Gender Disparities in the Development of ICT Literacy across Adulthood: A Two-Wave Study

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We have no conflicts of interest to disclose. The study was not preregistered. This paper uses data from the National Educational Panel Study (NEPS; see Blossfeld & Roßbach, 2019). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network. The raw data, including the study material, are available after registration at https://doi.org/10.5157/NEPS:SC6:15.0.0. The analysis code is provided at https://osf.io/fvqth/. A preprint of the manuscript is available at https://doi.org/10.31234/osf.io/7p9mc.

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Abstract

Despite the increasing importance of digital skills in modern society, the development of information and communication technology (ICT) literacy in adulthood has received limited attention, particularly regarding gender differences over the course of life. Therefore, this study investigated between-person differences and within-person changes in ICT literacy over approximately nine years in a sample of N = 2,266 adults from Germany. The result showed that younger adults exhibited higher ICT literacy than older adults, but within-person changes did not differ by age. On average, ICT literacy declined over time (Cohen's d = -0.30). Men consistently demonstrated higher ICT literacy than women (Cohen's d = 0.39), though gender did not influence changes in ICT literacy. Socioeconomic status did not robustly moderate these effects. These findings suggest that ICT literacy tends to decline across adulthood, while preexisting gender differences, likely rooted in earlier socialization processes, persist without substantial change.

Keywords: ICT literacy; digital competence; longitudinal; adulthood; gender

Public Significance Statement

The study showed that younger adults and men exhibited higher ICT literacy than older adults and women. While ICT literacy declined over nine years in all age groups, the gender gap was stable over nine years.

Introduction

Modern society is increasingly centred around online collaboration, remote learning, and digital work. In this context, the ability to effectively use information and communication technologies (ICT) is becoming more and more important. As individuals progress through different stages of adolescence and adulthood, their digital proficiencies can have a great impact on their educational attainment, employment opportunities, and overall quality of life (e.g., Chen et al., 2022; Lei et al., 2021; Livingstone et al., 2023). The development of digital competences across the life course has, however, received limited attention thus far, with some notable exceptions focusing on children and adolescents (Gnambs, 2021; Lazonder et al., 2020; Senkbeil, 2022). But an understanding of how disparities in digital competencies, such as ICT literacy, emerge and persist across different life stages is essential for the development of effective interventions to reduce barriers for digital participation and to systematically address skill improvement.

Cross-sectional research indicates that older adults are often at a disadvantage when it comes to digital skills (Llorente-Barroso et al., 2023; Olsson et al., 2019; Papí-Gálvez & La Parra-Casado, 2023; Van-Deursen & Van-Dijk, 2019). This can have far-reaching implications such as difficulties in accessing essential online services, participating in the digital economy, maintaining independent living, and staying connected with family and friends. To gain a deeper understanding of how disparities in digital competencies emerge or change across adulthood, it is important to consider individual characteristics that contribute to and perpetuate these inequalities. One determinant that has been shown to contribute to digital disparities, at least among children and adolescents, is gender (Campos & Scherer, 2024; Qazi et al., 2022; Siddiq, & Scherer, 2019). Whether gender disparities can also explain changes in the digital divide among adults, however, is the focus of the present research. Adopting a developmental perspective, the study examines within-person changes in ICT literacy across approximately nine years in a random sample of German adults aged between

26 and 67 years. The analyses focus on differential change trajectories for men and women to investigate gender-dependent heterogeneity in ICT literacy.

Information and Communication Technology Literacy

The concept of ICT literacy refers to a broad set of cognitive and technical skills required for the proficient use of digital technologies and communication tools, such as computers, smartphones, and internet platforms, to access, manage, integrate, evaluate, create, and communicate information in digital environments (ETS, 2002). This definition outlines six key components of ICT literacy which are adopted in the theoretical frameworks of numerous international large-scale assessments (e.g., Fraillon & Duckworth, 2025; Senkbeil et al., 2013). The first component (*access*) pertains to the ability to operate diverse devices and software applications, enabling individuals to efficiently search for and retrieve information from digital sources. The capacity to organize and store digital information effectively (*maintain*) is an important requirement for individuals to be able to handle large volumes of data. The ability to synthesize information from multiple digital sources (*integrate*) enables individuals to compare, analyze, and combine content in meaningful ways. Furthermore, the ability to critically assess digital information (*evaluate*) allows individuals to determine the credibility, accuracy, and relevance of digital resources. Finally, ICT literacy encompasses the ability to produce new content using digital tools (*create*) and to share information effectively across diverse digital platforms (*communicate*). These components emphasize that ICT literacy goes beyond basic technical proficiency. It reflects a comprehensive ability to use digital tools and successfully manipulate information.

The precise components subsumed under ICT literacy, however, can vary depending on the adopted theoretical framework (e.g., Fraillon & Duckworth, 2025; Van Laar et al., 2017; Vuorkari et al., 2022). Adult literacy research, for example, frequently focuses on problem-solving abilities in technology-rich environments (Kirsch & Lennon, 2017) which emphasizes individuals' ability to solve practical, work-related tasks in digital contexts, like filling out forms or troubleshooting software. But it does not cover information-related competencies, such as the ability to locate, process, and communicate information effectively (see Table 1). Newer definitions of ICT literacy, on the other hand, sometimes expand the scope of the concept to include additional skills, such as computational thinking or the ethical and responsible use of digital technologies (e.g., Fraillon & Duckworth, 2025; Vuorkari et al., 2022). In some cases, ICT literacy is also viewed as part of a more expansive set of 21st-century skills, which also encompass soft skills like creativity and critical thinking (Kain et al., 2024; Van Laar et al., 2017). The concept of ICT literacy has also significant overlap with related terms, such as critical online reasoning (Molerov et al., 2020), data literacy (Gebre, 2022), algorithmic literacy (Oeldorf-Hirsch & Neubaum, 2025), or artificial intelligence literacy (Pinski & Benlian, 2024), which can result in *jingle-jangle fallacies* or a *déjà-variable phenomenon* (see Hanfstingl et al., 2024; Rubach, 2024) - whereby different concepts are labeled similarly or identical terms are used refer to different concepts (see Table 1). Despite the ambiguity in terms, most definitions concur that ICT literacy is a general competence that comprises both declarative knowledge about digital technologies and procedural abilities that enable individuals to utilize digital environments effectively (Senkbeil et al., 2013; Senkbeil, 2022).

ICT Literacy in Adulthood

Digital technologies permeate nearly every aspect of daily activities, work, and societal participation. Therefore, proficiency in the use of ICT has become essential for routine tasks such as online banking, telehealth consultations, and digital communication. In the workplace, ICT literacy is critical for maintaining competitiveness in the job market (Van Laar et al., 2017). Workers across diverse sectors are increasingly required to demonstrate proficiency in complex software systems such as platforms for data management, project management, and digital collaboration. Consequently, higher ICT skills have become a sought-after competence in the workplace, leading to better employability and higher wages (e.g., Falck et al., 2021;

Eggenberger & Backes-Gellner, 2023). Notably, also older workers with stronger ICT skills often experience significant monetary returns, emphasizing the importance of digital competences throughout the life course (Lee et al., 2022). Beyond the professional realm, ICT literacy is also critical for preventing social exclusion (Regneeda et al., 2022). By helping individuals to stay connected through digital communication platforms, individuals can maintain relationships with family, friends, and broader social networks, thus reducing the risk of social isolation that often accompanies aging. Consequently, those lacking adequate ICT skills are at a significant disadvantage in their personal and professional lives, underscoring the importance of ICT literacy for full participation in today's digital society.

