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Digital Engagement Activities and Internet Adoption Among Chinese Older Adults: Roles of Family Relations and Personality Traits in China Family Panel Studies

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Abstract

Objective

To examine how personality traits and family factors (number of children, parent–child relationship) are associated with internet use among older adults in China, including adoption, weekly time online, and breadth of online functions used.

Methods

We analysed 2018 China Family Panel Studies (CFPS) data for adults aged ≥ 60 years (n = 8,003). Internet adoption (computer and/or mobile) was modelled with multivariable logistic regression. Weekly hours online and online functions used were modelled with OLS. Covariates included age, gender, education, urban residence, subjective social status, employment, and self-rated health.

Results

Internet adoption was higher with better education (OR = 2.05, 95% CI 1.91–2.20), urban residence (OR = 2.52, 2.07–3.07), openness (OR = 1.30, 1.17–1.43), and closer parent–child ties (OR = 1.15, 1.01–1.30); but lower with older age (OR = 0.93, 0.91–0.94), being employed (OR = 0.52, 0.43–0.63), more children (OR = 0.82, 0.75–0.91), and neuroticism (OR = 0.80, 0.71–0.90). Among internet users, weekly time online increased with openness (β = +1.90 hours/week) and education (β = +0.66 per schooling level) but decreased with conscientiousness (β = −1.66), current employment (β = −4.79), spousal presence (β = −2.63), number of children (β = −1.47 per child), and closer parent–child ties (β = −1.53 per point). Breadth of online functions increased with education (β = +0.27) and openness (β = +0.28) and decreased with number of children (β = −0.20).

Conclusion

Among Chinese older adults, openness consistently predicts deeper and broader internet engagement. More children and closer parent–child ties are linked to shorter use among users, even though better relationships facilitate initial adoption. Interventions tailored to personality (e.g., motivating less-open users) and targeting older adults with poor family ties could narrow digital divide.

Highlights

· that family embeddedness may both facilitate access and constrain heavier use.

Applications of study findings:

· Assessment of digital needs should consider personality, family resources, and caregiving or household responsibilities.

· Training should move beyond access support to encourage confident, varied, and sustained online engagement.

· Future gerontological research should test how intergenerational support shapes different stages of digital ageing.

Digital Engagement Activities and Internet Adoption Among Chinese Older Adults: Roles of Family Relations and Personality Traits in China Family Panel Studies

1. Introduction

Rapid advances in internet infrastructure and digital device functionality have driven substantial growth in internet adoption in China. By December 2024, there were 1.108 billion internet users and a national penetration rate of 78.6% (China Internet Network Information Center, 2025). Yet older Chinese remain substantially underrepresented in the increasingly digitalized society: only roughly half of people aged 60 and over use the internet, and older cohorts account for 46.8% of the country's 301 million non-users. Rural and remote older adults in China are especially disadvantaged, facing persistent forms of digital exclusion shaped by structural and psychosocial barriers (Wang et al., 2023), feeding concerns that some older people have become 'digital refugees' excluded from services, information and social exchanges increasingly mediated online (Lu & Wei, 2021; Stockwell et al., 2021). At the same time, older people are not a homogeneous group—many adopt the internet and use it intensively for intergenerational and family contact (Li & Zhou, 2021), social media engagement (He et al., 2020), online health information seeking (Wu & Li, 2016), and leisure-oriented online activities, while others either do not adopt or limit their activity to a narrow set of functions (Heponiemi et al., 2022; Pantelaki et al., 2023; Shi et al., 2023; Ren & Zhu, 2024). Understanding these heterogeneous patterns is crucial because the benefits, and risks, of internet engagement depend on what older people do online (Kajal & Rathod, 2025).

Literature review: Conceptualizing digital divide and its determinants

Contemporary research frames these inequalities as a multi-dimensional digital divide comprising access, usage and outcome dimensions (Hargittai et al., 2019). The access divide captures unequal availability of infrastructure and devices; in China, uneven economic development and urban–rural disparities partly explain why many older adults remain offline (Lu & Wei, 2021). The usage divide, by contrast, emphasizes differences in skills, motivations and activity repertoires. Even where physical access exists, older adults vary in how frequently they use online resources—whether for communication, information, commerce or leisure—and those differences shape the outcomes they obtain (Büchi et al., 2016; O'Brien & Toms, 2008; Xu et al., 2017). The outcome divide

thus reflects unequal returns from internet use, including disparities in knowledge acquisition, social capital, health and economic opportunities (Hargittai et al., 2019). Research that treats internet use as a binary choice risks obscuring these qualitatively distinct pathways and the mechanisms through which digital engagement produces benefits or harms.

Empirical studies identify five broad clusters of determinants for older adults' internet engagement: demographic characteristics, socioeconomic resources, health, psychological attributes, and family dynamics (Shi et al., 2023; Yang et al., 2022). Demographic and socioeconomic factors—age, gender, education, subjective social status, occupation, and urban–rural residence—have been consistently associated with both internet access and patterns of use (Shi et al., 2023; Fan, 2025). Education in particular predicts a broader and more instrumental repertoire of online activities, while higher subjective social status and urban residence increase opportunities for adoption, though subjective social status alone does not guarantee sustained engagement (Peng, 2018; Schradie, 2018; Stockwell et al., 2021; Jiang & Chen, 2021; Lan & Lu, 2019). Health status, typically measured by self-rated health or functional ability, also matters: healthier older adults are more likely to go online, and internet engagement has been linked to improvements in psychological well-being (Peng, 2018; Wang et al., 2019; Li & Yang, 2021). Importantly, once older adults adopt internet technologies, later declines in physical function do not necessarily lead to abandonment, which underscores the importance of supporting initial uptake (Liu et al., 2012).

