[-0.12, -0.07]	< .001
DUI ~ Log (Age)	-0.03	0.01	[-0.05, -0.01]	0.01
DUI ~ Gender	-0.04	0.01	[-0.06, -0.02]	< .001
DUI ~ Education	0.19	0.01	[0.16, 0.21]	< .001
DUI ~ Rural residence	-0.02	0.01	[-0.05, 0.00]	0.05
DUI ~ Marital status	-0.04	0.01	[-0.06, -0.02]	< .001
DUI ~ Health status	-0.03	0.01	[-0.05, -0.01]	0.01
DOI ~ Log (Age)	-0.22	0.01	[-0.24, -0.20]	< .001
DOI ~ Gender	0.01	0.01	[0.00, 0.03]	0.12
DOI ~ Education	0.48	0.01	[0.46, 0.50]	< .001
DOI ~ Rural residence	-0.09	0.01	[-0.11, -0.07]	< .001
DOI ~ Marital status	0.06	0.01	[0.04, 0.08]	< .001
DOI ~ Health status	-0.06	0.01	[-0.07, -0.04]	< .001
DAS ~ Log (Age)	-0.12	0.01	[-0.15, -0.09]	< .001
DAS ~ Gender	0.01	0.01	[-0.03, 0.03]	0.90
DAS ~ Education	-0.01	0.02	[-0.03, 0.03]	0.86
DAS ~ Rural residence	0.13	0.01	[0.11, 0.16]	< .001
DAS ~ Marital status	0.01	0.01	[-0.02, 0.03]	0.69
DAS ~ Health status	0.04	0.01	[0.01, 0.07]	0.01

DUS ~ Log (Age)	-0.41	0.02	[-0.44, -0.38]	< .001
DUS ~ Gender	0.02	0.01	[-0.01, 0.04]	0.13
DUS ~ Education	0.22	0.01	[0.19, 0.24]	< .001
DUS ~ Rural residence	-0.07	0.01	[-0.09, -0.05]	< .001
DUS ~ Marital status	0.01	0.01	[-0.02, 0.03]	0.57
DUS ~ Health status	-0.01	0.01	[-0.03, 0.01]	0.31
DOS ~ Log (Age)	0.03	0.03	[-0.04, 0.10]	0.36
DOS ~ Gender	-0.01	0.03	[-0.05, 0.05]	0.95
DOS ~ Education	-0.09	0.03	[-0.15, -0.02]	0.01
DOS ~ Rural residence	0.04	0.03	[-0.01, 0.09]	0.14
DOS ~ Marital status	-0.02	0.03	[-0.08, 0.03]	0.40
DOS ~ Health status	0.04	0.03	[-0.01, 0.09]	0.14
DAI ~ ~ DAS	-0.39	0.02	[-0.43, -0.35]	< .001
DUI ~ ~ DUS	-0.23	0.02	[-0.27, -0.19]	< .001
DOI ~ ~ DOS	-0.14	0.09	[-0.31, 0.02]	0.094

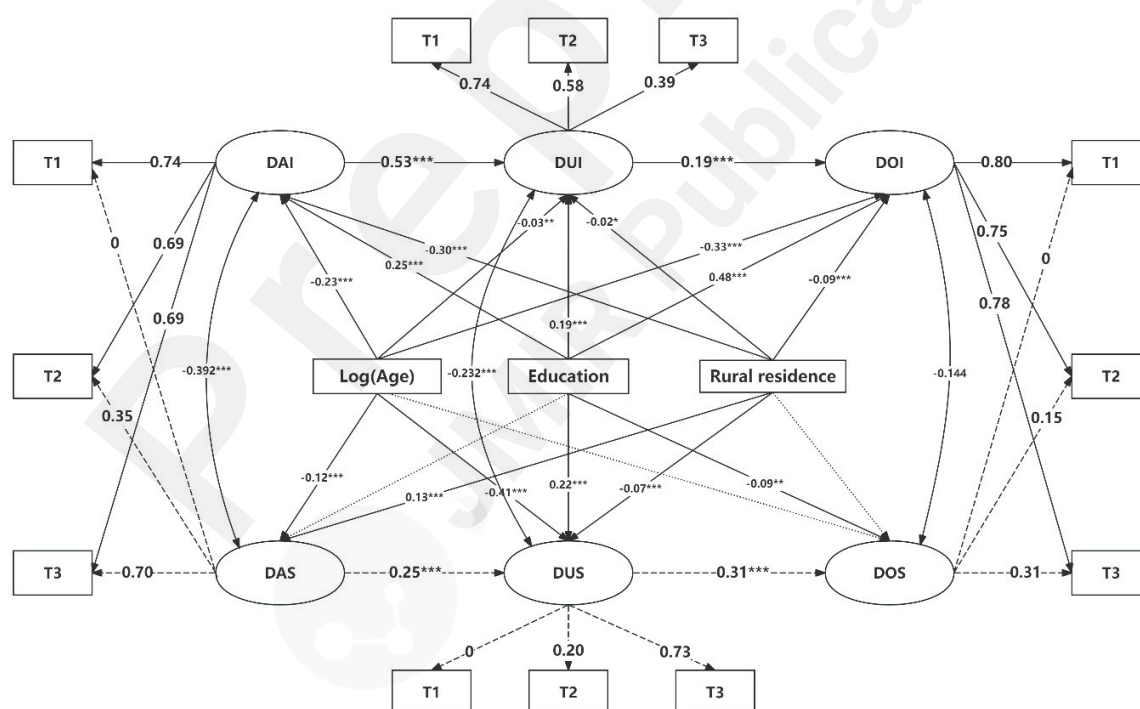
Note. β =standardized coefficients; SE= standardized error.