At the same time, numerous studies identified a substantial digital divide in terms of access to, literacy in, and benefits derived from digital technologies (see Estrela et al., 2023, Qazi et al., 2022; Scherer and Siddiq, 2019, and Siddiq, & Scherer, 2019, for meta-analytic evidence). This divide often follows along demographic lines, with age being a particularly important factor (e.g., Ertl et al., 2020; Olsson et al., 2019; Papí-Gálvez & La Parra-Casado, 2023; Van-Deursen & Van-Dijk, 2019). Age tends to increase the digital divide on at least three levels. The first level refers to reduced access to digital devices and the internet among older individuals. Although this first-level digital divide has diminished in recent decades and the majority of adults now have at least basic technical access to ICT (Vuorre & Przybylski, 2024; Zilian & Zilian, 2020), older adults still tend to own fewer types of digital devices and often have more limited internet access options compared to younger individuals (Quittschalle et al., 2020; Van-Deursen & Van-Dijk, 2019). The second-level digital divide concerns disparities in digital skills. Older adults often have less exposure to formal ICT education and less frequent technology use over their lifetimes which can contribute to reduced proficiency in using modern technologies (e.g., Olsson et al., 2019). Some studies seem to support this conjecture showing lower ICT skills among older as compared to younger age groups (Van Laar et al., 2020). The respective age gap in ICT literacy is sometimes even larger as respective gaps for more traditional competence domains such as numeracy or reading (Ertl et al., 2020). The third level of the digital divide pertains to tangible benefits derived from digital media use. As age increases, individuals tend to reap less benefits from online activities such as digital communication than younger individuals (Van Deursen & Helsper, 2018). Taken together, the available findings suggest generational differences in the digital divide on all three levels. So far, it is unclear whether the observed increase in the digital divide of ICT literacy is a consequence of different socializations within different age groups or developmental processes associated with different life stages.

Gender Differences in ICT Literacy

According to widely shared gender norms, that is, simplistic and generalized beliefs about how men and women are expected to behave in certain contexts (Ellemers, 2018), modern technologies and computers are traditionally perceived as stereotypically male domains, where women are expected to perform less proficiently (Gebhardt et al., 2019; Sieverding & Koch, 2009). The resulting gendered socialization processes then contribute to differences in interests and ICT skills between genders (see also Eccles & Wigfield's, 2020, situated expectancy value theory). Such gendered stereotypes can also influence individuals' self-perceptions, which, in turn, shape their engagement with ICT (Tellhed et al., 2023). Studies have shown that women frequently rate their digital competence lower than men do (Cai et al., 2017), even when controlling for their actual ICT skills (Gnambs, 2021). This tendency to undervalue their ICT skills can then negatively impact their digital engagement and impair further skill development (Senkbeil, 2022).

While the expansion of mobile devices and digital services may have shifted these stereotypical perceptions to some degree, reducing the automatic association between ICT and men, gender differences in usage patterns remain (Bünning et al., 2023). Additionally, women tend to shoulder a disproportionate share of domestic and caregiving responsibilities, leading to longer total work time per week compared to men (Kan et al., 2022), which might limit their time to develop digital skills. Men, on the other hand, are still more likely to work full-time and hold technical occupations, providing them with more opportunities to acquire and practice ICT skills. This pattern is particularly evident among older adults, where women may have less exposure to ICT tasks due to less frequent engagement in digital activities at work, while men may make more frequent use of digital tools, which further reinforces their ICT competences (Bünning et al., 2023). Additionally, more rigid gender stereotypes that were more prevalent some decades ago (Eagly et al., 2020), might further impact older women's technology-related self-efficacy and, thus, their willingness to engage with digital environments.

A broad body of research on gender differences in ICT literacy revealed, however, rather inconsistent findings. Among adolescents, some meta-analytic reviews showed higher ICT literacy among boys than girls (Long et al., 2023; Qazi et al., 2022), while others found reverse effects (Campos & Scherer, 2024; Siddiq & Scherer, 2019). Some research also suggests that gender differences in ICT literacy gradually emerge during adolescence. For example, Gnambs (2021) found negligible gender differences in ICT literacy disadvantaging boys at age 15, which grew more pronounced by age 18. In contrast, research on adult populations often showed that men tend to outperform women in areas like computer literacy and certain ICT skills (Long et al., 2023; Martínez-Cantos, 2017; Van Laar et al., 2020), although not consistently in all studies (Ertl et al., 2020). Some studies even indicate that the gender gap seems to be larger among older people (Long et al., 2023). Taken together, the available findings point to notable gender differences in the digital divide, though the specific direction and magnitude of these effects vary across studies and age groups. While there is substantial research on adolescent ICT literacy, much less is known about how these gender differences develop throughout the life course. It remains unclear whether the gap between men's and women's digital skills widens over time, particularly in adulthood and older age.

Objectives and Research Questions

Most research on ICT literacy has been conducted from a cross-sectional perspective, predominately focusing on adolescence (e.g., Campos & Scherer, 2024; Lei et al., 2021; Livingstone et al., 2023; Siddiq & Scherer, 2019). However, there is limited knowledge about how ICT literacy evolves across the life course, particularly in adulthood. The present study aims to address this gap by investigating changes in ICT literacy within a diverse sample of adults aged 26 to 67 years from Germany. Rather than simply examining between-person differences, this study emphasizes within-person changes in ICT literacy over a period of approximately nine years. The research is guided by three major research questions (RQ):

Social cognitive theory (Bandura, 1986) postulates that positive experiences with a task enhance self-efficacy, that is, an individual's confidence in their ability to successfully perform similar tasks in the future. Higher self-efficacy can, in turn, boost motivation to engage in progressively challenging tasks, which allow for new learning opportunities. Similar assumptions are formulated in practice engagement theory (Reder et al., 2020) which assumes that individual's proficiencies develop as a by-product of their engagement in practices at work, in the family, during leisure or other contexts. The thereby acquired proficiency affects the willingness to engage in such activities in return. Applied to ICT literacy, this theory suggests two dynamics: a generational divide between individuals, as older generations were exposed to fewer opportunities to engage with new technologies earlier in life, and lifelong growth within individuals, as the accumulation of experiences with digital technologies continues throughout life. In line with these assumptions and respective cross-sectional research (e.g., Olsson et al., 2019; Papí-Gálvez & La Parra-Casado, 2023; Van-Deursen & Van-Dijk, 2019), we therefore expect to observe pronounced differences in ICT literacy between age groups at the initial measurement. Younger individuals are likely to demonstrate higher digital skills compared to older adults, with ICT skills gradually declining with the age of the respondents. In addition, also within-person ICT literacy is expected to increase, on average, over the observational period, as digital technologies become more integral to daily life. The necessity of using devices such as smartphones or computers for work and personal tasks has grown substantially, particularly during the COVID-19 pandemic. This increase in the use of digital technologies may have contributed to increases in ICT literacy in the population. However, since older adults tend to use digital devices less frequently (Quittschalle et al., 2020; Van-Deursen & Van-Dijk, 2019) and are more likely to be retired, we expect younger participants to show greater increases in ICT literacy over the nine-year period compared to older individuals.

RQ1a: ICT literacy at baseline decreases with the individuals' age.

RQ1b: ICT literacy increases within individuals across measurement waves, but less so with increasing age.