This paper foregrounds psychological and familial influences because they operate close to behaviour and are amenable to intervention. Psychological dispositions are captured here by the Five-Factor Model (FFM) — conscientiousness, extraversion, agreeableness, openness to experience and neuroticism — together with depressive symptomatology. The FFM provides a parsimonious account of stable behavioural tendencies that plausibly shape curiosity, persistence in learning, and social engagement online. Empirical work suggests that openness should encourage exploratory and information-seeking behaviours, extraversion should predict socially oriented uses, and neuroticism may shape patterns of disclosure and emotional expression online (Ross et al., 2009; Zhang & Liang, 2023). Because these traits are relatively enduring, they reduce concerns about reverse causality in cross-sectional analyses of personality and internet use. Depressive symptoms are also relevant: higher levels of depression are associated with reduced motivation to learn and engage, and prior studies find negative associations between depressive symptoms and internet adoption and intensity among older adults (Zhang & Chen, 2013; Wang et al., 2019). Family dynamics further shape digital trajectories in later life. Adult children and spouses often provide the instrumental help—acquiring devices, configuring settings, troubleshooting—and the emotional encouragement that enables older people to go online and to persevere in learning digital skills (Lu & Li, 2022; Shi et al., 2023). Co-residence with younger family members and frequent intergenerational contact can foster learning and continued use (Liu et al., 2012; Zhang & Chen, 2013). Nevertheless, empirical findings are mixed. Some studies report that internet-using older adults have fewer children and that greater numbers of children are associated with lower adoption probabilities (Wang, 2020); others emphasise the facilitative role of close, regular contact. A notable limitation of prior work is reliance on coarse measures of family contact (e.g. contact/no contact), which overlooks qualitative aspects such as emotional closeness and the content of assistance.

Research gaps and study rationale

Two interrelated gaps motivate this study. First, much research focuses on the binary question of whether older adults are online rather than on the diversity of online behaviours (adoption, intensity, and activity type) that determine outcomes. Second, while demographic, socioeconomic, and health correlates are well-documented, psychological traits and nuanced family processes that shape usage patterns are understudied among older populations—especially in large, nationally representative Chinese samples. This paper addresses these gaps using CFPS 2018 by (1) developing a finer typology of older adults' internet behaviours—distinguishing adoption, time online and the diversity/type of activities—and (2) examining how FFM traits, depressive symptoms, and detailed family measures (number of living children, subjective closeness with children, and spousal involvement/co-residence) relate to these behavioural profiles while controlling for demographic, socioeconomic and health covariates. From these considerations we hypothesize that:

1. **Hypothesis of Psychological dispositions**: Stable personality traits and mental health influence patterns of internet engagement. Specifically, greater openness and related exploratory traits will be associated with longer time online and a broader repertoire of online activities, while higher depressive symptomatology will be associated with lower probability of adoption, less time online and narrower activity repertoires.
2. **Hypothesis of Family support and structure**: Family context affects internet behaviour. Closer emotional ties with children and active spousal involvement will be positively associated with adoption, intensity and diversity of internet use; conversely, a greater number of living children will be associated with lower odds of internet use.

2. Methods

2.1 Data and study populations

The data for this study were obtained from the China Family Panel Studies (CFPS), collected in 2018 by the Institute of Social Science Survey (ISSS) at Peking University. It aims to capture dynamic changes in Chinese society, economy, population, education, and health by recording data at the individual, family, and community levels. This study especially employs elements pertaining to internet usage, familial circumstances, and psychological status derived from the personal questionnaire segment of the CFPS. After data cleaning and screening, a total of 8,003 valid cases were selected from the original dataset. The selection was based on two inclusion criteria: respondents were aged 60 or above, and relevant variables concerning internet use were available.

2.2 Key outcome variables

Consistent with prior research (Jin & Zhao, 2019), internet use was designated as the dependent variable and measured using three indicators: access to the internet (coded as a binary variable with values of 0 or 1), time spent online (total hours of internet use per week), and the breadth of online content engagement. *Internet access* was determined based on respondents' answers to two items: "Do you use mobile devices, such as smartphones or tablets, to access the internet?" and "Do you use a computer to access the internet?". *Digital engagement duration (Time spent on the internet)* was measured by the

question: “How many hours per week do you spend online during your leisure time?”. *Internet skills* were assessed by aggregating responses to five items regarding the frequency of specific internet uses: (1) “How frequently do you use the internet for learning (e.g., searching for study materials, taking online courses)?” (2) “How frequently do you use the internet for work-related purposes?” (3) “How frequently do you engage in social activities online (e.g., chatting, posting on social media)?” (4) “How frequently do you use the internet for entertainment (e.g., watching videos, downloading music)?” and (5) “How frequently do you conduct commercial activities online (e.g., online banking, shopping)?” Each item provided seven response options: almost every day, 3–4 times a week, 1–2 times a week, 2–3 times a month, once a month, once every few months, and never. For the purposes of analysis, responses were recoded into a binary variable indicating whether the respondent engaged in the activity. Any response other than “never” was coded as indicating usage. The total breadth of content engagement was then computed by summing the number of content categories for which the respondent reported any usage.

