

# Who Gets Online? Exploring Digital Access and Inequality in the United States

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This study examines how age, education, race, and sex shape internet use in the United States, using nationally representative data from the 2000–2022 General Social Survey (N = 37,583). Logistic regression models reveal that education is the strongest predictor of regular internet use, but its effect is moderated by age, race, and sex. Older adults remain less likely to use the internet regardless of education level, highlighting persistent age-based digital divides. Race and sex show secondary moderating effects, indicating that social characteristics interact to influence digital engagement. These results underscore the multidimensional nature of digital inequality and the relevance of Bourdieu's forms of capital and Tichenor's knowledge gap hypothesis.

The digital divide is more than who has a computer or internet access, it is also about how people use technology and the opportunities it provides. Research has shown that even among college students, internet use patterns differ by race and gender (Jones et al., 2009). Mirazchiyski (2024) argues that focusing only on access to technology hides deeper inequalities in digital skills and how effectively people engage with online resources, while Sanders (2021) emphasizes that these disparities are shaped by social and structural factors, affecting education and long-term economic outcomes.

Age and education strongly shape digital inequality. Older adults often face challenges in learning new technologies and encounter assumptions that they are less capable with digital tools, reflecting the continuous ageism in today's social environments (Vogels, 2021). Younger adults tend to adopt and adapt to new technologies more easily, yet disparities still exist across socio-economic and racial groups (Pew Research Center, 2022). Education amplifies these differences, with people who have higher levels of education more likely to use digital resources for complex tasks, while those with lower education engage less fully with technology, widening existing gaps (van Dijk, 2020; van Deursen and van Dijk, 2019).

Social characteristics like race and gender also shape how people engage with technology. Non-White students and women may face barriers from less exposure to technology early on or underrepresentation in tech-focused fields, which can limit opportunities to develop technical skills or pursue tech-related careers (Gonzales, 2016; DiMaggio & Hargittai, 2001). While these gaps can seem smaller in highly educated populations, they still accumulate over time, affecting outcomes from academic performance to career opportunities. Drufovka (2015) explored these patterns in her thesis, showing how age, race, gender, and education interact to influence internet use, emphasizing that multiple social factors matter simultaneously. Tichenor's knowledge gap hypothesis also underscores that those already advantaged tend to gain more from technological opportunities, widening disparities in information access and skill over time (Tichenor, Donohue, & Olien, 1970).

This study examines how age, education, race, and gender jointly shape internet use. By looking beyond simple measures of access or frequency, it explores the social dynamics that influence who benefits from digital technologies. Using nationally representative data, this approach highlights where inequalities persist and provides a clearer picture of the social factors that contribute to the digital divide.

## METHODS AND DATA

This analysis examines whether and to what extent age, education, race, sex, and region predict internet use in the United States, drawing on nationally representative data from the 1974–2024 General Social Survey (GSS). The General Social Survey is a nationally representative survey of adults in the United States conducted by NORC at the University of Chicago. Although the GSS includes data from 1972 through 2022, questions about internet use were first asked in 2000. The analytic sample is therefore restricted to respondents from 2000 through 2022. The analytic sample includes 37,583 respondents, and all analyses are weighted using the GSS survey weights to account for the complex sampling design. Variables taken from the GSS include measures of internet use, age, education, race, sex, and region. Internet use, the dependent variable in this analysis, is measured with a dichotomous variable indicating whether respondents reported using the internet or apps more than occasionally. All other variables were coded as categorical for analysis. Age was grouped into ranges representing different stages of life (Young Adult, Adult, Middle-Aged, Older Adult, Senior), and education was categorized as lower (no formal schooling or primary education), moderate (secondary education), and higher (college or higher). Race was coded as White and Non-White (Black and Other), and region was categorized into Northeast (New England, Middle Atlantic), Midwest (East North Central, West North Central), South (South Atlantic, East South Central, West South Central), and West (Mountain, Pacific). Lastly, sex was coded as a binary variable (Male, Female).