Despite inconsistent findings on a gender gap in ICT literacy, particularly among youths (Campos & Scherer, 2024; Qazi et al., 2022; Siddiq & Scherer, 2019), studies on adults generally indicated that men tend to exhibit higher digital skills than women (Long et al., 2023; Martínez-Cantos, 2017; Van Laar et al., 2020). It is also plausible to assume that gender disparities in ICT literacy are more pronounced among older adults, who were more exposed to traditional gender roles for a longer time (Eagly et al., 2020). Additionally, ICT literacy may increase more strongly among men than within women over time because men are more likely to be in full-time employment, often in technical fields. In contrast, women who are more frequently employed part-time and bear greater domestic and caregiving responsibilities (Kan et al., 2022) may have fewer opportunities to develop ICT skills (Bünning et al., 2023).

RQ2a: ICT literacy at baseline is higher for men than women, more so for older individuals.

RQ2b: The increase in ICT literacy within persons across measurement waves is stronger for men as compared to women.

Gender does not influence skill development in isolation but interacts with other social categories such as ethnicity or social class (Codiroli Mcmaster & Cook, 2019; Collins, 2015).

For example, individuals with higher cultural capital are often exposed to more egalitarian gender roles at work and their social circle and, thus, are less likely to accept traditional gender stereotypes (Davis & Greenstein, 2009). Women from higher socioeconomic backgrounds are also more likely to pursue careers in traditionally male-dominated fields such as science, technology, engineering, and mathematics (Codiroli Mcmaster, 2017). As a result, it is plausible that gender differences in ICT literacy are smaller among individuals with higher socioeconomic status, who are also more exposed to diverse technologies as part of their work, than among those with lower status.

RQ3a: The gender difference in ICT literacy at baseline decreases with the socioeconomic status of the respondents.

RQ3b: The gender difference in ICT literacy growth within persons is smaller among individuals with higher socioeconomic status than those with lower status.

Most existing research on ICT literacy focuses on mean differences between social groups, such as men and women, while the distribution of ICT literacy within these groups, that is, the extent to which digital skills vary, remains unexplored. Research on cognitive abilities, however, indicates pronounced variance in cognitive functioning between the genders, with men more often observed at both tails of the competence distribution and women exhibiting more homogenous cognitive profiles (Hyde, 2014; Johnson et al., 2008). So far, it is unclear whether these findings also extend to ICT literacy and how factors such as age and socioeconomic status influence the variability of digital skills among men and women. Since there is no prior research on this topic and limited theoretical guidance for formulating precise hypotheses, we adopt an exploratory approach to examine the role of gender, age, and socioeconomic status in shaping the variance of ICT literacy over the nine-year period.

Materials and Method

Transparency and Openness

We report how we determined our sample size and describe all data exclusions and manipulations in the study. The raw data, including the study material, are available after registration at NEPS Network (2024). In addition, the computer code to reproduce the presented findings and the results of the statistical analyses are available at https://osf.io/fvqth/. The study was not preregistered. Information on the software used for the analyses can be found in Online Supplement A.

Sample and Procedure

The *National Educational Panel Study* (NEPS) is an ongoing longitudinal study that follows representative samples of the German population over the course of their lives (Blossfeld et al., 2019). Participants in the adult cohort, the focus of the present study, were selected using a two-stage cluster sampling approach to cover the target population of people living in Germany born between 1944 and 1986 (see Aßmann et al., 2019, for details). They received annual surveys and cognitive tests in their private homes, administered by experienced interviewers from a professional survey institute. For this study, $N = 2{,}266$ respondents (49% women) who participated in the assessment of digital competencies were considered. The first assessment was conducted between October 2013 and April 2014, while the second assessment window was between September 2021 and April 2022. The median time between the two assessments was 8.92 years ($Min = 8.47$, $Max = 9.46$). The age of the participants in the first wave was roughly evenly distributed between 26 and 67 years, with a mean of 48.22 years ($SD = 9.66$). They had an average of 14.80 years of education and most of them (85%) were employed in different occupations. The occupations of the respondents' covered a wide range, including both blue-collar and white-collar jobs, with about 52% of the participants working in high-skilled occupations (i.e., ISCO 1 to 3) according to the *International Standard Classification of Occupations* (ISCO; International Labour

Organization, 2024). About 7% of the participants had a migrant background, meaning that they or at least one of their parents were born outside Germany. Most of them (70%) reported that they were married.

Instruments

ICT Literacy

ICT literacy was measured with achievement tests developed specifically for the NEPS. Following established frameworks from international large-scale assessments (e.g., ETS, 2002), the study adopted a literacy concept that focuses on the relevance of competencies for successful participation in modern societies. ICT literacy was conceptualized as a unidimensional construct based on the ETS (2002) definition, which refers to four process components (i.e., accessing, creating, managing, and evaluating information; see Senkbeil et al., 2013, for details). Each item referred to one or two process components and presented realistic problems to be solved using a software application. Therefore, all items integrated common technologies such as an Internet browser, a search engine, or a spreadsheet into the task stimulus. The tests administered at the two measurement occasions contained 29 and 19 multiple-choice items, respectively, with up to six response options, including one correct option. Each item was scored as correct or incorrect. The second test also contained 14 interactive items (see Gnambs & Senkbeil, 2023). These represented software simulations that required participants to interact with technology and complete several steps to achieve a goal (e.g., open a web browser, navigate through a menu structure). The number of successful task completions represented the item score.

On the first measurement occasion, all respondents received all items of the test. In contrast, the second test used a multistage design (Pohl, 2013). Thus, each respondent received only a subset of 20 items, depending on their responses during the test. The test was administered on paper in the first wave and on computer in the second wave. Both assessments were conducted individually at the respondents' homes, supervised by experienced test administrators. In both waves the test time was limited to 28 minutes.

Both tests were scaled using the unidimensional partial credit model (Masters, 1982). Item responses at each wave showed a good fit to the item response model, essential unidimensionality, and negligible differential item functioning across various subgroups (see Gnambs & Senkbeil, 2023; Senkbeil & Ihme, 2015). Additional analyses reported in Online Supplement B also confirmed the approximate measurement invariance of both tests across gender, age, and socioeconomic status. The marginal reliabilities of the tests were .80 and .71, respectively. To allow longitudinal mean-level comparisons, the two tests were placed on a common scale across waves using an independent bridge study in which respondents received both tests at the same time (see Gnambs & Senkbeil, 2023). The bridge study allowed both tests to be scaled concurrently, and then the tests administered in the present sample to be placed on a common metric using a mean/mean linking approach (see Fischer et al., 2016, for more details). Respondents' digital competencies were given by 100 plausible values that were drawn for each respondent and allow acknowledging the uncertainty in the measurements (see Online Supplement C).

Gender

The gender of the respondents was measured as a self-rating with two response options (0 = male, 1 = female). Additional gender categories (e.g., non-binary) were not presented. However, respondents were allowed to skip the question without providing an answer.

Socioeconomic Status

Following previous research (Antonoplis, 2023), two indicators were created to represent socioeconomic status, namely, years in education and occupational prestige. As these two indicators are likely to vary with the age of the respondent (e.g., people get better jobs as they progress in their careers), information on socioeconomic status was used when the respondent was 30 years old. This age roughly corresponds to the age of the youngest participants in the sample and is also an age at which most people have completed their education and have a job. As the NEPS aims to collect complete educational and occupational histories for all respondents, information on socioeconomic status was reconstructed from the biographical data for a respondent at a given age.

The *years in education* of each respondent at age 30 were derived from an internationally comparable classification of educational qualifications (CASMIN; Brauns et al., 2003). Years of education represent the average number of years required to obtain a given qualification (e.g., bachelor's degree). The indicator can take values between 9 (equivalent to compulsory schooling) and 18 (equivalent to a master's degree from a university). Doctoral degrees are not separately coded in this measure and, thus, are included in the highest category. *Occupational prestige* at age 30 was given by the international socioeconomic index of occupational status (ISEI; Ganzeboom, 2010), which is derived from the respondent's job while taking into account the education required for the job and the income received. The ISEI ranges from 10 (e.g., cleaning staff) to 98 (e.g., judges), with higher values reflecting higher socioeconomic status. For respondents out of the labor force at the age of 30, the corresponding values were taken from jobs held in adjacent years (i.e., between the ages of 27 and 33).