2.3 Key independent variables

Psychological factors encompass the Big Five personality traits and depression. *Big Five personality traits* are calculated by averaging the scores of three items for each factor, with each factor's scores ranging from 1 to 5. The Big Five personality traits were measured using 15 items, with three items assigned to each dimension. Conscientiousness was measured by the following items: being thorough and careful in one’s work, tending to be lazy, and working efficiently. Extraversion was assessed using items capturing being talkative, being outgoing and sociable, and being reserved and conservative. Agreeableness was measured by items indicating being sometimes rude or impolite to others, being forgiving by nature, and being considerate of others and kind to almost everyone. Openness to experience was assessed using items reflecting being original and coming up with new ideas, valuing artistic and aesthetic experiences, and having a vivid imagination. Emotional stability was measured by items capturing often worrying, getting nervous easily, and being relaxed and able to handle stress well. All reverse-coded items were recoded so that higher values indicated higher levels of the corresponding personality trait, and the mean score of the three items was calculated for each dimension. The internal consistency of these subscales was evaluated using Cronbach’s alpha. In this sample of Chinese older adults, the alpha coefficients were as follows: Openness (0.604), Conscientiousness (0.387), Neuroticism (0.345), Extraversion (0.321), and Agreeableness (0.273). While these coefficients fall below the traditional 0.70 threshold often cited in clinical psychology, they are consistent with the reliability levels typically reported for brief 3-item personality measures within large-scale national surveys. **Depression** is measured using the CESD-8 scale (8-item Center for Epidemiologic Studies Depression Scale), which has a scoring range from 1 to 8, with higher scores indicating more depressive symptoms, as it sums responses (0 or 1) to eight items (e.g., feeling sad, trouble sleeping, lack of happiness) (Turvey et al., 1999).

Family factors include the (1) relationship with children, (2) number of children, and (3) marital status. The relationship with children is scored on a scale from 1 (very distant) to 5 (very close). The number of children refers to the total number of living offspring. Spouse status is indicated by a binary value, with 1 representing married or cohabiting and 0 representing single or widowed. Due to the inherent characteristics of the independent variables selected in this study, it is better able to control for potential bidirectional causality between the independent and dependent variables.

2.4 Covariates

Since internet use by older adults is affected by psychological and family factors, this study selected three variables that involved demographics (gender and age), health, and socioeconomic status. Gender is coded as a binary variable, with males represented by 1 and females by 0. Age is restricted to individuals aged 60 and above. Self-rated health is self-assessed on a scale from 1 to 5, where 1 indicates excellent health and 5 indicates poor health. Socioeconomic status is operationalized using four indicators: educational attainment, place of residence, employment status, and subjective social status level. Education is measured on a five-point ordinal scale, ranging from 1 to 5, where 1 represents no formal education, followed by primary school, middle school, high school or vocational school, and finally university education or above. Residential location differentiates between rural and urban areas, encoded as a binary variable with rural as 0 and urban as 1. Employment status is measured by a binary variable, with those still working coded as 1 and those no longer working as 0. Subjective social status is operationalized as subjective income satisfaction, measured on a five-point Likert scale ranging from 1 (very low) to 5 (very high). Variable definitions and coding are provided in Supplementary Table 1. Supplementary Tables 1–3 are located in the Supplementary Material section following the main tables.

2.5 Statistical analysis

This study employs a multi-stage analytical approach to investigate the influence of psychological and family factors on the internet use behaviour of older adults. First, descriptive statistics are conducted to summarize sample characteristics, including frequency distributions, means, standard deviations, and ranges, to establish an initial comprehension of internet usage in this cohort. Subsequently, correlation analyses are performed to explore preliminary associations between variables: for the total sample, Spearman’s rank correlation coefficient is used to examine the associations between demographic, health, socioeconomic, psychological, and family factors and the binary variable of internet access ; for the subsample of internet users, the Pearson correlation coefficient is employed to assess the relationships between these factors and the intensity (time spent online) and breadth (number of functions used) of digital engagement (Supplementary Table 3). Given that internet access is a binary categorical variable (coded as 0 or 1), this study first employs multivariable binary logistic regression for the analysis. This model is designed to identify the factors that significantly influence the probability of older adults becoming internet users, representing the extensive margin of digital engagement. The effects of the independent variables are estimated using odds ratios (ORs), where an OR greater than one indicates that the factor is associated with an increased likelihood of internet adoption. For the subset of older adults who have already crossed the "access divide," Ordinary Least Squares (OLS) regression models are utilized to examine the intensive margin of use, specifically "weekly internet usage duration" and "breadth of online functions". The coefficients in the OLS model are directly interpreted as the change in the dependent variable associated with a one-unit increase in the independent variable. The general formula of the OLS regression model can be expressed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n + \varepsilon$$

Where Y represents the internet use behaviour of older adults, including the two dependent variables of “weekly internet access time” and “amount of internet access content.” X_1 to X_n were the independent variables; β_0 is the intercept term; β_1 to β_n were the slope, that is, the value of dependent variable Y changed by each unit of the corresponding independent variable X; ε is random error. Prior to the regression analyses, multicollinearity diagnostics were performed using Variance Inflation Factors (VIF) and tolerance levels (Supplementary Table 2). The results indicated that all predictors yielded a VIF of less than 10, suggesting that the models are free from serious multicollinearity issues. Regarding missing data, this study utilized listwise deletion, whereby an observation was excluded from the final analytical sample if it contained a missing value for the dependent variable, any of the key independent variables.

