Gender Differences in Cognitive Decline Among Older Adults and the Role of Digital Inclusion: Evidence from European countries

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Abstract

This study examines the association between digital inclusion and gender differences in episodic memory — adopting an intersectional perspective that considers gender inequality across different levels of urbanization. Using panel data from the Survey of Health, Ageing and Retirement in Europe (2013–2022), we provide new insights into previously inconclusive literature. Our findings suggest that, once common time trends are accounted for, the beneficial effect of internet use on episodic memory — and thus on cognitive functioning — no longer differs significantly by gender. Over time, women appear to catch up, with the initially observed disadvantage gradually diminishing. However, gender does interact with urbanization level: internet use (used as a proxy for digital inclusion) exhibits a substantially stronger and highly statistically significant protective effect on cognitive functioning for urban men. Conversely, urban women appeared to gain comparatively less cognitive benefit from internet use. By highlighting the exacerbating role of urbanization, our results underscore the importance of digital access and usage for both older women and men in preventing cognitive decline and supporting social participation and inclusion.

Digital divide, Cognitive health, Gender gap; Urbanization

Introduction

Cognitive abilities in older age are not only relevant at the individual level but are also gaining importance at the population level, given the growing share of older adults. Maintaining cognitive functioning in later life is increasingly important for both economic productivity and social participation. Differences in cognitive performance between men and women are well documented (Arnhold et al., 2025; Asperholm et al., 2019) and are shaped by both individual and environmental factors such as education, social networks, and living conditions (Roth, 2022; Weber et al., 2014). Recent societal changes — particularly the rapid digitalization of everyday life — may exacerbate potential gender disparities, as older adults are especially vulnerable to digital exclusion, defined as limited access to or use of digital technologies such as internet. This study therefore aims to investigate gender inequalities in digital inclusion and their potential effect on cognitive functioning among older Europeans.

A substantial body of research shows that women tend to outperform men in reading comprehension (Guiso et al., 2008) and episodic memory (Asperholm et al., 2019), while men often perform better on visuospatial and some numerical tasks (Lippa et al., 2010; Stoet & Geary, 2013). These differences are generally modest but consistent, observable from childhood through old age, and found across diverse global regions (Bedard & Cho, 2010; Guiso et al., 2008; Herlitz et al., 2017). While these studies often refer to biological "sex differences," such differences likely reflect the cumulative influence of gendered life-course experiences. Importantly, the size and direction of these differences vary across countries, depending on contextual factors such as living standards and gender equality (Breda et al., 2018; Else-Quest et al., 2010; Herlitz et al., 2017; Weber et al., 2014). For instance, Weber and colleagues (2014), using SHARE data, found that improved living conditions and more equitable access to education were associated with greater female advantages in episodic memory, as well as reductions or even eliminations of male advantages in numeracy and semantic memory. These findings suggest that women's cognitive functioning is particularly responsive to improvements in environmental and societal conditions.

Digitalization has become a fundamental component of modern life, potentially facilitating the participation of older adults in society. Although digital infrastructure and competencies are steadily improving across Europe, significant disparities may persist between men and women and likely intersect with urbanization level (Lucendo-Monedero et al., 2019). On the one hand, urban regions benefit from faster and more widespread internet access, while rural areas often face challenges related to both connectivity and digital literacy. On the other hand, digital inclusion in urban regions may be particularly relevant due to higher risks of loneliness and reduced social connectedness (Long et al., 2024). These geographical divides are further exacerbated by a North-West versus South-East gradient across Europe (Kessel et al., 2022).

