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Investigating Factors Associated with Digital Inclusion Among Older Adults in China: A Latent Profile Analysis

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Abstract

This study aimed to investigate the impact mechanism and diversity of digital inclusion among elderly people in China. As digital technologies become ubiquitous, older adults face varying degrees of challenges in adapting to digital life, yet research in this area remains insufficient. The study utilized data from the 2020 China Longitudinal Aging Social Survey (CLASS), including 10,198 participants aged 60 and above. Latent Profile Analysis (LPA) was employed to identify different types of digital inclusion, and multinomial logistic regression was used to analyze the influence of various factors on digital inclusion types. LPA identified four types of digital inclusion: Class 1(utilitarian type ,14.4%), Class 2(social type, 18.1%), Class 3(digital disabled type, 35.4%), and Class 4(highly adaptive type, 32.1%). Multinomial logistic regression analysis revealed that factors such as age, education level, family annual income, hukou status, living alone status, cognitive ability, Internet access, and age-friendly design significantly influenced different types of digital inclusion. Notably, cognitive ability and Internet access negatively affected all classes. Age-friendly design negatively impacted Classes 1 and 2 but positively influenced Class 3. Regarding psychosocial variables, self-efficacy had a slight but significant negative effect on Class 3, while social support positively influenced Class 2 but negatively affected Class 3. This study reveals the complex factors influencing digital adaptability among elderly Chinese people, highlighting the diverse needs and challenges faced by different groups when engaging with digital technology. These findings have important implications for developing targeted digital inclusion policies and interventions to better integrate older adults into the digital society.

Keywords: digital inclusion, older adults, latent profile analysis, multinomial logistic regression

1. Introduction

The technological revolution driven by information technology is profoundly shaping modern Chinese society. In this digital era, the integration of digital technologies is redefining human behavior and everyday habits, with China feeling these impacts acutely. While younger and middle-aged groups have largely embraced these changes by developing digital competencies, older adults often find themselves excluded. As China's aging population expands rapidly, the challenge of integrating seniors into the digital society and ensuring they share in its benefits has become an increasingly pressing social issue.

Digital integration encompasses factors such as access to electricity, internet connectivity, and the use of computers and the internet, particularly among vulnerable populations (Xie et al, 2023). The challenges of achieving digital integration arise from a complex interplay of biological, psychological, and social factors. Barriers to technology adoption are multifaceted, including a lack of awareness, access, technical skills, and prior experience, which often prevent individuals from engaging with new technologies (Hargittai, 2002). Inadequate training further exacerbates these challenges, leaving many users underprepared to navigate digital tools effectively (Cotton et al., 2016; Czaja & Sharit, 2013). Additionally, low confidence in technological abilities discourages adoption (Czaja et al., 2006; Siren & Knudsen, 2017). These difficulties are often exacerbated by physical and cognitive declines, particularly among older adults, creating additional barriers to digital engagement (Cotten et al., 2016; Hanson, 2010).

Traditional longitudinal studies often rely on general linear models or linear mixed models to analyze factors associated with successful aging. While linear mixed models account for variations in baseline measures and time trends, they fall short in identifying different developmental trajectories among specific subgroups (Tian et al., 2022). To address these limitations, we employed Latent Profile Analysis (LPA), an advanced method that identifies distinct ecological practice profiles by classifying respondents' behaviors into underlying patterns of similarity (Nylund et al., 2007).

This research utilizes data from the 2020 China Longitudinal Aging Social Survey (CLASS) to explore the factors influencing successful aging among elderly populations in China. CLASS, conducted by the Gerontology Research Institute at Renmin University of China, is a comprehensive national survey that explores topics such as personal information, health services, socioeconomic conditions, and the use of digital technology. With 10,198 participants aged 60 and above, the dataset offers a robust and representative sample for examining various dimensions of aging in China.

Using Latent Profile Analysis (LPA), this research explores how various factors influence digital integration among older adults by identifying distinct developmental paths and their predictors. The findings will enable us to provide more tailored, evidence-based recommendations for promoting successful aging and improving quality of life outcomes for older adults in China's rapidly aging population.