Auxiliary Variables

Control variables used in the analyses included the time lag (in years) between the two measurements of ICT literacy. In addition, the sampling weights provided in the NEPS were used to adjust for unequal sampling probabilities (see Hammon et al., 2006).

Statistical Analyses

The research questions were addressed using latent location-scale change score analyses, which model the latent competence scores at baseline and latent difference scores between the two measurements. Although an ongoing debate revolves around the appropriate analysis strategy for longitudinal two-wave data (e.g., Castro-Schilo & Grimm, 2018), there is a growing consensus that change score analyses are often preferable because they allow controlling for unobserved confounders (Lüdtke & Robitzsch, 2025). Age differences in ICT literacy at baseline and their change over nine years were examined by regressing the competence scores at the first measurement and the difference between the two measurements on age. Potential nonlinear age trajectories were evaluated using piecewise age models that specified different linear age trajectories for five age groups (i.e., up to 30 years, between 30 and 40 years, between 40 and 50 years, between 50 and 60 years, and over 60 years). Then, gender differences in ICT literacy were examined by including gender and its interactions with age and socioeconomic status as predictors of baseline and difference scores. These analyses were specified as location-scale models (Rigby & Stasinopoulos, 2005) with identity and log links for the mean and variance components, respectively. This allowed exploring whether gender explained not only mean ICT scores but also variance in ICT scores. In these models, ICT scores were z-standardized with respect to the first measurement. Therefore, the regression coefficients for the mean of ICT scores can be interpreted similarly to traditional standardized effect sizes in the normal metric. In contrast, the regression coefficients for the variance of ICT scores are reported in the logarithmic metric. These analyses were repeated for each plausible value of ICT literacy and then combined using Rubin's rules to examine latent effects corrected for measurement error (Mislevy, 1991).

The analyses adjusted for the varying time lag between the two measurements by including the time lag as a covariate in the models. Sampling weights were used to adjust for the disproportionate sampling probabilities. Missing values were imputed 100 times with classification and regression trees using chained equations (Doove et al., 2014). However, the missing rates were rather low for all variables (see Table 2). The analysis results of the multiple imputed data sets were combined using Rubin's rules. A Type I error level of 1% was assumed for all inference tests.

Ethics Statement

The study was conducted in full compliance with the ethical standards outlined in the Declaration of Helsinki and the requirements of the general data protection regulation in Germany. All data collection procedures and instruments were approved by a special data protection and security officer of the NEPS in line with national ethical and legal regulations. All participants provided written informed consent before study enrolment and could withdraw from the longitudinal study at any time.

Results

Descriptive Analyses

ICT literacy scores were significantly ($p < .01$) negatively associated with respondents' age (see Table 2) on both measurement occasions, $r = -.47$ and -.56, respectively, showing that it declined with age. Mean-level analyses of within-person change over nine years mirrored this pattern, showing a small decrease in ICT literacy with Cohen's $d = -0.30$, 99% CI [-0.37, -0.23]. In addition, the variance of ICT literacy decreased across measurement occasions by a factor of 0.72, 99% CI [0.60, 0.84] (see standard deviations in Table 2).

To illustrate the age-related trajectories in ICT literacy, Figure 1 plots the predicted effects of local polynomial regressions using either ICT scores at the first measurement or the difference in ICT scores between measurement occasions. The plot shows that the age-related differences in ICT literacy between respondents decreased almost linearly by about two standard deviations from respondents in their twenties to those in their sixties. In contrast, the nine-year change within persons showed no age-related variation. Rather, ICT literacy declined comparably across all age groups.

Age-Related Change Trajectories

The latent change score model without moderating effects of gender was identified by comparing a model with linear age effects on the latent baseline and difference scores with a latent change score model with piecewise age effects on both latent scores. Model comparisons using the Bayesian Information Criterion (BIC) favored the simpler models with linear age over the more complex piecewise models for baseline digital competence scores (BIC = 5823 vs. 5852) and difference scores between measurements (BIC = 4702 vs. 4733). These results were also confirmed by non-significant likelihood ratio tests, $F(8, 809.77) = 2.29$, $p = .020$, and $F(8, 266.20) = 0.96$, $p = .468$, which also favored the simpler models with linear age effects. Therefore, a linear age trend was modeled in the subsequent analyses.

On average, an age difference of 10 years corresponded to a difference in baseline ICT literacy of about -0.49 standard deviations, 99% CI [-0.54, -0.43] (see Table 3); thus, ICT literacy declined continuously across age. In contrast, the decline in ICT literacy within persons over nine years was more or less stable across ages, changing by only about -0.01 standard deviations, 99% CI [-0.07, 0.09], over a 10-year period. The variance in ICT scores at baseline appeared to gradually decrease over 10 years by a factor of 0.95, 99% CI [0.90, 1.00]. However, the respective effect was not significant, $p = .018$. The variance of the difference scores was not affected by the age of the respondents, as indicated by the non-significant age effect, $B = -0.03$, 99% CI [-0.04, 0.10] (see Table 3).

Gender Differences in ICT Literacy

The baseline model with linear age effects was extended to include a main effect of gender and its interaction with age. As summarized in Table 3, gender showed a main effect with men having higher ICT literacy than women, $B = -0.37$, 99% CI [-0.60, -0.13], but did not moderate age differences in baseline ICT scores. This effect is also shown in Figure 2 (top row, left column), which shows the predicted ICT scores for men and women. The plot shows that, over the observed age range of the respondents, the difference in ICT scores between gender remained almost constant, neither increasing nor decreasing. In contrast, the difference in ICT scores between the two measurements was not affected by gender, $B = 0.07$, 99% CI [-0.19, 0.33]. Thus, the nine-year change within persons was comparable for men and women. Also, the variance in ICT scores showed no gender differences (see Table 3).

Moderating Effects of Socioeconomic Status

The two indicators of socioeconomic status, that is, years in education and occupational prestige, were evaluated in independent analyses to examine the robustness of the results to the chosen operationalization. The results summarized in Table 4 show that socioeconomic status did not moderate gender differences in ICT scores, either at baseline or for the nine-year difference score. However, both indicators showed main effects, suggesting an additive effect. Baseline digital competence scores increased by 0.24 standard units, 99% CI [0.17, 0.31], for each additional year of education and by 0.53 standard units, 99% CI [0.35, 0.71], for an increase of one standard deviation in occupational prestige. The respective main effects are visualized in Figure 2 (top row) which shows the predicted ICT scores for respondents with 13 years of education (equivalent to a university entrance qualification or vocational master's degree) and 16 years of education (equivalent to a bachelor's degree). The chosen values of years in education correspond approximately to the first and third quartiles of the variable in the present sample. The plot shows that, regardless of the age of the respondents, the ICT scores were significantly higher for high status respondents compared to low status respondents. A similar pattern emerged for occupational prestige (see Table 4). Figure 2 (right plot) shows that the predicted effects were significantly smaller for respondents with low prestige, such as service or clerical workers, than for respondents with high prestige, such as managers or professionals. Again, the chosen values of occupational prestige corresponded approximately to the first and third quartiles of the variable in the present sample.