Although literature examining the intersection of gender and urbanization and their joint effects on cognition is generally lacking, first cross-sectional studies show that women with lower educational attainment who reside in rural areas are particularly vulnerable to multiple forms of exclusion, including digital and social exclusion (Gallistl et al., 2020). At the same time, some evidence suggests that the digital gender gap may be narrowing across life stages

(Bünning et al., 2023), although this trend may not be uniform across regions or population subgroups. Digital proficiency is also strongly associated with younger age and higher levels of education, whereas older adults are more likely to experience digital exclusion, especially those living in rural areas (Diana et al., 2025; Mubarak & Suomi, 2022). These digital inequalities may have downstream effects on cognitive health, particularly among disadvantaged subgroups. In recent years, growing evidence has linked digital exclusion to adverse cognitive outcomes, including poorer cognitive functioning and a higher risk of cognitive decline and impairment (Benge & Scullin, 2025; Duan et al., 2024; K. Wang et al., 2024; Xavier et al., 2014). However, whether the relationship between digital exclusion and cognitive functioning differs by gender remains unclear. While two recent studies found no statistically significant gender differences in this association (Duan et al., 2024; Y. Wang et al., 2024), a study of older adults in China reported that being male conferred a protective effect against the cognitive consequences of digital exclusion (Liu et al., 2023). These mixed findings highlight the need for further investigation, particularly in diverse cultural and regional contexts such as Europe.

Building on Eagly's social role theory (Eagly & Wood, 2012) — which posits that societal participation is shaped by entrenched gender roles, cultural beliefs, and structural barriers — we investigate whether changes in digital inclusion moderate the relationship between gender and cognitive functioning. That is, in a first step, we explore whether the impact of gender on cognitive outcomes is moderated by individuals' digital access, using internet use as a proxy for digital inclusion. Specifically, we test whether gender differences in cognitive functioning are strengthened or weakened depending on levels of digital inclusion. In a second step, we examine whether this moderating effect of digital inclusion varies by the level of urbanization among older adults in Europe. By adopting an intersectional approach to gender inequality, we aim to address some of the shortcomings in preceding literature. Our study further adds to the literature by shedding light on how these patterns evolve over time.

As digital participation becomes an increasingly vital means of engaging in society and accessing essential resources, including health-related information and services, exclusion from digital technologies may deepen existing inequalities. Older adults who are socially marginalized are more likely to lack digital skills, which may reinforce their exclusion and negatively affect their cognitive health (Ragnedda et al., 2022). In this study, we propose that digital exclusion disproportionately increases the risk of cognitive decline among older women thus exacerbating gender-based disparities in cognitive functioning. Drawing on social role theory, structural inequalities may intersect with gender to shape cognitive outcomes in later life. By further highlighting the joint effects of gender, digital inclusion, and urbanization level, this study contributes to a more nuanced understanding of cognitive aging in an increasingly digital and spatially divided society.

Data & Methods

In this study we use panel data from the Survey of Health, Ageing and Retirement in Europe (SHARE) – waves 5, 6, 8 and 9 collected between 2013 and 2022 (SHARE-ERIC, 2024b, 2024c, 2024d, 2024a). SHARE is a cross-national panel survey that collects information on health and cognitive functioning of older adults aged at least 50 years since 2004 (Börsch-Supan et al., 2013). We restrict the sample to individuals who participated in all four waves. To mitigate concerns of reverse causality, we further exclude respondents with cognitive impairment at baseline (wave 5), defined as scoring more than 1.5 standard deviations below the mean memory performance of their respective country–age group (Han et al., 2021; Luchetti et al., 2020). Our final analytical sample consists of 15,676 individuals observed across four waves and 13 countries, summing up to 62,704 observations in total (see sample statistics in Table A.1).

Episodic memory

Given its high sensitivity to age-related decline and strong correlation with general cognitive abilities, our key dependent variable is episodic memory. It reflects integrative brain processes involving multiple cognitive domains, making it a reliable proxy for global cognition. Moreover, episodic memory performance—as assessed in large surveys such as SHARE—has shown strong predictive validity for functional decline, dementia, and health outcomes in later life.

In this study, we use a summary score based on participants' immediate and delayed word recall tests. In the immediate recall test, the interviewer reads out a list of ten nouns, asking the respondent to recall as many words as possible within one minute. The delayed recall test takes place about five minutes later, with the respondents having to recall as many words as possible from the previously read-out words without rehearing them. Since we use a summary score of the immediate and delayed word recall tests, variable values range from 0 to a maximum of 20 words (see Table A.1).