3. Results

3.1 Sample characteristics

Approximately 12% of older adults reported using the internet, with the highest proportion observed among those aged 60 to 69. In this age group, around 15% used the internet, accounting for 79% of all older adult internet users. This was followed by individuals aged 70 to 79, among whom approximately 7% reported internet use, while the lowest rate was found among those aged 80 and above, at about 4% (Table 1). Among the 987 older adults who reported their weekly internet usage, the average duration was 11.77 hours per week, with a maximum reported value of 112 hours. Approximately 11% exceeded the national average weekly internet usage time for people in the same age group, and this proportion was broadly similar across the three age groups of older adults, ranging from about 9% to 13% (Table 1).

Table 1
Sample characteristics and internet usage stratified by internet access, CFPS 2018, persons aged ≥ 60 years (N = 7,993)

Variables	Online sample	Offline sample	Total sample	t / X^2 Test	P-value
Internet access(0□1)	992 (12.41%)	7,001 (87.59%)	7,993 (100%)	—	—
Estimating digital engagement duration(0-112)	989 (12.37%)	7001(87.59%)	7,990 (99.96%)	—	—
Estimating digital engagement aspects(0–5)	992 (12.41%)	7001 (87.59%)	7,993 (100%)	—	—
Age(60–96)	65.93 (5.06)	68.59 (6.48)	68.26 (6.38)	t = 12.41	< 0.001
Gender				X^2 = 47.14	< 0.001
Female	394 (39.72%)	3,596 (51.36%)	3,990(49.92%)	—	—
Male	598 (60.28)	3,405(48.64%)	4,003 (50.08%)		
Self-rated health(1–5)	3.36 (1.24)	3.33 (1.93)	3.34 (1.86)	t = -0.47	0. 636
Education				X^2 = 1304.68	< 0.001
Illiterate	115 (11.59%)	3,689 (52.69%)	3,804 (47.59%)	—	—
Primary	161 (16.23%)	1,676 (23.94%)	1,837 (22.98%)		
Junior middle	330 (33.27%)	1,130 (16.14%)	1,460 (18.27%)		
High schooll	275(27.72%)	428 (6.11%)	703 (8.80%)		
college	111 (11.19%)	78(1.11%)	189 (2.36%)		
Employment status				X^2 = 165.15	< 0.001
Unemployment	679 (68.45%)	3,266 (46.65%)	3,945 (49.36%)	—	—
Employment	313 (31.55%)	3,735 (53.35%)	4,048 (50.64%)		
Subjective SES(1–5)	2.95 (1.02)	3.05 (1.22)	3.04 (1.19)	t = 2.33	0.020
Residence				X^2 = 404.28	< 0.001
Rural	215 (21.67%)	3,904 (55.76%)	4,119 (51.53%)	—	—
Urban	777 (78.33%)	3,097 (44.24%)	3,874 (48.47%)		
Depression(8–32)	12.41 (3.73)	14.03 (4.60)	13.82 (4.53)	t = 10.56	< 0.001
Neuroticism(1–5)	3.25 (0.71)	3.38 (0.79)	3.37 (0.78)	t = 4.88	< 0.001
Openness(1–5)	3.24 (0.85)	3.03 (0.95)	3.06 (0.94)	t = -6.53	< 0.001
Agreeableness(1–5)	3.97 (0.60)	3.88 (0.62)	3.90 (0.62)	t = -4.00	< 0.001
Extraversion(1–5)	3.47 (0.69)	3.42 (0.73)	3.43 (0.73)	t = -1.74	0.082
Conscientiousness(1–5)	4.03 (0.63)	3.93 (0.67)	3.95 (0.67)	t = -4.11	< 0.001
Marital status				X^2 = 43.72	< 0.001
Single	113 (11.39%)	1,415 (20.21%)	1,528 (19.12%)	—	—
Married	879 (88.61%)	5,586 (79.79%)	6,470 (80.88%)		
Relation w/ children(1–5)	4.49 (0.66)	4.42 (0.69)	4.43 (0.69)	t = -2.65	0.008
Number of children(0–5)	1.68 (1.02)	2.26 (1.28)	2.19 (1.26)	t = 13.71	< 0.001
For continuous variables, values in parentheses represent standard errors (SE); for categorical variables, values in parentheses represent percentages (%).					

In terms of online activities, entertainment and social contact were the two most frequently used internet functions among older adults across all age groups, reported by 73.41% and 73.31% of users, respectively. Online learning ranked third, with 35.15% of older adults engaging in this activity. In addition, approximately one-quarter of older internet users accessed business-related online content, such as online shopping and financial management, whereas online work was least common, reported by only 7.57%. Overall, older adults used an average of 2.14 internet functions, and only 2.53% of those who were online reported using all five functions, with almost all of these respondents belonging to the 60–69 age group (Table 1). Correlation analyses further showed that demographic characteristics, health status, socioeconomic factors, psychological factors, and family circumstances were all associated with internet access. Among older adults who were already online, weekly duration of internet use was positively associated with educational attainment, urban residence, and openness, but negatively associated with employment status and family-related factors. By contrast, the number of online functions used was positively associated with education, urban residence, openness, neuroticism, and conscientiousness, and negatively associated with self-rated health, age,

depressive symptoms, and number of children (Supplementary Table 3). Multicollinearity diagnostics showed no evidence of problematic collinearity, with all predictors satisfying the conventional thresholds of VIF < 10 and tolerance > 0.10 (Supplementary Table 2).