A multiple logistic regression analysis was conducted to estimate the effect of age, education, race, sex, and region on internet use, while accounting for the categorical nature of the independent variables. Interaction terms between education and other demographic characteristics were tested to explore whether the relationship between education and internet use varies across different groups. All analyses were weighted using the GSS survey weights to adjust for the complex sampling design, and model diagnostics were examined to ensure adequate fit. Predicted probabilities from the fitted models were visualized using margin plots to aid interpretation of the relationships.

## FINDINGS

Table 1 presents odds ratios from logistic regressions estimating the likelihood of using the internet more than occasionally, based on age, education, race, sex, and region. In Model 1, age shows a strong negative association with internet use. Compared to Young Adults, Middle-Aged adults have substantially lower odds of internet use ( $OR = 0.22$ , CI [0.14, 0.34]), Older Adults even lower ( $OR = 0.14$ , CI [0.09, 0.21]), and Seniors the lowest ( $OR = 0.04$ , CI [0.03, 0.07]). Females report slightly higher odds of internet use compared to Males ( $OR = 1.26$ , CI [0.99, 1.61]). In Model 2, education emerges as the strongest predictor. Respondents with moderate education are more likely to use the internet than those with a lower education ( $OR = 6.13$ , CI [1.24, 30.28]), and those with higher education show the highest odds ( $OR = 23.34$ , CI [4.72, 115.41]). Model 3 adds controls for region, but regional differences are not statistically significant and do not substantially alter the age, sex, race, or education effects. Across models, race is also a meaningful factor, with Non-White respondents generally showing lower odds of internet use, though the strength and precision of these effects are smaller compared to those of age and education.

Table 1: Logistic Regression Results for Internet Use by Age Group, Sex, Race, Education, and Region

	Model 1	Model 2	Model 3
Age (Ref: Young Adult)			
Adult	0.69 [0.44, 1.09]	0.65 [0.41, 1.05]	0.65 [0.40, 1.04]
Middle-Aged	0.22*** [0.14, 0.34]	0.20*** [0.13, 0.32]	0.20*** [0.13, 0.32]
Older Adult	0.14*** [0.09, 0.21]	0.12*** [0.07, 0.18]	0.11*** [0.07, 0.18]
Senior	0.04*** [0.03, 0.07]	0.04*** [0.02, 0.07]	0.04*** [0.02, 0.07]
Sex (Ref: Male)			
Female	1.26 [0.99, 1.61]	1.26 [0.98, 1.62]	1.25 [0.97, 1.61]
Race (Ref: White)			
Non-White	0.38*** [0.29, 0.50]	0.41*** [0.31, 0.55]	0.42*** [0.31, 0.56]
Education (Ref: Lower)			
Moderate Education		6.13* [1.24, 30.28]	6.80* [1.31, 35.22]
Higher Education		23.34*** [4.72, 115.41]	25.54*** [4.94, 132.11]
Region (Ref: Northeast)			
Midwest			0.74 [0.49, 1.13]
South			0.72 [0.48, 1.05]
West			0.89 [0.59, 1.36]
Observations	1939	1935	1935