Digital inclusion

As a proxy for digital inclusion (or, conversely, digital exclusion), we rely on a binary variable capturing internet use (yes/no). In SHARE, every participant is asked whether they have used internet (e.g. for e-mailing, searching for information, making purchases, or for any other purpose) at least once within the most recent 7 days.

Gender

In SHARE, gender is coded dichotomous (1 for female, 0 male).

Urbanization level

To examine heterogeneous (gender) effects by urbanization level, we also employ a binary indicator distinguishing between urban and non-urban populations. While a big city or the suburbs or outskirts of a big city are categorized as urban, living in a town, rural area or village are categorized as non-urban.

Other controls

To account for other time-varying factors, we include age and the log of wealth (PPP-adjusted). In subsequent analyses *(to be done)*, we further extend the set of controls to improve robustness. In addition to individual fixed effects (FE; see estimation strategy), which absorb all time-invariant individual characteristics, we include time FE to capture common shocks and period-specific influences that affect all respondents (e.g. macroeconomic trends or pandemic effects).

Estimation strategy

To investigate the role of digital inclusion on gender differences in episodic memory, a two-way fixed effects (FE) approach using balanced panel data will be applied. The baseline FE model we estimate is the following:

$$Memory_{it} = \beta_1 internet\ use_{it} + \beta_2 X_{it} + \alpha_i + \lambda_t + u_{it},$$

with $i=1,\ldots,n$ and $t=1,\ldots,t$ (for each wave). The α_i are individual-specific intercepts that capture heterogeneities across individuals (i.e., time-invariant unobserved heterogeneity). λ_t captures wave/time fixed effects. Other possibly time-varying regressors are included in X_{it} and u_{it}, represents the idiosyncratic error term (Stock and Watson, 2015).

Our parameter of interest is β_1, measuring the effect of a change in internet use (*e.g., from non-use to use*) on our cognition indicator (i.e., *memory score*). As we rely on a FE approach, our analysis focuses exclusively on within-individual changes in internet use. Supporting this strategy, we observe 3,221 unique individuals in our sample who switch their internet usage status at least once during the period under investigation, with some switching multiple times. Our data captures changes in both directions: 2,804 transitions from non-use to use, and 1,822 transitions from use to non-use. Notably, more individuals shift from non-use to use in later waves, reflecting the overall upward trend in internet adoption within our sample (see also Figure 1).

Gender differences in internet use are assessed via the interaction between gender and internet use. Additionally, we conduct subset analyses comparing urban women to urban men and rural women to rural men, allowing us to capture the joint effect of gender and urban status. For the purpose of this paper, we include only individuals whose urban status remains constant across all waves, comparing urban individuals to rural ones (for both genders). This approach allows us to isolate the gendered effect of internet use on cognition by urbanization level, thereby improving the interpretability of our findings.

Sensitivity analyses and robustness checks

Additional analyses examining the interaction between internet use and urban status are presented in the Appendix (Tables A.8–A.9). We also complement our main analyses by exploring different subsets based on baseline work status (Tables A.10–A.12) and baseline education level (Tables A.13–A.14).

In subsequent steps and robustness checks, we aim to further account for additional time-varying factors, such as changes in social connectedness, and further support the validity of our result by using lagged internet use as the dependent variable, based on a subset of three waves instead of four (waves 6, 8 and 9). Finally, we also estimate our models using errors clustered at the individual level, providing a more conservative approach. Overall, the results remain qualitatively similar (results can be provided upon request).

Results

Average memory scores are 10.24 words for men and 10.9 for women in wave 5, declining to 9.18 for men and 9.98 for women in wave 9 (see Figure 1 and Table A.2-A.4). While both genders experience a general cognitive decline, women consistently score higher than men and show a slightly slower rate of decline. In contrast, internet use shows an upward trend. On average, men are more likely than women to use the internet: 67.96% of men in wave 5 and 71.89% in wave 9, compared to 58.06% of women in wave 5 and 65.90% in wave 9 (see also Table A.4). Thus, the gender gap in internet use narrows over time, with women gradually catching up.