2. Method

2.1 Sample and Data

This study draws on data from the 2020 China Longitudinal Aging Social Survey (CLASS) a comprehensive national survey project designed and conducted by the Institute of Gerontology at Renmin University of China. The CLASS survey covers a wide range of topics, including basic demographic information, health services, socioeconomic conditions, and digital technology usage

The original sample consisted of 11,398 participants. After excluding samples that did not meet the criteria, multiple imputation using chained equations within a multilevel model framework was employed to address missing data. The final analysis included a total of 10,198 participants aged 60 and above.

2.2 Digital Inclusion

Consistent with prior research (Wang, 2021), digital inclusion is measured through a comprehensive assessment of how currently prevalent Internet technologies affect eight aspects of life for older adults: social interaction, shopping and consumption, access to news, leisure and entertainment, travel and tourism, health services, investment and financial management, and learning and training. Each aspect is measured using a scale with four options, ranging from "least adaptive" (inconvenient) to "most adaptive" (convenient), and coded from 1 to 4, respectively.

2.3 Covariates

In line with previous studies (Berner et al., 2015; Zhou et al., 2013), this study incorporated a comprehensive set of covariates to examine factors influencing digital inclusion among older adults. The covariates included demographic characteristics (age, gender, marital status), socioeconomic factors (educational level, residence, family annual income, current work status), living arrangements (living alone), health-related measures (Activities of Daily Living, Instrumental Activities of Daily Living, cognitive ability), technology-related factors (Internet access, age-friendly design), and psychosocial variables (self-efficacy, social support).

Age was measured as a continuous variable, while variables such as gender, marital status, residence, work status, living alone, internet access, and age-friendly design are categorized. Educational level was divided into four categories ranging from illiterate to college and above. Health-related measures, family income, self-efficacy, and social support were assessed using continuous scales.

2.4 Statistical Analysis

Latent Profile Analysis (LPA) was conducted based on the scores using the R package "tidyLPA." Models with 2 to 6 latent profiles were estimated, and several model fit metrics were calculated, including the Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC), log-likelihood (LogLik), integrated completed likelihood (ICL), and entropy. The optimal model was selected according to established guidelines (Peng & Liao, 2023).

Specifically, the following indicators were considered: (1) lower relative fit information criteria, which includes lower AIC and BIC, (2) high entropy of at least 0.8, and (3) the results of bootstrap likelihood ratio test (BLRT). BLRT p-value less than 0.05 indicated a significant improvement in model fit when compared to the solution with one less class.

To further examine the factors influencing digital inclusion pattens, multinomial logistic regression analysis was conducted, with the highly adaptive type (Class 4) set as the reference group. Relative risk ratios (RRR) with 95% confidence intervals were calculated to estimate the associations between various factors and the likelihood of belonging to each digital inclusion class. All statistical analyses were performed using R software version 4.1.0.

3. Results

3.1 Latent Profile Analysis

Table 1 presents the fit indices for the Latent Profile Analysis (LPA). As shown, the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Information Criterion for Likelihood (ICL) values consistently decreased as the number of latent classes increased. Following the "elbow criterion", the change in these indices began to level off at the 4-class solution, suggesting this as the optimal number of latent classes.

The entropy values for the 4-class solution (0.902) also indicated good classification quality. Therefore, based on these fit indices and the principle of parsimony, the 4-class solution was chosen as the best-fitting model to represent the digital social life states of the older adults. This classification allows for a nuanced understanding of the varying levels and patterns of digital inclusion among older adults, capturing the heterogeneity in their engagement with and adaptation to digital technologies across different life domains.

Table 1. Indicators for each latent profile of digital inclusion in older adults

Classes	LogLik	AIC	BIC	ICL	Entropy	BLRT(p)
1	-124053	248138.5	248254.2	-248254	1	
2	-116394	232837.3	233018	-233716	0.898	< 0.01
3	-115503	231074.7	231320.5	-232688	0.865	< 0.01
4	-113642	227370.3	227681.2	-228769	0.902	< 0.01
5	-113040	226183.5	226559.4	-228405	0.872	< 0.01
6	-112580	225282.5	225723.5	-228118	0.852	< 0.01

Note: Abbreviations: LogLik: Log-likelihood; AIC: Akaike information criterion; BIC: Bayesian information criteria; ICL: Integrated completed likelihood; Entropy: A measure of classification quality; BLRT bootstrap likelihood ratio test, $p < 0.05$ suggesting significant better performance.