3.2 Multivariable regression results

Given that most older adults in the sample did not use the internet, logistic regression was first conducted to examine whether older adults had internet access, followed by OLS regression analyses of weekly duration and breadth of use among those who were already internet users. As shown in Table 2, in the fully adjusted logistic model (Model 4), age, subjective social status, employment status, emotional instability, and number of children were significantly and negatively associated with internet access, whereas educational attainment, urban residence, openness, and relationship with children were significantly and positively associated with the likelihood of going online. Gender was not significantly associated with internet use in the fully adjusted model. Substantively, the magnitude of several coefficients was notable: a one-unit increase in educational level was associated with an approximately 67% increase in the odds of internet use; living in an urban area was associated with about 72% higher odds of internet use compared with rural residence; and each one-unit improvement in relationship with children was associated with an approximately 53% increase in the odds of going online.

Table 2
Logistic regression models of internet access among Chinese older adults, CFPS 2018, persons aged ≥ 60 years (N = 8,003)

Variable	Model 1			Model 2			Model 3			Model 4		
	OR	95% CI	p-value	OR	95% CI	p-value	OR	95% CI	p-value	OR	95% CI	p-val
Age	0.92	[0.90,0.93]	**< 0.001**	0.93	[0.92,0.95]	**< 0.001**	0.91	[0.90,0.93]	**< 0.001**	0.93	[0.91,0.94]	**< 0.0**
Gender (ref: Female)	1.23	[1.05,1.45]	**0.011**	1.22	[1.03,1.45]	**0.020**	1.11	[0.94,1.32]	0.159	1.12	[0.93,1.33]	0.2
Self-rated health	1.03	[0.98,1.08]	0.216	1.01	[0.96,1.07]	0.713	1.03	[0.96,1.11]	0.558	1.01	[0.95,1.11]	0.7
Education	2.22	[2.08,2.37]	**< 0.001**	2.14	[1.99,2.29]	**< 0.001**	2.12	[1.98,2.27]	**< 0.001**	2.06	[1.91,2.20]	**< 0.0**
Employment status (ref. unemployment)	0.51	[0.43,0.61]	**< 0.001**	0.53	[0.44,0.64]	**< 0.001**	0.51	[0.41,0.58]	**< 0.001**	0.53	[0.43,0.63]	**< 0.0**
Subjective SES	0.95	[0.88,1.02]	0.175	0.93	[0.86,1.00]	0.059	0.92	[0.99,1.00]	**0.018**	0.91	[0.98,1.00]	**0.0**
Urban (ref: Rural)	2.77	[2.32,3.33]	**< 0.001**	2.55	[2.11,3.10]	**< 0.001**	2.68	[2.05,2.96]	**< 0.001**	2.51	[2.07,3.07]	**< 0.0**
Depression							0.97	[0.95,0.99]	**0.005**	0.98	[0.96,1.00]	0.0
Neuroticism							0.82	[0.73,0.92]	**< 0.001**	0.80	[0.71,0.90]	**< 0.0**
Openness							1.31	[1.19,1.44]	**< 0.001**	1.30	[1.17,1.43]	**< 0.0**
Agreeableness							1.04	[0.91,1.20]	0.591	1.01	[0.88,1.17]	0.9
Extraversion							0.97	[0.86,1.08]	0.683	1.00	[0.88,1.12]	0.9
Conscientiousness							1.02	[0.89,1.17]	0.707	1.04	[0.90,1.19]	0.6
Marital status (Ref: Single)				1.11	[0.86,1.42]	0.422				1.07	[0.80,1.35]	0.6
Relation w/ children				1.21	[1.07,1.36]	**0.002**				1.15	[1.01,1.30]	**0.0**
Number of children				0.81	[0.74,0.89]	**< 0.001**				0.82	[0.75,0.91]	**< 0.0**
Constant	4.80	[1.76,13.15]	**0.002**	1.45	[0.41,5.08]	0.565	7.76	[2.00,26.60]	**0.002**	2.44	[0.58,12.63]	0.2
Pseudo R2	0.245			0.247			0.251			0.253		
Log likelihood	-2262.47			-2091.44			-2179.29			-2020.23		

Among older adults who were already internet users, the determinants of internet-use intensity and breadth showed a somewhat different pattern. Table 3 indicates that, in the fully adjusted duration model (Model 8), men spent about 1.7 additional hours per week online compared with women, while each additional level of schooling was associated with about 0.8 more hours of internet use per week. By contrast, employment status was negatively associated with duration, with older adults who remained employed spending about 5.6 fewer hours online per week than those not working. Other structural variables, including age, subjective social status, self-rated health, and urban residence, were not statistically significant in the user-only sample. Table 4 shows that breadth of internet use, measured by the number of online functions used, was more weakly stratified by the control variables. In the fully adjusted model (Model 12), educational attainment was the only control variable that remained statistically significant, with each additional level of education associated with an increase of approximately 0.3 in the number of online functions used. Taken together, these results suggest that the factors associated with going

online are not identical to those associated with how long older adults spend online or how many different online functions they use once they have adopted the internet.