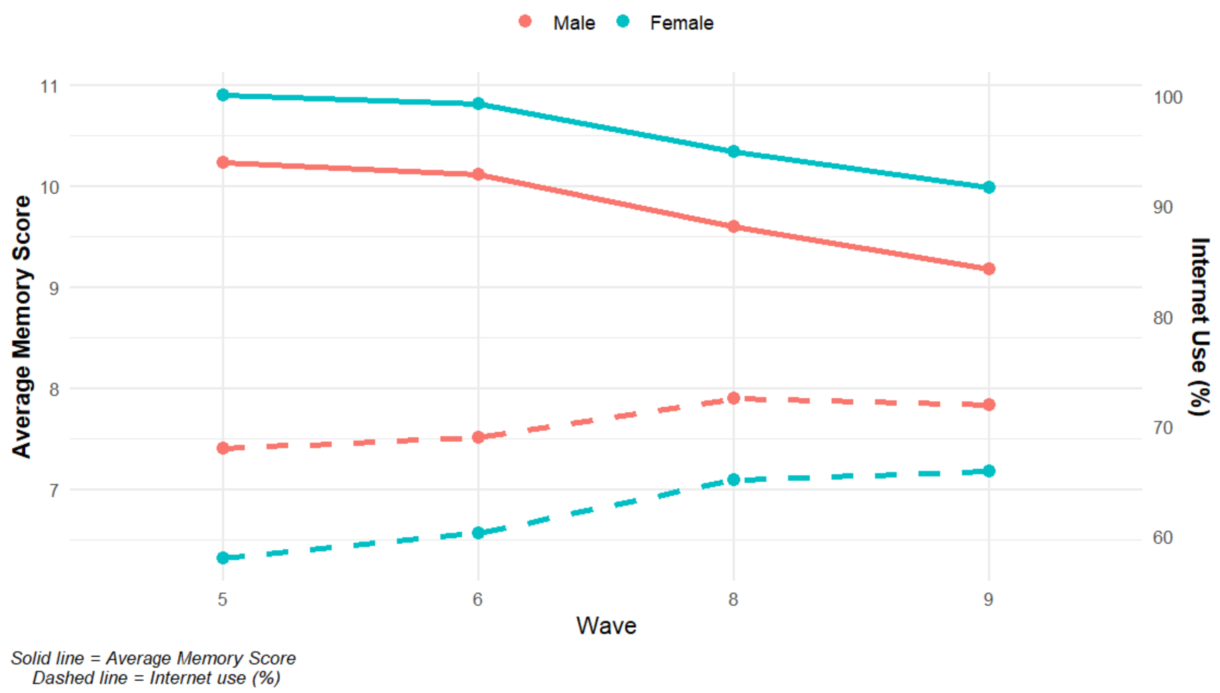

Figure 1: Trends in average memory score and internet use over time. Data source(s): SHARE waves 5,6,8, and 9

Overall, the results suggest that using internet improves general cognition among older adults, regardless of gender, as reflected in higher average memory scores, although the effect sizes remain consistently larger for men than for women. However, once controlling for common time trends (by adding wave FE to the model), the gender difference becomes statistically insignificant, consistent with the descriptively observed convergence in internet use over time (see Figure 1 and Table 1, column 1).

Further, we report notable gender differences by urbanization level. Internet use has a significantly stronger positive effect on memory scores for the urban population (see Tables A.8 and A.9), with urban men benefiting more than women (see Table 1, column 4). That is, when urban men switch from non-use to internet use, their average memory score increases by 1.13 words. In contrast, no significant gender differences are observed in the non-urban population (see Table A.7). These results remain robust when clustering standard errors at the individual level.