Figure1 illustrates the pattens of digital inclusion for four distinct classes of older adults. Class 4, labeled as the "highly adaptive type," consistently demonstrates the highest mean scores across all domains, particularly excelling in social interaction, news and information, and leisure and entertainment. This group appears to be the most comfortable with digital technologies across various aspects of life. Class 2, termed the "social type," shows a unique pattern with high adaptability in social interaction and news and information, while demonstrating lower scores in areas like leisure and entertainment and travel and tourism. Class 1, the "utilitarian type," starts with the lowest score in social interaction but shows improvement across other domains, particularly in health services and financial management. Class 3, designated as the "digital disabled type," maintains relatively consistent moderate scores across all domains, indicating a stable but not advanced level of digital engagement.

This classification provides valuable insights into the varying patterns of digital engagement among the older adults, highlighting areas of strength and potential intervention for each group.

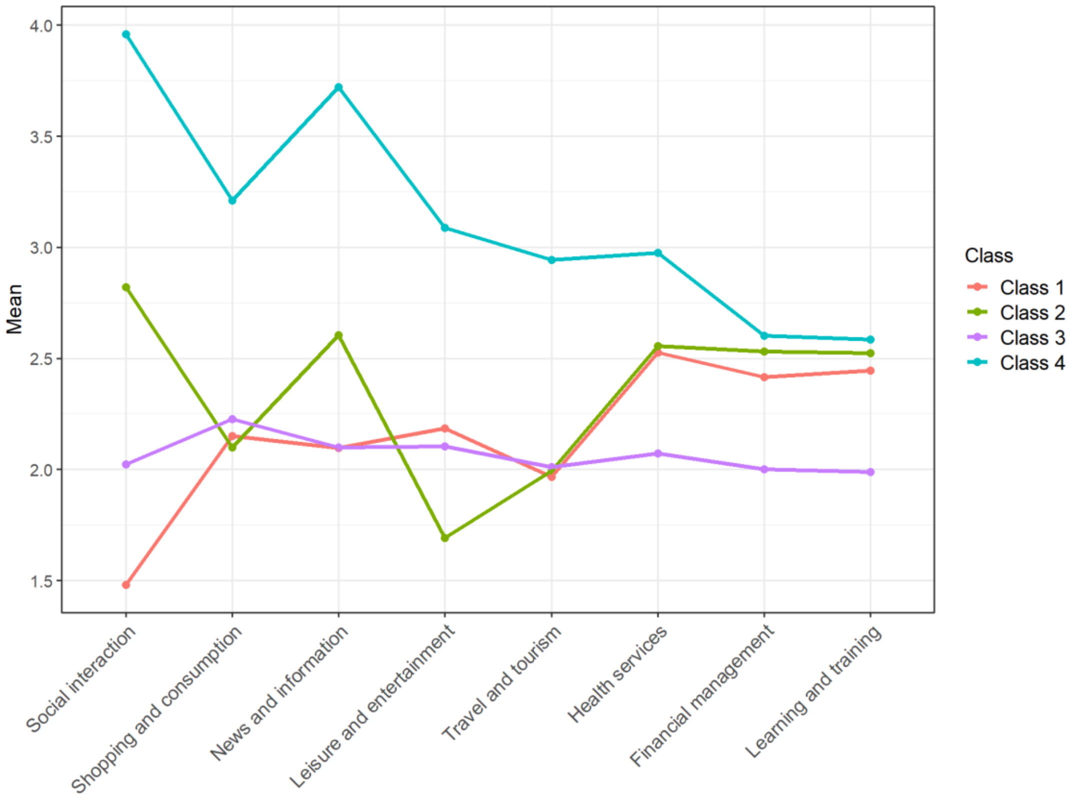

Figure 1. Latent profile model of digital inclusion in older adults

The definition of the classes: Class1, utilitarian type (14.4%); Class2, social type (18.1%), Class3, digital disabled type (35.4%), Class4, highly adaptive type (32.1%).