Exponentiated coefficients; 95% confidence intervals in brackets

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

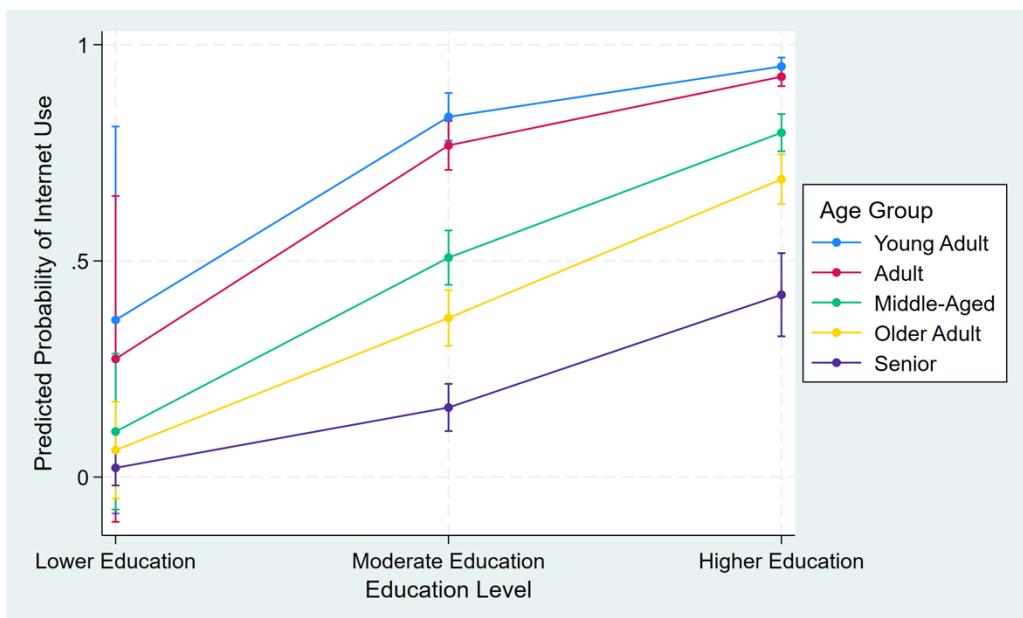
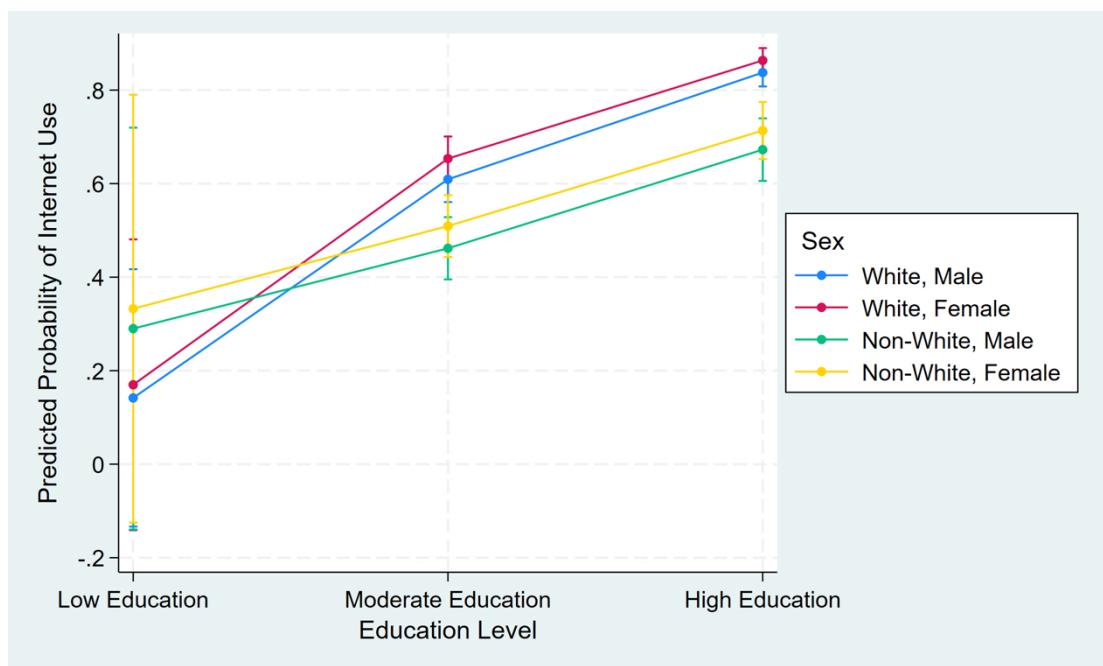


Figure 1. Predicted Probability of Internet Use by Education Level and Age Group

Figure 1 displays predicted probabilities of internet use across education levels, broken down by age group. The figure highlights that education strongly increases the likelihood of internet use across all groups, but age substantially moderates this relationship. Among Young Adults, predicted probabilities rise from 0.62 at lower education to 0.94 at higher education. For Middle-Aged respondents, the increase is smaller (0.41 to 0.84), while for Older Adults the rate of increase is slower (0.29 to 0.66). Seniors show the lowest predicted probabilities, rising only from 0.18 at lower education to 0.44 at higher education. These patterns show that education increases internet use for everyone, but even high education does not completely make up for the lower usage among older adults, showing a lasting age-based digital divide.