Table 1: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Urbanization Level

	Dependent variable:			
	Memory score			
	Total	Urban Women	Urban Men	Total Urban
	(1)	(2)	(3)	(4)
internet use	0.462***	0.593***	1.142***	1.134***
	(0.070)	(0.132)	(0.199)	(0.198)
internet × female	−0.116			−0.534**
	(0.088)			(0.237)
age	0.028	0.018	0.069	0.039
	(0.030)	(0.094)	(0.122)	(0.074)
log_wealth_(ppp-adjusted)	0.025***	0.048**	0.040	0.045**
	(0.007)	(0.021)	(0.032)	(0.018)
wave 6	−0.157**	0.026	−0.110	
	(0.066)	(0.204)	(0.263)	
wave 8	−0.791***	−0.638	−1.029	
	(0.198)	(0.612)	(0.791)	
wave 9	−1.240***	−1.035	−1.644	
	(0.264)	(0.818)	(1.055)	
Observations	62,704	6,168	3,764	9,932
R^2	0.042	0.043	0.060	0.008
Adjusted R^2	−0.278	−0.277	−0.256	−0.324

Note: *p<0.1; **p<0.05; ***p<0.01

Finally, while our main focus is on gender differences and the role of urbanization in the effects of changes in internet use among older adults, we also provide additional analyses that account for baseline work status and educational level. Interestingly, our findings reveal no statistically significant differences by work status at baseline (e.g., being employed, retired, or a homemaker in wave 5; see Table A.10 – A.12), but they do show differences by educational level. In particular, gender differences in the effect of changing internet use persist among the highly educated, whereas they remain insignificant among the lowest educated (see Tables A.13 – A.14).

Future analyses will assess the validity of our results by modifying and expanding the set of controls in our model (accounting for potential other time-variant factors) and by varying the threshold for the degree of urbanization. In addition, we will use the lag of internet use in a subset of three waves (instead of four). Taken together, these robustness checks are intended to further strengthen our findings.

Discussion

This study investigated gender differences in the effect of digital inclusion — proxied by changes in internet use — on cognitive functioning, measured using memory scores. Applying SHARE panel data and using a fixed effects (FE) approach, we found evidence that digital inclusion helps prevent cognitive decline for both men and women in line with previous literature (Benge & Scullin, 2025; Duan et al., 2024; K. Wang et al., 2024; Xavier et al., 2014). Although gender differences were not statistically significant, effect sizes tended to be higher for men, suggesting that digital access may have a stronger protective effect for them (Liu et al., 2023). Extending the literature by examining intersectional inequalities between gender and urbanization level, we found robust evidence that internet use is particularly beneficial among urban populations. Moreover, significant gender disparities persist, especially between urban men and urban women, highlighting the importance of considering both gender and place in digital inclusion policies.

While (older) women generally perform better in terms of episodic memory, the opposite pattern is observed for digital access. Men are more likely to report internet use throughout the study period (2013 – 2022), although the gender gap in usage is gradually closing (Bünning et al., 2023). These patterns align with our FE model results, which suggest that common time trends largely account for gender differences in the effect of internet use on cognition. Nevertheless, gender disparities persist when considering urbanization level, providing novel insights. Urban regions often benefit from faster and more widespread internet access (Lucendo-Monedero et al., 2019), and digital inclusion is particularly important in these areas due to higher risks of loneliness and reduced social connectedness (Long et al., 2024). Studies show that gender norms and cultural ideals of masculinity and older men's poorer quality friendships have adverse consequences on their health (Eagly & Wood, 2012; Ratcliffe et al., 2024). Accordingly, internet use — as means to facilitate societal participation—may exert a stronger protective effect for men.

While Europe continues to advance in digital infrastructure and cultural competency, significant disparities between men and women persist and appear to intersect with levels of urbanization. By examining changes over time (spanning almost ten years) and considering intersectional inequalities (particularly gender and urbanization degree), this research makes a meaningful contribution to previously inconclusive studies on gender differences in cognitive functioning

(Duan et al., 2024; Y. Wang et al., 2024). Despite offering robust insights, this study is not without limitations. First, our analysis focuses on identifying robust associative effects as a strict causal interpretation is limited. We use a balanced panel and exclude participants with cognitive impairment in wave 5, which helps reduce selection bias and the potential for reverse causality. Additionally, individual and wave fixed effects control for time-invariant confounders.