To examine the cascade effect of digital divide, a parallel growth model was built to simultaneously estimate the latent growth for broadband access, internet use, and cognitive outcomes as shown in Table 5 and presented in Figure 3. The result of the model provided an excellent fit to the data was estimated with $\chi^2(43) = 20.30$, CFI = 0.979, TLI = 0.956, RMSEA = 0.038, SRMR = 0.028. Specifically, the intercept of internet use (DUI) was significantly predicted by the intercept of broadband access (DAI; $\beta = 0.53$, 95% CI [0.49, 0.55]). Similarly, the slope of internet use (DUS) was positively influenced by the slope of broadband access (DAS; $\beta = 0.25$, 95% CI [0.22, 0.28]). In addition, the intercept of cognitive function (DOI) was significantly predicted by the intercept of internet use (DUI; $\beta = 0.19$, 95% CI [0.16, 0.21]), and the slope of cognitive function (DOS) was significantly influenced by the slope of internet use (DUS; $\beta = 0.31$, 95% CI [0.20, 0.42]). These findings suggest a cascading effect where broadband access influences internet use, which in turn affects cognitive outcomes, both at baseline and in terms of developmental trajectories over time.

Sociodemographic factors also influenced the cascade. At initial levels, age was related to lower digital access ($\beta = -0.23$), cognitive performance ($\beta = -0.22$), and the least effect on internet use. Higher education strongly predicted better baseline levels across all domains, significantly for cognitive function ($\beta = 0.48$) and digital access ($\beta = 0.25$). Rural residence was associated with lower initial digital access ($\beta = -0.30$) and cognitive function ($\beta = -0.09$). Gender, marital status, and health status showed more variable and generally smaller effects across the cascade components. For latent slope, age consistently impedes digital progression, with older adults exhibiting markedly slower growth in digital access ($\beta = -0.41$), more moderate reductions in internet use development ($\beta = -0.12$), and constrained cognitive outcomes. In contrast, education mitigates these age-related disadvantages, enhancing digital access trajectories ($\beta = 0.22$) while concurrently supporting cognitive performance and its longitudinal change.

Rural residence exhibits a more nuanced pattern, exerting minimal influence on digital use development ($\beta = -0.07$) yet unexpectedly contributing to positive growth in digital access ($\beta = 0.13$, $p < .001$).

Figure 3. Digital divide in cognitive function using PP-LGCM. For latent variables, dashed lines represent slope ones and their relationships, solid lines for intercept latent ones and their relationships; For regressions of sociodemographic variables, solid lines represent significant relationships, and dotted lines represent nonsignificant ones; double-headed arrows represent correlations; numbers on the lines from sociodemographic variables to latent variables are standardized coefficients, and numbers on the lines from latent variables to items are loadings. *** $P < .001$, ** $P < .01$, and * $P < .05$.



Discussion

Principal Results

Our study confirmed the three-level digital divide framework, demonstrating a clear cascade from digital access to internet usage to cognitive outcomes among aging Chinese adults. This longitudinal investigation extended previous research by documenting how these relationships evolve, revealing temporal dynamics that had significant implications for understanding digital disparities and cognitive health.