3.2 Baseline Characteristics

Table 2 presents an analysis of the covariates across the four digital inclusion pattens. The mean age of participants was 71.46 years (SD = 6.53), with significant differences across classes ($p<0.001$). Gender distribution was relatively balanced (51.1% male, 48.9% female) with no significant differences between classes ($p=0.058$). Marital status showed significant variations ($p<0.001$), with 75.6% of participants being married. Educational levels varied significantly across classes ($p<0.001$), with 22.2% illiterate, 41.0% having primary education, 34.2% with middle or high school education, and 2.6% with college education or above. Residence also differed significantly ($p<0.001$), with 52.6% living in rural areas. Family annual income showed significant differences ($p<0.001$) across classes, with a mean of 11.30 (SD 2.14). Current work status varied significantly ($p=0.001$), with 25.8% of participants working. 10.2% of participants reported living alone, with significant differences across classes ($p<0.001$). ADL scores (mean 21.42, SD 1.83), IADL scores (mean 17.15, SD 2.21), and cognitive ability scores (mean 13.52, SD 3.00) all showed significant differences across classes ($p<0.001$). Internet access (49.5% of participants) and age-friendly design (62.7% of participants) both showed significant differences across classes ($p<0.001$). Self-efficacy scores (mean 15.18, SD 3.30) and social support scores (mean 1.60, SD 3.48) demonstrated significant variations across classes ($p<0.001$).

Table 2. Baseline characteristics of the total sample and the sample by the different groups[a]

Variables	Overall (n=10198)	Class1 (n=1468)	Class2 (n=1843)	Class3 (n=3512)	Class4 (n=3275)	p^b
Gender						0.058
Female	4990(48.9)	728(49.6)	856(46.4)	1815(50.2)	1591(48.6)	
Male	5208(51.1)	740(50.4)	987(53.6)	1797(49.8)	1684(51.4)	
Age, mean (SD)[c]	71.46(6.53)	71.34(6.31)	71.30(6.17)	72.35(6.73)	70.61(6.47)	<0.001
Marital status						<0.001
Other	2484(24.4)	353(24.0)	433(23.5)	983(27.2)	715(21.8)	
Married	7714(75.6)	1115(76.0)	1410(76.5)	2629(72.8)	2560(78.2)	
Residence						<0.001
Rural	5366(52.6)	839(57.2)	1046(56.8)	2071(57.3)	1410(43.1)	
Urban	4832(47.4)	629(42.8)	797(43.2)	1541(42.7)	1865(56.9)	
Educational level						<0.001
Illiterate	2268(22.2)	317(21.6)	403(21.9)	947(26.2)	601(18.4)	
Literacy class & Primary school	4186(41.0)	586(39.9)	770(41.8)	1619(44.8)	1211(37.0)	
Middle school & High school	3483(34.2)	509(34.7)	612(33.2)	994(27.5)	1368(41.8)	
College and above	261(2.6)	56(3.8)	58(3.1)	52(1.4)	95(2.9)	
Family annual income, mean (SD)[c]	11.30(2.14)	11.62(2.06)	11.60(2.09)	11.38(2.16)	10.90(2.13)	<0.001
Current work status						0.001
Not working	7572(74.2)	1027(70.0)	1358(73.7)	2707(74.9)	2480(75.7)	
Working	2626(25.8)	441(30.0)	485(26.3)	905(25.1)	795(24.3)	
Living alone						<0.001
No	9153(89.8)	1286(87.6)	1614(87.6)	3228(89.4)	3025(92.4)	
Yes	1045(10.2)	182(12.4)	229(12.4)	384(10.6)	250(7.6)	
ADLs, mean (SD)[c]	21.42(1.83)	21.59(1.24)	21.51(1.79)	21.26(2.13)	21.48(1.70)	<0.001
IADLs, mean (SD)[c]	17.15(2.21)	17.24(1.88)	17.19(2.15)	16.92(2.52)	17.34(2.00)	<0.001
Cognitive ability, mean (SD)[c]	13.52(3.00)	13.24(3.11)	13.39(3.02)	13.22(3.11)	14.07(2.75)	<0.001
Internet access						<0.001
No	5152(50.5)	860(58.6)	1068(57.9)	2059(57.0)	1165(35.6)	
Yes	5046(49.5)	608(41.4)	775(42.1)	1553(43.0)	2110(64.4)	
Age-friendly design						<0.001
No	3806(37.3)	737(50.2)	814(44.2)	1131(31.3)	1124(34.3)	
Yes	6392(62.7)	731(49.8)	1029(55.8)	2481(68.7)	2151(65.7)	
Self-efficacy, mean (SD)[c]	15.18(3.30)	15.35(3.66)	15.32(3.49)	14.94(3.09)	15.29(3.24)	<0.001
Social support, mean (SD)[c].	1.60(3.48)	1.87(3.73)	2.20(4.02)	1.13(2.98)	1.67(3.47)	<0.001

[a] Data are presented as counts (percentage) unless otherwise indicated.