In subsequent steps and robustness checks, we further account for additional time-varying factors, such as changes in health status or social contacts, and mitigate potential reverse causality by using lagged internet use as the dependent variable, based on a subset of three waves instead of four. Although these restrictions and additional robustness tests further support the validity of our findings, other unobserved time-varying factors or life events could still affect both internet use and cognitive performance. Consequently, while our findings reveal robust associations, causal inference remains limited. Finally, restricting the sample to cognitively healthier and fully observed individuals may reduce the generalizability of our results to the broader older population.

Second, a key limitation concerns our primary measure of digital inclusion. While relying on internet use as a proxy for digital inclusion is a common approach adopted in literature, the SHARE data have inherent constraints. In particular, the dataset does not provide information on the specific purposes for which the internet is used, making it difficult to capture the full scope and quality of digital engagement. Additionally, respondents are asked to report their internet use over the past seven days, which may introduce recall bias or fail to reflect habitual usage patterns. First studies indicate that men had higher odds than women of performing informational and instrumental (e.g., online banking) but not social online activities (Bünning et al., 2023; Schehl et al., 2019). Despite these limitations, future research could benefit from more detailed measures of digital inclusion that capture both the frequency and purpose of internet use, allowing for a more nuanced understanding of how digital engagement relates to outcomes such as cognitive functioning.

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Appendix

Table A.1: Sample statistics of key variables

Variables	**Mean/%**	**Min**	**Max**	**N**
memory	10.22	0	20	62,704
internet use (*yes*)	65.54	0	1	41,099
gender (*female*)	59.87	0	1	37,544
age	69.19	36	101	62,704
log wealth (ppp-adjusted)	10.91	0	23.04	62,704

Table A.2: Memory and internet use by gender

Memory	**Mean**	**SD**	**N**
Male	9.782552	3.229754	25,160
Female	10.510601	3.497465	37,544
Internet use		**%**	**N**
Male		70.33	25,160
Female		62.33	37,544

Table A.3 Memory score by wave and gender

Wave	**Gender**	**Memory (Mean)**	**Memory (SD)**	**N**
5	Male	10.24	2.88	6,290
5	Female	10.90	3.17	9,386
6	Male	10.12	3.18	6,290
6	Female	10.82	3.40	9,386
8	Male	9.59	3.27	6,290
8	Female	10.35	3.56	9,386
9	Male	9.18	3.45	6,290
9	Female	9.98	3.76	9,386

Table A.4 Internet use by wave and gender

Gender	**Wave**	**Internet use (%)**	**N**
Male	5	67.96	6,290
Male	6	68.95	6,290
Male	8	72.53	6,290
Male	9	71.89	6,290
Female	5	58.06	9,386
Female	6	60.26	9,386
Female	8	65.12	9,386
Female	9	65.90	9,386

Table A.5 Country sample statistics

Country	**N**
Austria	3,432
Germany	7,724
Sweden	5,936
Spain	2,816
Italy	4,608
France	5,372
Denmark	5,096
Switzerland	4,880
Belgium	4,664
Czech Republic	5,944
Luxembourg	1,448
Slovenia	4,040
Estonia	6,744

Main regression output

Table A.6: Fixed Effects Estimates of Internet Use on Memory Score, by Gender

	Dependent variable:		
	Memory Score		
	Women	Men	Total
	(1)	(2)	(3)
internet	0.331***	0.476***	0.462***
	(0.054)	(0.070)	(0.070)
internet × female			−0.116
			(0.088)
age	0.057	−0.015	0.028
	(0.040)	(0.047)	(0.030)
log_wealth (ppp-adjusted)	0.028***	0.019	0.025***
	(0.009)	(0.012)	(0.007)
wave 6	−0.198**	−0.094	−0.157**
	(0.086)	(0.102)	(0.066)
wave 8	−0.939***	−0.569*	−0.791***
	(0.258)	(0.308)	(0.198)
wave 9	−1.432***	−0.952**	−1.240***
	(0.344)	(0.411)	(0.264)
Observations	37,544	25,160	62,704
R^2	0.037	0.050	0.042
Adjusted R^2	−0.284	−0.267	−0.278
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.7: *Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Urbanization Level (Non-urban)*