Table 3
Linear regression models of digital engagement duration among Chinese older internet users, CFPS 2018, persons aged ≥ 60 years (N = 989 in Model 5)

Variable	Model 5			Model 6			Model 7			Model 8		
	beta	**SE**	**p-value**	**beta**	**SE**	**p-value**	**beta**	**SE**	**p-value**	**beta**	**SE**	**p-value**
Age	-0.03	0.08	0.702	-0.03	0.08	0.649	-0.01	0.08	0.993	-0.00	0.08	0.984
Gender (ref: Female)	1.80	0.77	**0.020**	1.35	0.80	0.091	1.70	0.81	**0.035**	1.15	0.83	0.164
Employment status (ref. unemployment)	-5.00	0.92	**< 0.001**	-5.211	0.92	**< 0.001**	-4.69	0.96	**< 0.001**	-4.75	0.96	**< 0.001**
Subjective SES	0.17	0.37	0.643	0.163	0.38	0.667	0.30	0.39	0.443	0.23	0.39	0.560
Health	-0.23	0.30	0.447	-0.222	0.36	0.540	-0.21	0.31	0.491	-0.13	0.37	0.734
Education	0.71	0.31	**0.024**	0.848	0.31	**0.007**	0.58	0.32	0.072	0.69	0.33	**0.034**
Urban (ref: Rural)	1.74	1.01	0.084	1.716*	1.01	0.089	0.67	1.07	0.533	0.46	1.07	0.670
Conscientious				-1.293	0.64	**0.045**				-1.67	0.66	**0.011**
Extraversion				-0.33	0.56	0.557				-0.38	0.57	0.507
Agreeableness				-0.368	0.66	0.574				-0.32	0.69	0.638
Openness				1.590	0.49	**0.001**				1.86	0.50	**< 0.001**
Neuroticism				-0.68	0.56	0.220				-0.62	0.58	0.284
Depression				0.14	0.11	0.216				0.02	0.12	0.876
Number of children							-1.36	0.45	**0.003**	-1.49	0.45	**0.001**
Relation w/ children							-1.52	0.58	**0.009**	-1.59	0.59	**0.007**
Spouse							-2.40	1.25	0.056	-2.63	1.27	**0.039**
Constant	10.77	5.25	**0.041**	14.22	6.45	**0.028**	21.15	6.48	**0.001**	27.105	7.68	**< 0.001**
R-squared	0.065			0.084			0.086			0.110		
Observations	989			973			920			906		

Table 4
Linear regression models of breadth of online functions used among Chinese older internet users, CFPS 2018, persons aged ≥ 60 years (N = 992 in Model 9)

Variable	Model 9			Model 10			Model 11			Model 12		
	beta	SE	p-value	beta	SE	p-value	beta	SE	p-value	beta	SE	p-value
Age	-0.02	0.01	**0.014**	-0.02	0.01	**0.026**	-0.02	0.01	0.066	-0.01	0.01	0.114
Gender(ref: Female)	0.01	0.08	0.912	-0.03	0.08	0.693	-0.01	0.08	0.915	-0.07	0.08	0.421
Self-rated health	-0.03	0.03	0.272	-0.02	0.04	0.549	-0.03	0.03	0.362	-0.02	0.04	0.662
Education	0.32	0.03	**< 0.001**	0.31	0.03	**< 0.001**	0.28	0.03	**< 0.001**	0.27	0.03	**< 0.001**
Employment status (ref. unemployment)	0.10	0.09	0.302	0.08	0.09	0.800	0.12	0.10	0.233	0.11	0.10	0.273
Subjective SES	0.05	0.04	0.153	0.03	0.04	0.478	0.04	0.01	0.144	0.03	0.04	0.424
Urban (ref: Rural)	0.15	0.10	0.140	0.14	0.10	0.168	0.10	0.11	0.357	0.07	0.11	0.540
Depression				-0.01	0.01	0.245				-0.02	0.01	0.093
Neuroticism				0.09	0.06	0.096				-0.08	0.06	0.158
Openness				0.28	0.05	**< 0.001**				0.27	0.05	**< 0.001**
Agreeableness				-0.07	0.07	0.315				-0.08	0.07	0.223
Extraversion				-0.06	0.06	0.289				-0.05	0.06	0.407
Conscientiousness				-0.05	0.07	0.454				-0.08	0.07	0.220
Marital status (Ref: Single)							-0.01	0.13	0.981	-0.05	0.13	0.710
Relation w/ children							-0.05	0.01	0.427	-0.07	0.06	0.259
Number of children							-0.18	0.01	**< 0.001**	-0.20	0.05	**< 0.001**
Constant	2.16	0.54	**< 0.001**	1.80	0.66	**0.006**	2.62	0.66	**< 0.001**	2.72	0.78	**0.001**
Pseudo R2	0.118			0.160			0.136			0.176		
Observations	992			976			923			909		
Supplementary Material												
Supplementary Table 1. Definitions and coding of outcome and independent variables												

3.3 Psychological factors and internet use behaviour (H1)

Psychological factors were differentially related to the two dimensions of internet use behaviour examined in this study. According to Table 3, among the Big Five traits, openness exhibited a statistically significant and positive association with weekly internet-use duration. Holding all other covariates constant, a one-point increase in openness corresponded to approximately 1.9 additional hours per week online. Conscientiousness, by contrast, was significantly and negatively associated with weekly duration, with a one-point increase corresponding to an average reduction of about 1.7 hours per week. Depressive symptoms did not show a statistically significant association with weekly duration among older adults who were already internet users. When attention shifts from duration to breadth of use, Table 4 shows that both openness and neuroticism were positively associated with the number of online functions used. On average, a one-point increase in openness was associated with approximately 0.3 additional categories of internet content, while a one-point increase in neuroticism corresponded to about 0.1 additional categories. Extraversion did not significantly predict either weekly duration or breadth of use in this sample, and depressive symptoms were likewise not significantly associated with breadth. Overall, these findings provide support for H1a, indicating that personality traits are associated with older adults' internet-use behaviours, but do not support H1b.