[b] P value determined using $\chi 2$ test or analysis of variance F-test.

[c] For continuous variables, mean (SD) for each group and significance from analysis of variance F-test are reported.

The definition of the classes: Class1, utilitarian type; Class2, social type, Class3, digital disabled type, Class4, highly adaptive type.

3.3 Multinomial Logistic Regression of the Impact Mechanism of Digital Inclusion on Elderly People

This study investigates the impact of digital inclusion on older adults in China using multinomial logistic regression analysis, categorizing subjects into three classes with a highly adaptive type as the reference group.

Regarding demographic characteristics, age shows a slight but significant positive effect on Class 3 (RRR = 1.02), while gender and marital status have no significant impact. Among socioeconomic factors, college and above education strongly positively influences Class 1 (RRR = 2.86) and Class 2 (RRR = 1.96), while middle school & high school education shows a slight negative effect on Class 3 (RRR = 0.85). Literacy class & primary school education demonstrates no significant impact across all classes. Family annual income positively influences all classes (Class 1: RRR = 1.13; Class 2: RRR = 1.12; Class 3: RRR = 1.04); hukou status negatively affects all classes (Class 1: RRR = 0.84; Class 2: RRR = 0.82; Class 3: RRR = 0.76). In terms of living arrangements, living alone has a significant positive effect on Classes 1 and 2 (Class 1: RRR = 1.58; Class 2: RRR = 1.67).

In terms of health-related measures, cognitive ability significantly negatively influences all classes (see Table 2, $p < 0.001$ for all classes). Regarding technology-related factors, Internet access negatively affects all classes (see Table 2, $p < 0.001$ for all classes), while age-friendly design negatively impacts Classes 1 and 2 but positively influences Class 3 (Class 1: RRR = 0.54; Class 2: RRR = 0.69; Class 3: RRR = 1.14).

For psychosocial variables, self-efficacy has a slight but significant negative effect on Class 3 (RRR = 0.97), while social support positively influences Class 2 (RRR = 1.04) but negatively affects Class 3 (RRR = 0.96).

These findings reveal the complex factors influencing digital adaptability among elderly Chinese people, highlighting the diverse needs and challenges faced by different groups when engaging with digital technology.

Table 3. Multinomial logistic regression of digital inclusion profiles (Reference: Class4, highly adaptive type)

Variable	**Class 1**	**Class 2**	**Class 3**
	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Gender (Ref.=Female)	0.9(0.79,1.02)	1.05(0.93,1.19)	0.96(0.87,1.06)
Age	1.01(1,1.02)	1.01(1,1.02)	1.02(1.01,1.02) ***
Marital status (Ref.=Others)	1.17(0.97,1.42)	1.22(1.02,1.45)	1.01(0.88,1.17)
Hukou status (Ref.=Rural)	0.84(0.71,0.99) *	0.82(0.71,0.96) *	0.76(0.67,0.87) ***
Education (Ref.= Illiterate)			
Literacy class & Primary school	1.18(0.99,1.41)	1.15(0.98,1.36)	1.08(0.94,1.23)
Middle school & High school	1.37(1.12,1.67) **	1.15(0.95,1.38)	0.85(0.73,0.99) *
College and above	2.86(1.93,4.23) ***	1.96(1.34,2.86) ***	0.83(0.57,1.2)
Family annual income	1.13(1.09,1.17) ***	1.12(1.08,1.16) ***	1.04(1.01,1.07) **
Employment (Ref.=Unemployment)	1.07(0.91,1.25)	0.85(0.73,0.99) *	0.87(0.76,0.99) *
Living alone (Ref.=No)	1.58(1.23,2.04) ***	1.67(1.32,2.11) ***	1.17(0.95,1.43)
ADLs	1.16(1.09,1.23) ***	1.09(1.04,1.15) **	1.04(1,1.08)
IADLs	0.94(0.89,0.98) **	0.94(0.9,0.98) **	0.95(0.92,0.98) **
Cognitive ability	0.92(0.89,0.94) ***	0.94(0.92,0.96) ***	0.95(0.93,0.97) ***
Internet access (Ref.=No)	0.46(0.4,0.53) ***	0.48(0.42,0.54) ***	0.51(0.46,0.56) ***
Age-friendly design (Ref.=No)	0.54(0.47,0.61) ***	0.69(0.61,0.77) ***	1.14(1.03,1.27) *
Self-efficacy	1(0.98,1.02)	1(0.98,1.02)	0.97(0.95,0.98) ***
Social support	1.02(1,1.04)	1.04(1.02,1.06) ***	0.96(0.94,0.97) ***