	Dependent variable:		
	Memory Score		
	Non-urban Women	Non-urban Men	Total Non-urban
	(1)	(2)	(3)
internet	0.267***	0.325***	0.308***
	(0.067)	(0.084)	(0.085)
age	0.110**	−0.011	0.060
	(0.050)	(0.059)	(0.038)
log_wealth (ppp-adjusted)	0.016	0.006	0.012
	(0.011)	(0.015)	(0.009)
wave 6	−0.327***	−0.129	
	(0.108)	(0.127)	
wave 8	−1.296***	−0.635*	
	(0.325)	(0.382)	
wave 9	−1.891***	−1.014**	

	(0.434)	(0.511)	
internet × female			−0.021
			(0.107)
Observations	24,252	16,700	40,952
R^2	0.036	0.051	0.001
Adjusted R^2	−0.286	−0.266	−0.332
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.8: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Urbanization Level (Women sample)

	Dependent variable:		
	Memory Score		
	Rural Women	Urban Women	Women
	(1)	(2)	(3)
internet	0.267***	0.593***	0.265***
	(0.067)	(0.132)	(0.066)
age	0.110**	0.018	0.091**
	(0.050)	(0.094)	(0.044)
log_wealth (ppp-adjusted)	0.016	0.048**	0.022**
	(0.011)	(0.021)	(0.010)
wave 6	−0.327***	0.026	−0.255***
	(0.108)	(0.204)	(0.095)
wave 8	−1.296***	−0.638	−1.161***
	(0.325)	(0.612)	(0.287)
wave 9	−1.891***	−1.035	−1.715***
	(0.434)	(0.818)	(0.384)
internet × urban			0.325**
			(0.151)
Observations	24,252	6,168	30,420
R^2	0.036	0.043	0.037
Adjusted R^2	−0.286	−0.277	−0.285
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.9: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Urbanization Level (Men sample)

	Dependent variable:		
	Memory Score		
	Rural Men	Urban Men	Men
	(1)	(2)	(3)
internet	0.325***	1.142***	0.322***
	(0.084)	(0.199)	(0.084)
age	−0.011	0.069	0.004
	(0.059)	(0.122)	(0.053)
log wealth (ppp-adjusted)	0.006	0.040	0.012
	(0.015)	(0.032)	(0.014)
wave 6	−0.129	−0.110	−0.126
	(0.127)	(0.263)	(0.114)
wave 8	−0.635*	−1.029	−0.708**
	(0.382)	(0.791)	(0.344)
wave 9	−1.014**	−1.644	−1.130**
	(0.511)	(1.055)	(0.460)
internet × urban			0.826***
			(0.216)
Observations	16,700	3,764	20,464
R^2	0.051	0.060	0.052
Adjusted R^2	−0.266	−0.256	−0.264
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.10: *Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Work status at baseline (Employed in wave 5)*

	Dependent variable:		
	Memory Score		
	Women	Men	Interaction
	(1)	(2)	(3)
internet	0.184*	0.183	0.130
	(0.109)	(0.127)	(0.128)
internet × female			0.095
			(0.167)
age	−0.003	−0.016	−0.011
	(0.070)	(0.078)	(0.052)
log_wealth_(ppp-adjusted)	−0.001	−0.005	−0.004
	(0.016)	(0.020)	(0.013)
wave 6	0.048	0.012	0.037
	(0.152)	(0.169)	(0.113)
wave 8	−0.097	−0.265	−0.154
	(0.461)	(0.512)	(0.343)
wave 9	−0.269	−0.561	−0.374
	(0.613)	(0.681)	(0.456)
Observations	11,332	9,028	20,360
R^2	0.005	0.023	0.011
Adjusted R^2	−0.328	−0.303	−0.319
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A.11: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Work status at baseline (Homemaker in wave 5)