3.4 Family support and internet use behaviour (H2)

Family factors were more consistently associated with weekly duration of internet use than with the breadth of online engagement. As shown in Table 3, number of children, relationship with children, and spousal presence were all negatively associated with older adults' weekly internet-use duration, net of the full set of covariates. On average, each additional child was associated with about 1.5 fewer hours online per week, and each one-point increase in relationship with children was likewise associated with about 1.5 fewer weekly hours of internet use. Having a spouse was also associated with shorter weekly duration. With respect to breadth of use, Table 4 shows that number of children had a modest but statistically significant negative association with the number of online functions used, with each additional child associated with approximately 0.2 fewer content categories. Relationship with children displayed a more differentiated pattern across outcomes: as shown earlier in the logistic models, stronger parent–child ties were positively associated with internet access, but among users they were negatively associated with weekly duration. By contrast, spousal presence was not significantly associated with

breadth of use or with internet access, although it remained negatively associated with duration. Taken together, these results support H2a and provide partial support for H2b and H2c, suggesting that family relationships are more strongly related to the intensity of internet use than to the diversification of online activities.

4. Discussion

4.1 Digital ageing as a differentiated process

The coexistence of rapid digitalisation and population ageing has become a defining feature of contemporary Chinese social change (Zhao et al., 2026). In this context, the present study shows that older adults' internet use is better understood as a differentiated process involving adoption, duration, and breadth of use rather than as a single behaviour. This distinction matters because the factors shaping whether older adults go online are not identical to those shaping how long they stay online or how many functions they use once connected. This interpretation is consistent with research showing that digital inequality in later life extends beyond access to include differences in skills, patterns of use, and outcomes (Wilson et al., 2023). It also supports the view that technology use is embedded in the social relationships and everyday circumstances of later life rather than being a purely individual or technical matter (Long et al., 2024). The findings therefore suggest a stratified picture of digital ageing. Structural resources such as education and urban residence remained especially important at the adoption stage, consistent with earlier studies on digital exclusion among older adults in China and elsewhere (Yang & Du, 2021). However, once access has been achieved, individual dispositions and family relationships become more important in explaining the intensity and variety of engagement. The question is therefore not simply whether older adults use the internet, but how digital activities are organised within their life histories, social roles, and relationships (Long et al., 2024; Wilson et al., 2023).

4.2 Personality and the heterogeneity of internet engagement in later life

The findings show that personality characteristics were more strongly associated with internet use patterns than with depressive symptoms. Openness was positively associated with both internet adoption and frequency of weekly use. Neuroticism was positively related to the breadth of internet engagement, while conscientiousness was negatively associated with duration of usage. These results suggest that digital engagement in later life is shaped not only by material resources but also by stable orientations toward novelty, uncertainty, and routine. Prior studies likewise report that openness tends to support internet use, whereas the role of conscientiousness may vary depending on whether online activity is leisure-oriented or practical (Roos & Kazemi, 2021).

From a social-gerontological perspective, these patterns challenge the tendency to treat older adults as a homogeneous digitally marginalised group. Openness may function as a psychological advantage by making individuals more willing to try unfamiliar interfaces, tolerate frustration, and gradually build digital skills. The positive association between neuroticism and breadth of activities, although initially unexpected, may indicate that emotionally vulnerable older adults use a wider range of online tools for information, reassurance, or everyday management. By contrast, the negative association between conscientiousness and duration may reflect a more selective and structured form of engagement. Overall, digital participation in later life should be understood not only in terms of capability or exclusion, but also in terms of stable psychological differences that shape motivation and digital habits (Roos & Kazemi, 2021).

4.3 Family embeddedness and the intergenerational organisation of digital life

The family-related findings are especially important in the Chinese context, where intergenerational ties remain central to everyday support and social organisation. In the present study, the number of children was negatively associated with duration of internet use and, to a lesser extent, breadth of online activities. At the same time, relationship quality with children showed a dual pattern: it was positively associated with internet adoption, yet negatively associated with duration among those already online. This suggests that family relationships may operate through both enabling and substitutive mechanisms. On the enabling side, closer ties with adult children may facilitate entry into digital life through encouragement, device setup, troubleshooting, and continued guidance. This interpretation is consistent with research showing that older adults' technology use is often sustained through interpersonal assistance rather than wholly independent learning (Hunsaker et al., 2019), and with evidence that intergenerational support is closely related to digital media engagement in later life (Li & Zhou, 2021; Cui et al., 2025). At the same time, the findings also point to a substitutive process. Once older adults are already online, strong family ties may reduce the need for prolonged digital engagement because companionship, practical help, and trusted information remain available through offline channels. A similar pattern appears in the negative association between spousal presence and weekly duration. Internet use in later life may therefore function partly as a compensatory resource when offline support is limited, but become less central when in-person companionship is readily available. Overall, these results extend the literature by showing that family embeddedness may simultaneously promote adoption while reducing the need for intensive use (Hunsaker et al., 2019; Long et al., 2024; Reis et al., 2021).