Figure 2 (bottom row) also shows that the differences in ICT scores between the two measurement occasions were moderated by socioeconomic status. Respondents with more years in education or higher prestige occupations exhibited a greater decline in ICT literacy than respondents with less education or lower prestige occupations, for whom the nine-year change was substantially smaller. The respective effects were B = -0.07, 99% CI [-0.14, 0.00] and B = -0.20, 99% CI [-0.39, -0.02], respectively (see Table 4).

The variance in ICT scores was not robustly moderated by socioeconomic status (see Table 4). Neither years in education nor occupational prestige showed a significant main effect or interaction with gender. Although there was a small three-way interaction between gender, socioeconomic status, and age of $B = 0.04$, 99% CI [0.00, 0.09], on baseline ICT scores for years in education, this effect did not replicate for occupational prestige. Therefore, this unexpected effect was not investigated further.

Discussion

Although modern communication and information technologies play an increasingly important role in daily work and private life for many people, the question of how ICT literacy changes across the lifespan and what disparities emerge during adulthood remains underexplored. While research on the correlation between age and ICT literacy has grown in recent years (e.g., Ertl et al., 2020; Olsson et al., 2019; Van Laar et al., 2020), the present research is among the first to adopt a longitudinal perspective to examine both performance differences between age groups and also within-person changes. A particular focus of these investigations was on gender disparities and how they evolve over the life course. A longitudinal two-wave study of a large sample of German adults revealed four key findings. First, younger individuals exhibited significantly higher ICT literacy on average than older individuals. However, ICT literacy declined gradually within all respondents, regardless of their age. Second, gender differences in ICT literacy consistently favored men and remained stable across age groups and over time. Third, socioeconomic status did not moderate gender disparities in ICT literacy. Finally, variance in ICT literacy was not systematically linked to gender or socioeconomic status. These findings highlight that while ICT literacy is subject to a systematic decline in adulthood, preexisting gender inequalities established during earlier socialization processes persist across the life course.

Towards an Explanation of Adult ICT Literacy Declines

Interpreting within-person changes in ICT literacy over time is inherently challenging as individual psychological processes are often confounded with broader societal and technological developments that affect the population as a whole. Given the rapid pace of technological change, technologies once considered cutting-edge can quickly become obsolete, as seen in the widespread replacement of, for example, optical media (e.g., CDs and DVDs) by cloud storage and streaming services. Consequently, the observed decline in ICT literacy could, in part, reflect a mismatch between the assessment content and the prevalent technologies that were in use. Although the administered tests focused on core applications such as office software, email, and search engines (see Senkbeil et al., 2013) that remained broadly relevant throughout the observation period, other technologies such as real-time collaboration platforms gained prominence (particularly, in the context of remote work during the Covid-19 pandemic). Because such emerging tools were not considered in the assessment, newer ICT competencies may not have been adequately captured. In this case, the observed decline may not reflect a true loss of digital skill, but rather a shift in the types of skills being used. For example, participants may have gained proficiency in newer tools while simultaneously losing fluency in applications that became less central to their daily lives. Moreover, the effect could have been amplified by differential relevance of specific technologies across age groups, for example, older adults relying more on traditional office software, while younger individuals preferring messaging software and mobile tools. Yet, the absence of age-related differences in longitudinal decline suggests that such age-specific shifts are unlikely to fully explain the observed pattern. Given that similar declines have been reported in cross-sectional panel research involving adolescent samples around the world (Fraillon et al., 2024), the findings may point to a genuine decline in the specific ICT skills measured, even as other, unmeasured digital competencies may have developed in parallel.

From a psychological standpoint, the observed decline in ICT literacy can be interpreted through, Baltes' (1993) life-span theory on intelligence development. From this perspective, ICT literacy can be understood as a domain-specific competence, a form of crystallized intelligence, that, however, also relies on fluid cognitive skills such as problem-solving and processing capacity (Senkbeil, 2022). Consequently, its developmental trajectory is likely shaped by the combined pattern of fluid and crystallized intelligence (Baltes, 1993). Fluid intelligence typically peaks in adolescence and begins to gradually decline after approximately age 15, while crystallized intelligence tends to increase slightly later and remains stable from around age 20. Combining these trajectories suggests a steep growth in ICT literacy until adolescence, followed by a plateau and a gradual decline starting from around age 50. Although this idea was originally proposed for reading and mathematical competencies (Lechner et al., 2021), it may also apply to ICT literacy. While this theory can explain the observed decline in ICT literacy–especially as the respondents in the present study were on average 48 years at the first measurement which represents the typical age the decline presumably onsets (Lechner, 2023)–, it would also predict age-related variations in growth, consistent with our original hypothesis. However, contrary to this expectation, the findings indicate a uniform decline in ICT literacy across all age groups. Thus, current models of intelligence development (Baltes, 1993) only partially account for the observed patterns of change in ICT development. These results suggest that further, still unknown, processes need to be considered to fully capture the patterns of ICT literacy development across adulthood.

Towards an Explanation of Gender Inequalities in ICT Literacy

When interpreting findings on gender differences in ICT literacy, it is essential to consider the age of the respondents, as the size and direction of these differences appear to shift over time. Meta-analyses focusing on students revealed a female advantage in ICT literacy (Campos & Scherer, 2024; Siddiq & Scherer, 2019) that was more pronounced in primary schools compared to secondary schools. In contrast, a meta-analysis that also included adult samples identified small effects favoring boys and men (Qazi et al., 2022). Similarly, longitudinal research has observed the emergence of a gender gap favoring boys during late adolescents (Gnambs, 2021), suggesting that gender disparities in ICT literacy may gradually evolve over the life course. Given that several studies with adult samples reported men to exhibit better digital skills than women (Long et al., 2023; Martínez-Cantors, 2017; Van Laar et al., 2020), we explored whether this trend continued in adulthood. We hypothesized that ICT literacy would be higher for men than for women, particularly as individuals grow older. However, our findings did not support this assumption. While men consistently demonstrated higher ICT literacy than women, the difference remained stable and did not grow with age or vary with baseline age or socioeconomic status. These results confirm a persistent digital divide in adulthood, favoring men.

Several explanations could account for the stability of gender disparities in ICT literacy. First, despite some evidence to the contrary (Bünning et al., 2023), ICT practices among men and women might be more similar than different. Both genders frequently develop consistent habits and applications of ICT aligned with their professional or personal needs. As modern workplaces and daily life increasingly require similar uses of ICT, the observed gap may neither narrow significantly nor widen further. Second, many adults may reach a plateau in ICT literacy, achieving a level sufficient to effectively use available digital devices. Without pronounced deficits or active engagement in advanced training, their skills may remain stagnant. This plateau effect could contribute to the stable gender gap observed. Third, gender differences in ICT literacy often emerge during adolescence or earlier due to societal norms, gender stereotypes, and differences in opportunities or encouragement to engage with technology (see Gnambs, 2021). These early influences tend to establish baseline differences in ICT skills that may persist into adulthood unless new factors intervene.

Therefore, the observed stability of gender differences in ICT literacy during adulthood might reflect the effect of stable ICT usage patterns, comparable demands on ICT skills in everyday contexts, and developmental processes already established during adolescence.

Limitations and Future Research

Despite several notable strengths of the present study, including the use of a large and diverse sample assessed in a repeated measurement design, several limitations should be considered that provide opportunities for future research. First, the study was unable to isolate periodic effects, as this would require a cohort-sequential design (Estrada & Ferrer, 2019). One such periodic factor was the Covid-19 pandemic, which was ongoing during the second measurement occasion. Given that the pandemic led to an abrupt shift of workplaces and personal interactions into digital spaces, an increase in computer and internet use seemed likely. However, the present findings did not reveal a corresponding improvement in ICT skills during the second wave. This highlights an important factor: increased ICT usage does not automatically translate into enhanced skill development, even though it provides more learning opportunities. It is possible that the abrupt and involuntary nature of the pandemic-driven digitization may have worsened attitudes towards technology, thereby mitigating potential improvements in ICT literacy. Future research should investigate the development in ICT skills further to explore how contextual factors influence skill acquisition.