At baseline, our findings indicated that digital access strongly influences internet usage ($\beta = 0.53$), while internet usage exerted a more modest direct effect on cognitive function ($\beta = 0.19$). This pattern aligned with the theoretical model⁵, which posited that material access is a necessary precursor to developing digital skills and usage. Similarly, our results were consistent with the distinction between first-level (access) and second-level (usage) digital divides³⁹. However, our longitudinal evidence emphasized that access was not merely an initial barrier, and it continuously shaped the trajectory of digital engagement over time.

Our results revealed that the strength of these associations increases over time, suggesting a cumulative benefit of sustained digital engagement. Initially, access served as the primary gateway to digital engagement. However, sustained usage growth exerted a stronger influence on cognitive trajectories ($\beta = 0.31$) than the effect of access growth on usage development ($\beta = 0.25$). This temporal development supported the concept of sequential amplification, in which early digital access led to cumulative benefits in digital engagement and tended to compound over time⁴⁰, like a deepening digital divide⁴¹ effect analogous to the

"Matthew effect" described by Merton in 1968^{42,43}.

Our findings supported a cascading pathway from digital access through internet use to cognitive outcomes. Previous studies had primarily focused on one-step associations between cognitive health and ownership of digital devices²⁵ or internet use⁴⁴. Similarly, a sequence of cumulative effects was found from physical access to internet use, then to informative-expressive use^{45,46}, ignoring these intermediary steps and simply regressing outcomes on sociodemographic factors might lead to a misinterpretation of the relationships. Several mechanisms might explain the observed cascade from digital access to usage to cognitive outcomes. First, digital access provided the opportunity for engagement with technology, but it was the actual usage with the frequency, diversity, and complexity of digital activities, that likely provided cognitive stimulation^{27,47}. Intervention studies explored the cognitive benefits of digital training for older adults⁴⁸. Second, internet usage might facilitate access to health information, social connections, and educational resources that indirectly support cognitive health^{49,50}. Third, the skills and confidence developed through continued internet use might transfer to other cognitive domains, contributing to overall cognitive maintenance or enhancement^{29,51}. This transfer effect has been documented in cognitive training literature^{52,53}. Although our modest yet significant correlation between digital use and cognitive performance could not provide a strong causal relationship, it implied that digital engagement might also be an important proxy for broader lifestyle or environmental factors^{54,55}. This dynamic interplay underscored the potential for digital technology to reinforce cognitive trajectories and highlights the importance of considering the evolving nature of digital engagement when studying cognitive aging processes.

Among the sociodemographic variables analyzed, age, rural residence, and education level were the most significant predictors of digital cascades,

demonstrating stronger associations compared to other demographic factors. Age emerged as a particularly strong negative predictor of digital usage growth ($\beta = -0.41$), suggesting that older adults face increasing challenges in maintaining and developing their digital engagement over time. This finding was similar with the previous studies that documented age-related barriers to technology adoption⁵⁶. However, our study extended this work by demonstrating how these age-related disparities in internet use could translate into cognitive disparities over time. This finding suggested that digital disparities might exacerbate existing age-related cognitive inequalities in the aging global population. In contrast, higher education was associated with better baseline digital access and use⁴⁵ and consistently enhanced the growth in use, with the strongest effects on initial cognitive performance. Rural residences showed improving access over time despite a lower baseline but continued facing second-level internet use after overcoming infrastructure limitations⁵⁷.

The results from this study identified that the socio-demographic factors mainly affected digital access and use, with indirect effects on cognitive outcomes through these digital pathways. This contrasted with single-step regression studies that missed these mediating effects^{44,51}. Their findings would indicate the emphasis on mitigating cognitive decline through internet use among the elderly independently. Our results suggested a multi-level approach would follow the natural pathway to address barriers to digital access, and then improve digital skills and usage, ultimately benefiting cognitive health. This would align with the current emphasis on an effective intervention for cognitive decline²⁷. By targeting interventions to each step in the cascade and the specific needs of different demographic groups, policymakers could more effectively promote digital inclusion and its associated cognitive benefits.

Limitations

Our study has several limitations that should be considered when interpreting the results. First, the reliance on self-reported measures of digital access and use may introduce reporting bias, particularly among older adults who may overestimate or underestimate their digital engagement. Second, our three-wave longitudinal design allows us to examine temporal relationships, experimental studies are needed to establish causal effects. Third, our measures of digital access and use are relatively simple indicators that may not fully capture the multidimensional nature of digital engagement, such as the quality of use or specific online activities. Finally, while our PP-LGCM approach reveals indirect pathways, it assumes linear trajectory in digital access and digital outcome, but two-phase linear trajectory in digital use, which may oversimplify the complex, potentially non-linear interactions between digital divide components and cognitive aging. Future research should address these limitations through more comprehensive measurement approaches and analytical techniques that can accommodate non-linear relationships.