4.4 Reconsidering the non-significant role of depressive symptoms

Another notable result is that depressive symptoms were not significantly associated with weekly duration or breadth among older adults who were already internet users. This does not mean that mental health is irrelevant to digital ageing. Rather, it suggests that the relationship may be stage-specific and more closely tied to adoption or to particular forms of online activity than to overall time spent online. Existing research has linked digital exclusion and internet access to depressive symptoms in older Chinese adults, but much of this literature focuses on differences between users and non-users rather than variation among those who have already crossed the access threshold (Li et al., 2023). This interpretation is consistent with broader work on digital inequality, which argues that later-life digital participation is not reducible to a simple binary of access versus non-access, but instead reflects layered inequalities in skills, confidence, support, and meaningful use (Büchi et al., 2016; Fang et al., 2019; Wilson et al., 2023). The present study therefore reinforces the argument that digital ageing is internally differentiated: digital inclusion does not end once older adults go online, because inequality persists in the intensity, range, and social meaning of use (Li & Zhou, 2021; Li et al., 2023; Wilson et al., 2023).

4.5 Contributions to debates in social gerontology

Taken together, these findings contribute to social gerontology by showing that digital engagement in later life is shaped simultaneously by structural, psychological, and relational factors. Structural inequalities remain important, particularly in the continuing significance of education and urban residence for internet adoption (Yang & Du, 2021). However, a purely resource-based account is insufficient, because digital practices are also shaped by personality, family support, social need, and everyday routines. These findings support a shift away from viewing the digital divide as a simple binary between users and non-users. Instead, digital inclusion in later life is better understood as a continuum involving access, patterns of use, support structures, and the extent to which technology is integrated into everyday life (Büchi et al., 2016; Fang et al., 2019; Long et al., 2024; Wilson et al., 2023). The study also challenges the assumption that more internet use is always preferable. For some older adults, selective or limited digital engagement may reflect stable preferences, strong offline support, and established routines rather than exclusion or incapacity (Long et al., 2024).

4.6 Limitations and directions for further research

Several limitations should be acknowledged. First, CFPS was not designed specifically to study internet behaviour, so important determinants such as connection quality, affordability, device ownership, prior occupational exposure to technology, and age at first adoption were not observed. Second, internet use was measured through self-report, which may involve recall error or social-desirability bias. Third, the cross-sectional design prevents firm causal inference. Finally, because the analysis relies on 2018 data, it cannot capture more recent platform changes, cohort replacement, or shifts in later-life internet use in post-pandemic China (Matthews et al., 2019). Future research should adopt longitudinal and function-specific approaches. Multi-wave analyses could help distinguish age, cohort, and period effects, while more refined measures of online activity could clarify whether family and psychological factors operate differently across communication, entertainment, information seeking, and transactional use. More broadly, future work should continue to conceptualise later-life technology use as a socially situated process rather than a narrow indicator of technical uptake (Cui et al., 2025; Hunsaker et al., 2019; Long et al., 2024; Wilson et al., 2023; Fang et al., 2019).

5. Conclusion

As digital ecosystems become more inclusive of older adults, the cost of learning to use these systems may further decrease. The number of older adults using the internet may also gradually approach that of younger demographics. However, narrowing the digital divide is only the first step. Significant disparities remain in how people use technology and the benefits they gain, as many older adults still face challenges related to ability, confidence, motivation, and access to information. These barriers hinder participation and deepen the divide within age groups. Historically, basic access capability has been the primary dimension of digital stratification. In the future, inequalities in usage practices and benefits will become the main source of disparity, with differences in capability, opportunity, and support determining who benefits and to what extent. These evolving dynamics point to clear directions for research and policy development. Future research should explore multi-level factors influencing participation, encompassing individual characteristics (such as educational attainment, cognitive and physical health, psychological disposition); family and kinship resources (including the robustness and reliability of social support); and program elements (such as the accessibility and effectiveness of technical training). Transforming information access into long-term benefits hinges on optimizing design and implementation approaches: ensuring information relevance, providing tiered progressive support, hands-on guidance, and sustained follow-up. A systematic analytical framework integrating these elements can guide targeted interventions and public services, empowering older adults to deeply engage with the information society and reap the multifaceted social, informational, and health benefits of digital participation.

Declarations

Author Contribution

S.L. supervised and oversaw the entire research process, providing overall guidance on study design, analysis, and manuscript development. Y.T. and B.L. conducted the statistical analyses and prepared the initial draft of the manuscript. J.Z. refined the data and analyses and undertook substantial revisions of the manuscript, including improvements to its structure, content, and interpretation of findings. All authors reviewed and approved the final manuscript.

Data Availability

The data analysed in this study were obtained from the 2018 China Family Panel Studies (CFPS), conducted by the Institute of Social Science Survey at Peking University. The dataset is available through the Peking University Open Research Data Platform at https://doi.org/10.18170/DVN/45LCSO. Access to the data is subject to the repository's registration and data use requirements.

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57. Main, & Tables.

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