Second, the conceptualization of ICT literacy in the present study focused primarily on diverse technical and operational aspects of using contemporary software and digital applications (Senkbeil et al., 2013). Other critical dimensions of digital competence such as the ability to critically evaluate online content, use social media responsibly, or manage social interactions in digital environments were not addressed. Yet, previous research indicates that gender disparities may vary across these dimensions. For example, girls have been found to outperform boys in areas related to communication and social networking, while boys tend to excel in tasks requiring technical knowledge and information processing (Aesart & Van

Braak, 2015; Christoph et al., 2015). Therefore, future research is encouraged to consider additional facets of digital competence to better capture the multifaceted nature of the concept (see Van Laar et al., 2017; Vuorkari et al., 2022).

Finally, future studies should explore how factors such as inequalities in ICT access, motivation, stereotype beliefs, and anxiety may contribute to the persistence of gender disparities (see Karpinski et al., 2023). Integrating these concepts into a broader theoretical context could help identify protective factors that may reduce gender-specific differences in ICT literacy and improve gender-equality. Moreover, incorporating behavioral measures such as frequency and intensity of technology use (beyond simple indicators of access or device ownership) may help uncovering mechanisms underlying the observed decline in ICT literacy over time.

Conclusion

A substantial digital divide persists in the German population that reflects both generational and gender-related inequalities. Notably, ICT literacy showed a decline across all generations, despite the rapid digitalization that was triggered by the recent pandemic. The stable gender gap across age groups and the life course underscores the importance of early socialization processes rooted in childhood and adolescence for the development of digital skills. These findings have profound implications, as digital competencies can exacerbate inequalities in educational achievement, economic mobility as well as social and civic participation, potentially widening existing social divides. Consequently, targeted strategies are required to address these disparities, particularly for ageing populations to catch up on ICT skills that enable active and effective participation in a digital society.

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Table 1

Description of ICT Literacy and Related Concepts

Construct	Description	Further reading
ICT literacy	The ability to use digital technologies in everyday information environments purposefully and effectively for gathering, managing, evaluating, and communicating information.	Fraillon & Duckworth (2025) Senkbeil et al. (2013)
Problem-solving in technology-rich environments	The ability to engage in goal-directed thinking and action with digital tools and resources to solve problems related to work and personal tasks.	Kirsch & Lennon (2017)
21st century skills	The abilities necessary for effective participation in a digital and knowledge-based society such as ICT literacy, collaboration, communication, creativity, critical thinking, and problem-solving.	Kain et al. (2024) Van Laar et al. (2017)
Computational thinking	The ability to identify real-world problems and to evaluate and develop algorithmic solutions for these problems in a way a computer can carry out.	Fraillon & Duckworth (2025)
Critical online reasoning	The ability to effectively search for, evaluate, and verify digital information, particularly in contexts where credibility, bias, and source reliability are in question.	Molerov et al. (2020)
Data literacy	The ability to read, interpret, create, and communicate data in various formats, including understanding how data is collected, analyzed, and used, as well as recognizing data quality, biases, and ethical considerations.	Gebre (2022)
Algorithmic literacy	The ability to understand how algorithms function and influence digital content, decision-making, and user experiences.	Oeldorf-Hirsch & Neubaum (2025)
Artificial intelligence (AI) literacy	The knowledge and skills needed to understand, use, and critically assess AI systems, including basic comprehension of how AI works, its capabilities and limitations, and the social, ethical, and legal implications of its use.	Pinski & Belian (2024)

Table 2

Means, Standard Deviations, and Correlations between Study Variables

					Correlations				
		M	*SD*	MV	1.	2.	3.	4.	5.
1.	ICT literacy in Wave 1	0.00	1.00	0.00					
2.	ICT literacy in Wave 2	-0.28	0.85	0.00	.72*				
3.	Gender (0 = men, 1 = women)	0.49	0.50	0.00	-.20*	-.13*			
4.	Years in education	14.65	2.32	0.18	.47*	.35*	-.04		
5.	Occupational prestige	50.25	18.58	0.71	.40*	.29*	-.08*	.52*	
6.	Age (in years)	48.26	9.66	0.00	-.47*	-.56*	.02	-.12*	-.10*

Note. $N = 2266$. MV = Percentage of missing values. Results are based on 100 plausible values and multiply imputed data sets.

* $p < .01$

Table 3

Parameter Estimates of Latent Location-Scale Change Score Models for Age and Gender

	Age				Gender			
	Baseline ICT literacy		Difference in ICT literacy		Baseline ICT literacy		Difference in ICT literacy	
Model	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Model for Location								
Intercept	0.69*	0.05	-0.21*	0.06	0.86*	0.06	-0.25*	0.07
Age	-0.49*	0.02	0.01	0.03	-0.48*	0.03	-0.02	0.04
Gender					-0.37*	0.09	0.07	0.10
Age x gender					0.00	0.04	0.04	0.05
Model for Scale								
Intercept	0.00	0.04	-0.40*	0.06	-0.06	0.05	-0.43*	0.07
Age	-0.05	0.02	0.03	0.03	0.00	0.03	0.04	0.04
Gender					0.08	0.08	0.05	0.11
Age x gender					-0.11*	0.04	-0.02	0.05

Note. *B* = Regression coefficient; *SE*= Standard error of *B*. Age in years was centered at 30 and divided by 10. Gender was coded 0 for men and 1 for women. Results for covariates are not presented. Based on 100 plausible values.

* $p < .01$

Table 4

Parameter Estimates of Latent Location-Scale Change Score Models for Moderation of Socioeconomic Status