Conclusions

To close the cognitive health divide associated with digital disparities, it is important to implement holistic interventions that address both infrastructural and individual determinants of digital engagement. By prioritizing strategies that enhance digital access and promote sustained internet use among older adults, less educated populations, and rural residents, it may be possible to mitigate the cognitive disadvantages associated with digital exclusion. Future research and policy efforts should therefore focus on bridging these digital gaps to support cognitive health across the lifespan.

Acknowledgements

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Data Availability

The data sets used and analyzed during the study are available on the China Health and Retirement Longitudinal Study (CHARLS) website⁵⁸.

Conflicts of Interest

None declared.

Abbreviations

CHARLS: China Health and Retirement Longitudinal Study

PP-LGCM: Parallel Process Latent Growth Curve Model

DA: Digital Access

DAI: Digital Access Intercept

DAS: Digital Access Slope

DU: Digital Use

DUI: Digital Use Intercept

DUS: Digital Use Slope

DO: Digital Outcome

DOI: Digital Outcome Intercept

DOS: Digital Outcome Slope

MMSE: Mini-Mental State Examination

Multimedia Appendix 1

The questionnaire section on broadband subscription, internet use, and cognitive function in China Health and Retirement Longitudinal Study (CHARLS).

Multimedia Appendix 2

Sociodemographic digital divide at different waves.

Multimedia Appendix 3

Digital divides in cognitive status remained significant across all longitudinal waves.