Note: Reference: stable improvement with low starting point.

RRR Relative Risk Ratio. *, **, *** statistically significant at the 10%, 5% and 1% levels, respectively.

The definition of the classes: Class1, utilitarian type; Class2, social type, Class3, digital disabled type.

4. Discussion

This study utilizes Latent Profile Analysis (LPA) and multinomial logistic regression to examine the impact mechanism of digital inclusion among the older adults in China. The results reveal the diversity of digital inclusion among older adults and the complex factors influencing this adaptability.

First, LPA identified four distinct types of digital adaptation patterns: utilitarian type (Class 1), social type (Class 2), digitally disabled type (Class 3), and highly adaptive type (Class 4). This classification illustrates the heterogeneity in digital technology use among the older adults, underscoring the need for tailored digital inclusion strategies that address the unique needs of each group.

The multinomial logistic regression results further reveal key factors influencing digital inclusion. Age has a slight but significant positive effect on the digitally disabled type (Class 3), suggesting that as individuals age, they may face greater challenges in adapting to digital technologies. Higher levels of education (college and above) strongly positively influence the utilitarian and social types (Class1 and Class2), while middle and high school education shows a slight negative effect on the digitally disabled type (Class 3), emphasizing the critical role of education and socioeconomic factors in the digital divide.

Living alone increases the likelihood of belonging to the utilitarian and social types (Class1 and Class2), potentially reflecting a higher reliance on digital technologies among elderly individuals who live independently. Cognitive ability significantly negatively influences all classes, emphasizing the critical role of cognitive function in digital adaptation.

Interestingly, Internet access negatively affects all classes, a seemingly counterintuitive finding that may suggest mere access is insufficient to overcome digital barriers. Age-friendly design negatively impacts the utilitarian and social types but positively influences the digitally disabled type, a result warranting further investigation and potentially reflecting different groups' varying needs and responses to technological design.

Finally, psychosocial factors also play a significant role. Self-efficacy has a slight but significant negative effect on the digitally disabled type, while social support positively influences the social type but negatively affects the digitally disabled type. These findings underscore the importance of psychological and social factors in the digital adaptation process among the elderly.

Several limitations of this study should be noted. First, the cross-sectional nature of our analysis limits causal inference regarding the relationship between various factors and digital inclusion patterns among older adults. Second, our reliance on self-reported measures for digital inclusion may introduce reporting bias.

5. Conclusion

This study provides important insights into the digital inclusion among older adults in China, revealing diverse patterns of digital inclusion influenced by complex demographic, socioeconomic, health, technological, and psychosocial factors. The findings highlight the need for tailored digital inclusion strategies that address the heterogeneous needs of different elderly groups.

The factors influencing digital inclusion identified in this study—particularly education, cognitive ability, and social support—align with findings from previous research. Studies have shown that cognitive ability (Freese et al., 2006), education (Augner,2022), and social support (Thatcher and Perrewe, 2002) are strongly associated with older adults' use of the Internet in the United States and several European nations. However, some unique characteristics of China's social context, such as the urban-rural divide and hukou status, present distinct considerations for digital inclusion strategies.

Future research should explore the interactions between these factors over time and evaluate targeted intervention strategies, while facilitating international comparative studies to identify best practices across different cultural and social contexts. This study lays a crucial empirical foundation for developing more effective digital inclusion policies and practices for the elderly, ultimately aiming to bridge the digital divide and improve quality of life for older adults in China. The findings contribute to the growing global discourse on digital equity and aging in the digital era, offering valuable insights for other nations facing similar demographic transitions and digital inclusion challenges.

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Data sharing statement

No additional data are available.

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