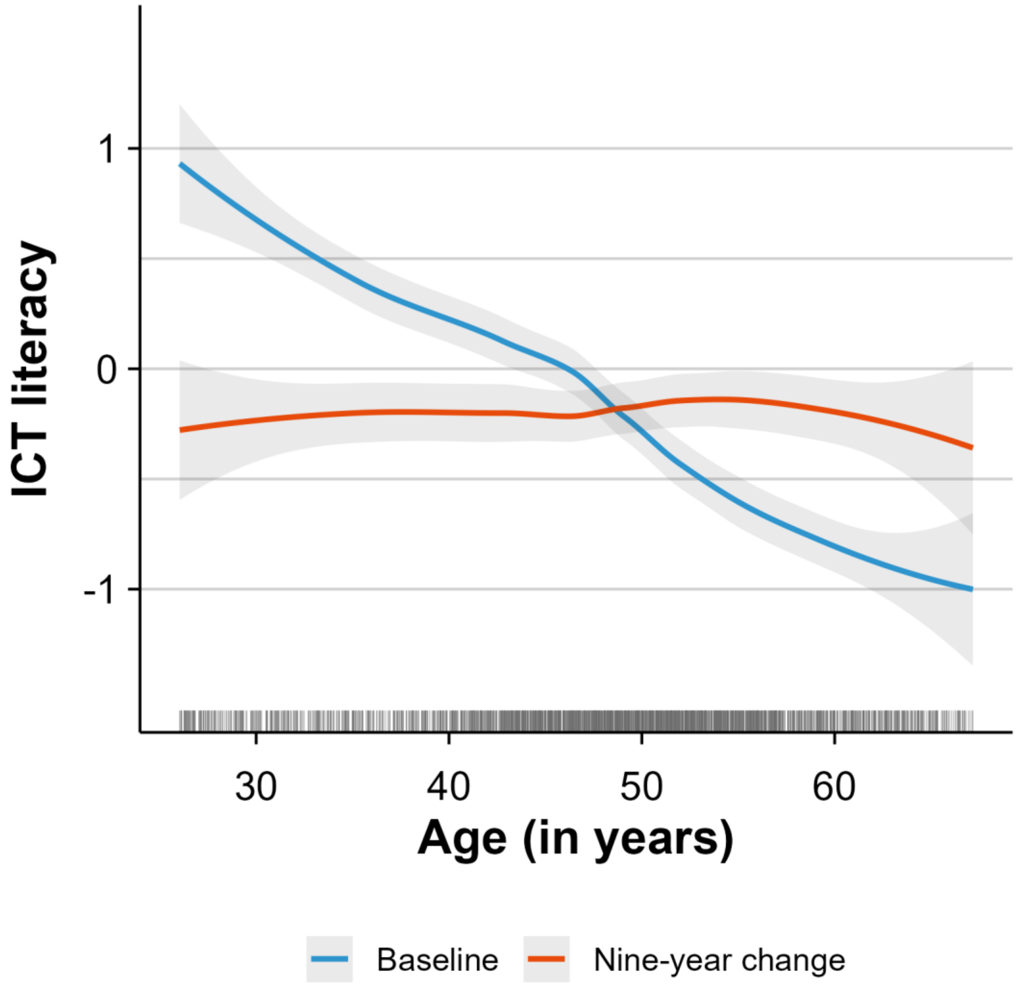
	Years in education				Occupational prestige			
	Baseline ICT literacy		Difference in ICT literacy		Baseline ICT literacy		Difference in ICT literacy	
Model	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Model for Location								
Intercept	0.57*	0.07	0.17	0.09	0.90*	0.06	-0.26*	0.07
Age	-0.44*	0.03	-0.01	0.04	-0.47*	0.03	-0.03	0.04
Gender	-0.35*	0.10	0.13	0.12	-0.40*	0.09	0.07	0.10
Socioeconomic status	0.24*	0.03	-0.07	0.03	0.53*	0.07	-0.20*	0.07
Age x gender	0.03	0.05	0.00	0.06	0.01	0.04	0.05	0.05
Age x socioeconomic status	-0.01	0.01	-0.01	0.01	0.00	0.03	-0.01	0.04
Gender x socioeconomic status	-0.06	0.04	-0.02	0.04	-0.13	0.10	0.01	0.10
Age x gender x socioeconomic status	0.00	0.02	0.02	0.02	-0.06	0.04	0.07	0.05
Model for Scale								
Intercept	-0.31*	0.06	-0.46*	0.09	-0.21*	0.06	-0.48*	0.07
Age	0.04	0.03	0.03	0.04	-0.02	0.03	0.04	0.03
Gender	0.26*	0.09	0.03	0.13	0.13	0.08	0.05	0.10
Socioeconomic status	0.03	0.03	0.00	0.03	-0.02	0.06	-0.04	0.07
Age x gender	-0.17*	0.04	-0.01	0.06	-0.08	0.04	0.00	0.05
Age x socioeconomic status	-0.02	0.01	0.00	0.01	-0.03	0.03	0.02	0.04
Gender x socioeconomic status	-0.08*	0.03	0.00	0.04	-0.08	0.08	-0.03	0.10
Age x gender x socioeconomic status	0.04*	0.02	0.01	0.02	0.07	0.04	0.01	0.05

Note. *B* = Regression coefficient; *SE*= Standard error of *B*. Age in years was centered at 30 and divided by 10. Gender was coded 0 for men and 1 for women. Occupational prestige was *z*-standardized. Results for covariates are not presented. Based on 100 multiply imputed data.

* $p < .01$

Figure 1

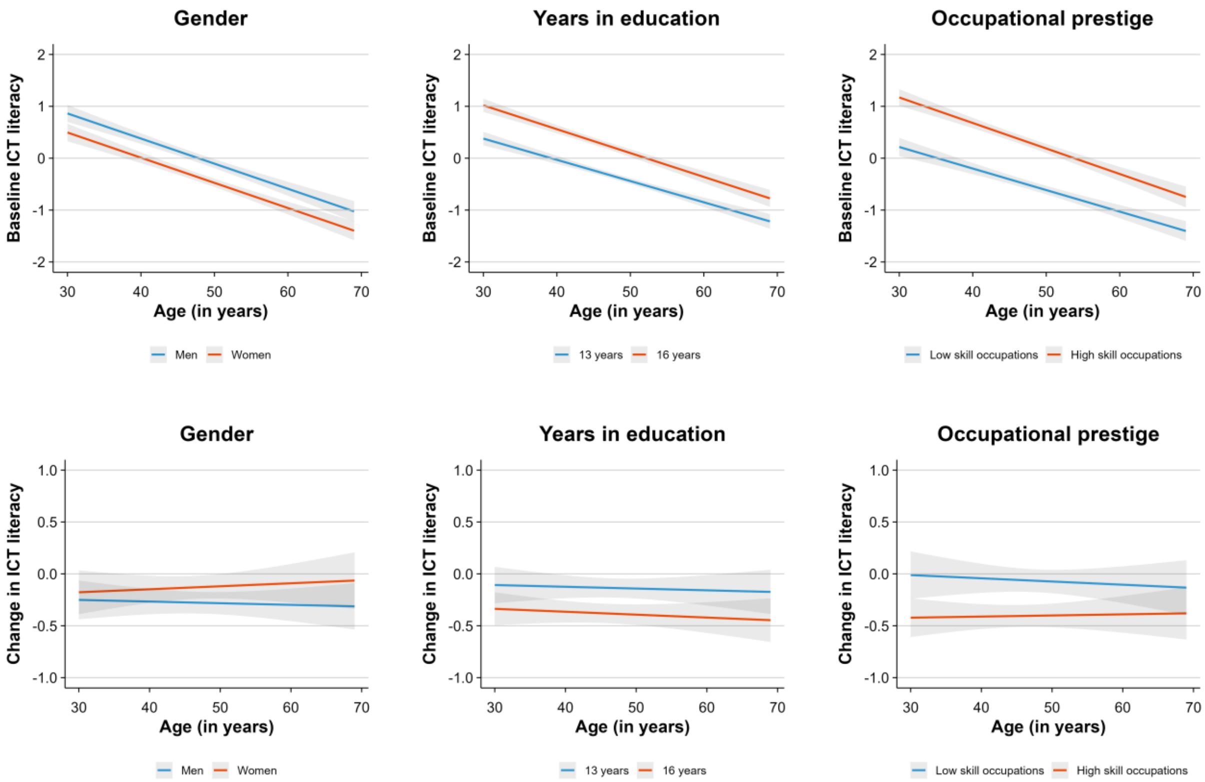
Age-Related Change of ICT Literacy in Adulthood



Note. Predicted effects from local polynomial regression analyses (solid lines) with 99% confidence intervals (gray shadings). Bars on the x-axis represent the distribution of respondents. ICT scores were *z*-standardized with respect to the first measurement.

Figure 2

Predicted Age-Trajectories for Baseline ICT Literacy and Difference in ICT Literacy



Note. Predicted effects from location-scale regression analyses (solid lines) with 99% confidence intervals (gray shadings). ICT scores were *z*-standardized with respect to the first measurement.