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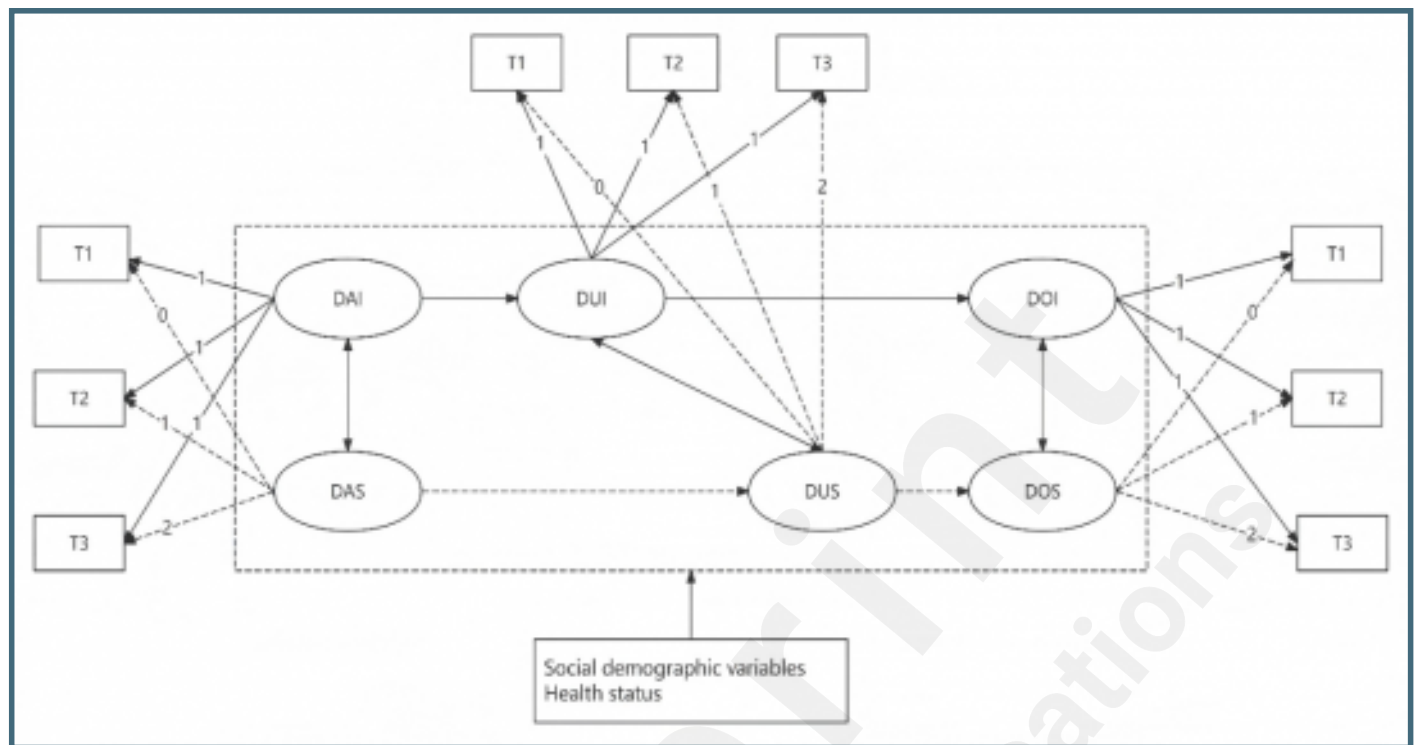
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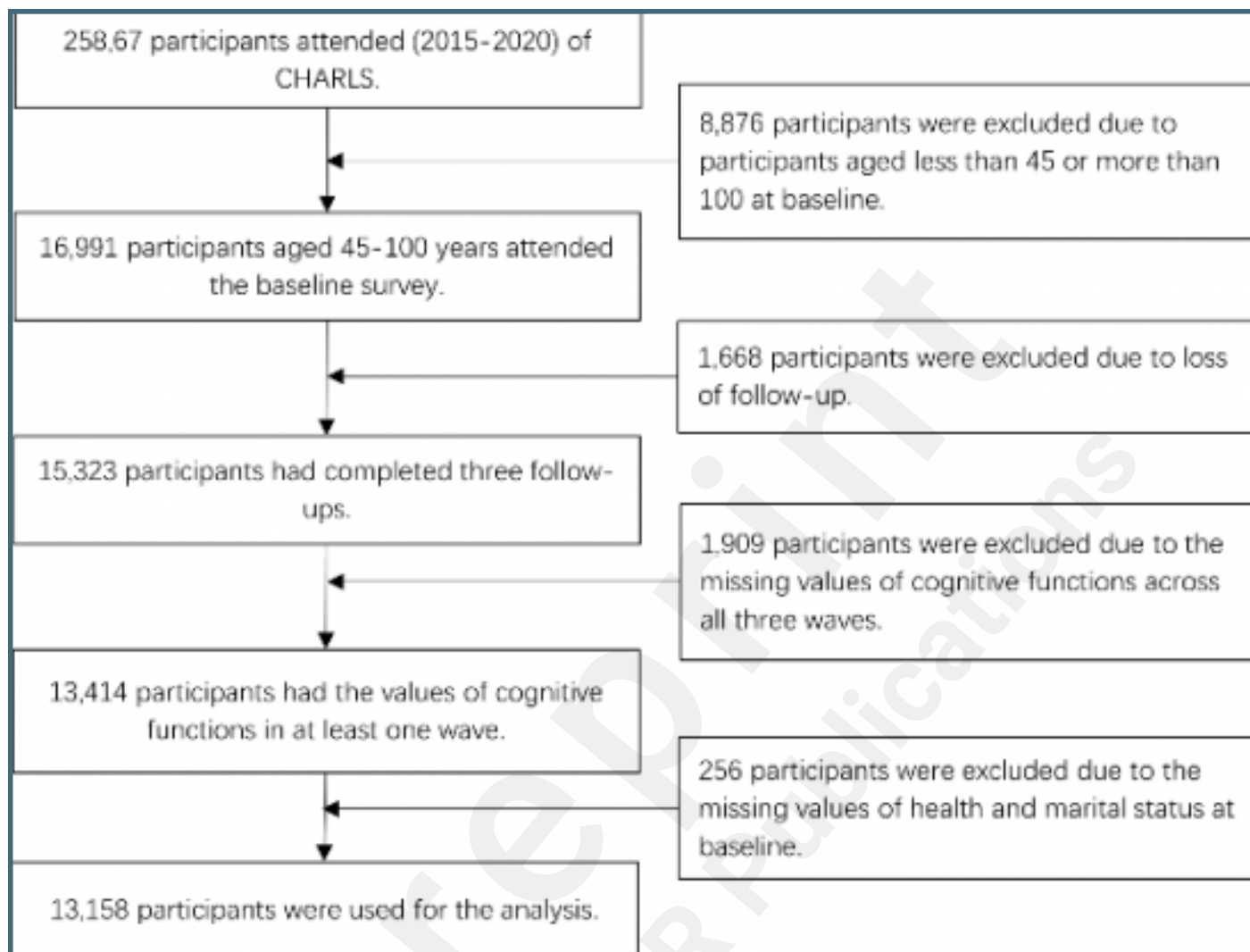
Supplementary Files