	Dependent variable:		
	Memory Score		
	Women	Men	Interaction
	(1)	(2)	(3)
internet	0.428***	1.925*	1.917*
	(0.142)	(1.098)	(1.106)
internet × female			−1.491
			(1.115)
age	0.092	−0.826	0.073
	(0.119)	(0.852)	(0.118)
log_wealth_(ppp-adjusted)	0.068**	0.313**	0.078***
	(0.027)	(0.121)	(0.026)
wave 6	−0.433*	1.131	−0.401
	(0.258)	(1.871)	(0.255)
wave 8	−1.456*	4.852	−1.329*
	(0.779)	(5.530)	(0.771)
wave 9	−1.961*	5.576	−1.802*
	(1.030)	(7.331)	(1.020)
Observations	3,988	72	4,060
R^2	0.054	0.225	0.056
Adjusted R^2	−0.263	−0.146	−0.262
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.12: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Work status at baseline (Retired in wave 5)

	Dependent variable:		
	Memory Score		
	Women	Men	Interaction
	(1)	(2)	(3)
internet	0.413***	0.599***	0.596***
	(0.073)	(0.089)	(0.091)
internet × female			−0.179
			(0.116)
age	0.068	0.015	0.046
	(0.055)	(0.062)	(0.041)
log_wealth_(ppp-adjusted)	0.026**	0.020	0.024**
	(0.012)	(0.018)	(0.010)
wave 6	−0.242**	−0.205	−0.226**
	(0.119)	(0.135)	(0.089)
wave 8	−1.221***	−0.931**	−1.098***
	(0.356)	(0.405)	(0.267)
wave 9	−1.861***	−1.437***	−1.682***
	(0.478)	(0.542)	(0.359)
Observations	19,984	14,512	34,496
R^2	0.065	0.072	0.068
Adjusted R^2	−0.247	−0.237	−0.243
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A.13: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Education at baseline (High education level in wave 5)

	Dependent variable:		
	Memory Score		
	Women	Men	Interaction
	(1)	(2)	(3)
internet	0.349***	0.733***	0.737***
	(0.133)	(0.176)	(0.177)
internet × female			−0.377*
			(0.221)
age	−0.013	0.081	0.030
	(0.078)	(0.086)	(0.057)
log_wealth_(ppp-adjusted)	0.027	0.029	0.027*
	(0.020)	(0.027)	(0.016)
wave 6	−0.025	−0.112	−0.067
	(0.168)	(0.185)	(0.124)
wave 8	−0.371	−1.065*	−0.689*
	(0.507)	(0.559)	(0.376)
wave 9	−0.729	−1.663**	−1.156**
	(0.676)	(0.746)	(0.501)
Observations	9,756	7,768	17,524
R^2	0.030	0.049	0.038
Adjusted R^2	−0.294	−0.270	−0.284
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A.14: Fixed Effects Estimates of Internet Use on Memory Score, by Gender and Education at baseline (Low education level in wave 5)

	Dependent variable:		
	Memory Score		
	Women	Men	Interaction
	(1)	(2)	(3)
internet	0.387***	0.459***	0.452***
	(0.091)	(0.121)	(0.120)
internet × female			−0.062
			(0.149)
age	0.119*	−0.119	0.032
	(0.072)	(0.095)	(0.057)
log_wealth_(ppp-adjusted)	0.043***	0.028	0.039***
	(0.014)	(0.023)	(0.012)
wave 6	−0.475***	−0.012	−0.306**
	(0.155)	(0.205)	(0.124)
wave 8	−1.637***	−0.174	−1.104***
	(0.466)	(0.621)	(0.373)
wave 9	−2.287***	−0.202	−1.526***
	(0.622)	(0.824)	(0.496)
Observations	11,608	6,488	18,096
R^2	0.061	0.062	0.061
Adjusted R^2	−0.253	−0.252	−0.253
Note:	*p<0.1; **p<0.05; ***p<0.01		