Supplementary Material for

Gender Disparities in the Development of ICT Literacy across Adulthood:

A Two-Wave Study

A. Software

The analyses were conducted in *R* (R Core Team, 2025). Plausible values were drawn with *TAM* (Robitzsch et al., 2024). DIF and DTF analyses were performed in *mirt* (Version 2.21; Chalmers, 2012) and *mstDIF* (Debelak & Debeer, 2024). Multiple imputations of missing values were conducted with *mice* (Version 3.18; Van Buuren & Groothuis-Oudshoorn, 2011). Univariate analyses of multiply imputed data relied on *miceadds* (Robitzsch & Grund, 2024). The latent location-scale models were estimated in *gamlss* (Version 6.1-1; Rigby & Stasinopoulos, 2005). Plots were generated with *ggplot2* (Version 3.5.2; Wickham, 2016). Parallel processing was conducted with *future* (Version 1.49.0; Bengtson, 2021). General data handling was supported by *tidyr* (Wickham et al., 2024), *dplyr* (Wickham et al., 2023), *lubridate* (Version 1.9.4; Grolemund & Wickham, 2011), and *rio* (Chan et al., 2023).

B. Differential Item and Test Functioning

Differential item functioning (DIF) across different subgroups and between the two tests administered at the two measurement occasions has been previously analyzed for the present sample (see Gnambs & Senkbeil, 2023; Senkbeil & Ihme, 2015). Therefore, these analyses are not replicated. In the following, differential item and test functioning are examined across age, gender, and the two indicators of socioeconomic status, that is, years of education and occupational prestige.

In the first step, score-based DIF tests (see Debelak & Strobl, 2019) compared the observed responses and responses predicted by the item response model. If item parameters differ significantly ($p < .01$) for various subgroups of respondents, systematic differences between the observed and predicted responses should be observed. Compared to other tests of DIF, score-based approaches can examine DIF for categorical as well as metric variables and often also exhibit a superior power (e.g., Debelak et al., 2023). In the second step, differential test functioning (DTF) evaluated the consequence of the non-invariance of items identified with DIF for the comparisons of test scores. Following Chalmers (2018), we calculated the differences in the test score functions between groups. In these analyses, the items previously identified as having DIF were freely estimated, while the remaining items were constrained across groups and functioned as anchor items. Metric variables were dichotomized at their means for these analyses. The estimated group differences are given in the raw score metric expressed as the expected differences in test scores between groups and also as percentage biases that reflect the relative increase in test scores for one group as compared to the other (see Chalmers, 2016). Percentage biases that are less than 5% are considered negligible.

The results of the DIF and DTF analyses for the ICT tests administered at the two measurement occasions are summarized in Tables S1 and S2. At the first measurement occasion, up to 41% of the items (i.e., 12 of the 29 administered items) exhibited significant DIF. However, the consequence of these effects on the test scores was negligible for all variables. The largest percentage bias was observed for age, falling at 1.59%, and thus did not indicate notable DTF. A similar pattern was observed for the test administered at the second measurement occasion. Up to 31% of the items (i.e., 9 of the 32 administered items) showed significant DIF. But the percentage bias of the test scores suggested negligible DTF, with the largest value being 1.33%

Taken together, these results show comparable measurement models of the two ICT literacy tests across age, gender, and two indicators of socioeconomic status. The test results can therefore be meaningfully compared across these variables.

Table S1

Summary of Differential Response Functioning Analyses at First Measurement Occasion

	Age	Gender	Years of education	Occupational prestige
Differential item functioning				
Number of items	9	4	12	10
Percentage of items	31%	14%	41%	34%
Differential test functioning				
Difference in raw score metric (95% confidence interval)	0.76 (0.58, 0.93)	0.19 (0.11, 0.27)	-0.86 (-1.07, -0.66)	-0.77 (-0.92, -0.60)
Percentage bias (95% confidence interval)	1.59% (1.21, 1.94)	0.40% (0.24, 0.56)	-1.80% (-2.23, -1.38)	-1.59% (-1.92, -1.26)

Table S2

Summary of Differential Response Functioning Analyses at Second Measurement Occasion

	Age	Gender	Years of education	Occupational prestige
Differential item functioning				
Number of items	10	5	5	6
Percentage of items	31%	16%	16%	19%
Differential test functioning				
Difference in raw score metric (95% confidence interval)	0.89 (0.62, 1.17)	0.52 (0.37, 0.66)	-0.47 (-0.61, -0.34)	-0.43 (-0.57, -0.30)
Percentage bias (95% confidence interval)	1.33% (0.93, 1.75)	0.77% (0.55, 0.99)	-0.70% (-0.91, -0.50)	-0.65% (-0.85, -0.45)

C. Plausible Value Estimation

ICT literacy at the two measurement occasions were represented by 100 plausible values drawn for each respondent. For this, the measurement models reported in Senkbeil and Ihme (2015) and Gnambs and Senkbeil (2023) were replicated. Plausible values were then drawn using the fixed item parameters from the unconditional scaling (see Khorramdel et al., 2020). Because many variables included in the background model had substantial rates of missing values, these were imputed 100 times using classification and regression trees (Burgette & Reiter 2010). One plausible value was then drawn from models estimated with each imputed background data (see Weirich et al., 2014).

Plausible value estimation requires the specification of a background model that predicts the latent competency (Khorramdel et al., 2020). These covariates are included as latent regressors to account for measurement error on the population level. In addition, an appropriately defined background model allows imputation of missing competences for non-responders who did not participate in the assessment (Braun & Von Davier, 2017). For the present analyses, a total of 18 variables were included in the background models of the latent variable models that have been shown to be associated with ICT literacy.

As *sociodemographic variables,* respondents' gender (coded 0 for men and 1 for women), age at the first wave (in years) including quadratic and cubic terms, migrant background (coded 0 for non-migrants and 1 for migrants), marital status (coded 0 for married and 1 otherwise), and employment status (coded 0 for employed and 1 otherwise) were selected. The number of books at home, measured on a six-point scale, was used as an indicator of cultural capital (Sieben & Lechner, 2019). In addition, socioeconomic status was represented by the number of years of education and occupational prestige of the respondents at age 30 (see main text). Furthermore, the skill level required for the job held at the age of 30 was determined based on the *International Standard Classification of Occupations* (ISCO; International Labour Organization, 2023) and distinguished into high-skilled (ISCO 1 to 3) versus medium- to low-skilled (ISCO 4 to 9) occupations. Finally, the number of years of education of the respondents' mother and father were considered which were measured comparably to the yeas of education of the respondents (see main text).

A range of *cognitive abilities* were acknowledged that were measured with standardized achievement tests at different measurement occasions. Figural reasoning abilities were assessed with a 12-item Raven-type matrices test, which required the identification of a logical rule to complete a figural sequence (see Lang et al. 2014). Despite its short length, the sum score had a good categorical ω reliability of .70. For a test of scientific literacy (see Haschke et al., 2017) with 26 items that were scaled using the unidimensional partial credit model, proficiency scores were available in the form of weighted likelihood estimates (WLE; Warm 1986). These showed a satisfactory marginal reliability of .77. Similarly, reading and mathematical competencies were measured using tests developed specifically for the NEPS (see Hardt et al., 2013; Jordan & Duchhart, 2013). The tests contained 32 and 22 items, respectively, and were scaled using the partial credit model. The WLE scores yielded good reliabilities of .72 and .78, respectively. Finally, vocabulary was measured with a picture selection task similar to the *Peabody Picture Vocabulary Test* (Dunn & Dunn, 2004). The 89 items presented sets of four pictures and required the identification of the correct picture from a spoken word. The sum score showed a good ω reliability of .87.

As *methodological design variables*, the design weights that acknowledged the disproportional sampling probabilities and the time lag between the two measurements of digital competencies were considered.

In addition to the main effects of these variables, also their interactions with gender, age, number of years of education, and occupational prestige were included.