Figures

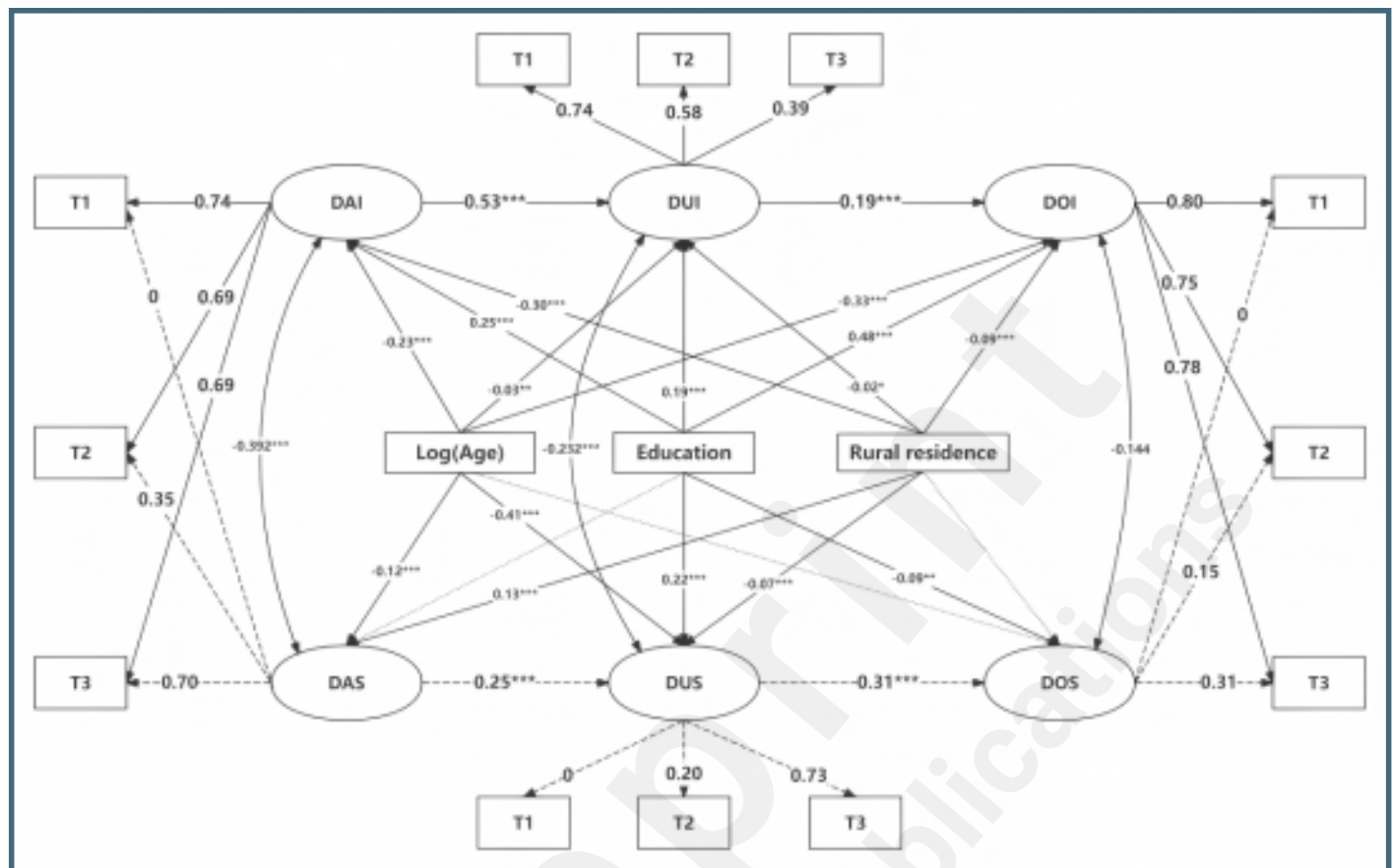
The hypothesised model of the digital divide across three waves.



Flowchart of participant selection.



Digital divide in cognitive function using PP-LGCM.



Multimedia Appendixes

The questionnaire section on broadband subscription, internet use, and cognitive function in China Health and Retirement Longitudinal Study (CHARLS).

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Sociodemographic digital divide at different waves.

URL: <http://asset.jmir.pub/assets/66239faa415cc38018f7f94d0726e6f0.docx>

Digital divides in cognitive status remained significant across all longitudinal waves.

URL: <http://asset.jmir.pub/assets/88a147c9cc1eb0860ed6c8f7d37182d1.docx>