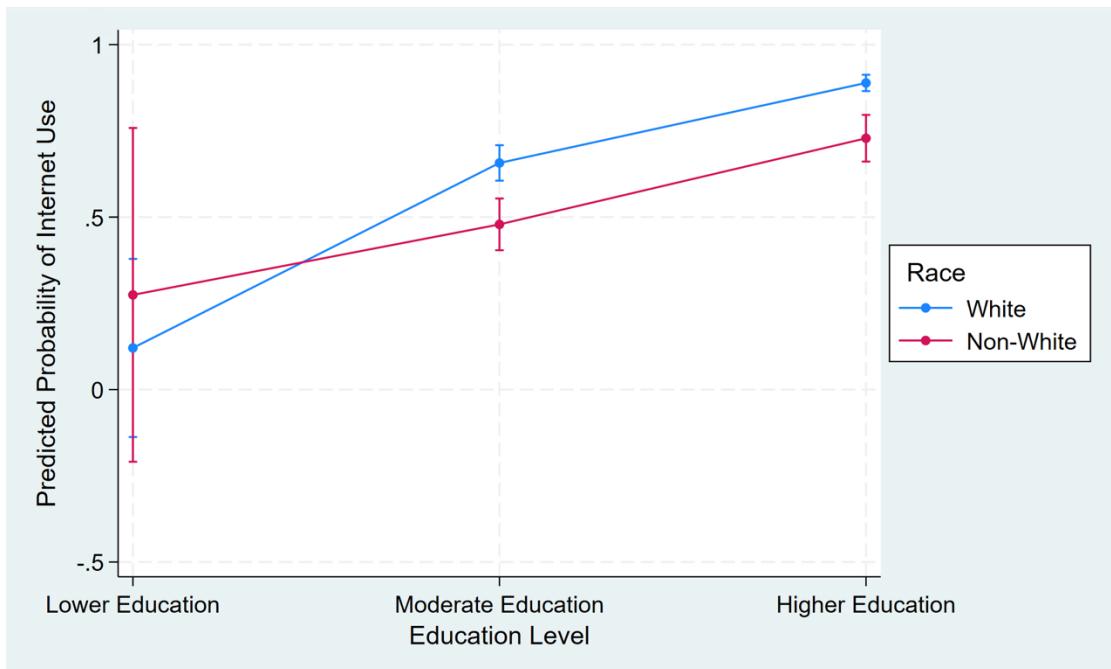
Figure 2 presents predicted probabilities of internet use across education levels, separately for males and females. The figure shows that education substantially increases internet use for both sexes, but females consistently report slightly higher predicted probabilities. Among respondents with lower education, the predicted probability of internet use is 0.42 for males and 0.49 for females. At moderate education, probabilities rise to 0.77 for males and 0.83 for females, and at higher education, they reach 0.91 for males and 0.95 for females. Although the differences between sexes are modest and not statistically significant, the results suggest that females may be slightly more likely than males to translate higher education into regular internet use.



*Figure 2. Predicted Probability of Internet Use by Education Level and Sex*

Figure 3 illustrates predicted probabilities of internet use across education levels, broken down by race. Education strongly increases internet use for both White and Non-White respondents, but the increase is more evident among Non-White respondents. At lower education, predicted probabilities are 0.43 for White respondents and 0.38 for Non-White respondents. At moderate education, probabilities rise to 0.78 for White respondents and 0.84 for Non-White respondents. At higher education, the predicted probability reaches 0.92 for White respondents and 0.96 for Non-White respondents. While confidence intervals overlap, these results suggest that higher education may close initial racial gaps in internet use,

with Non-White respondents catching up to and even slightly surpassing individuals who identify as White at higher education levels.



*Figure 3. Predicted Probability of Internet Use by Education Level and Race*

In summary, these results show that education is the strongest predictor of internet use, but its effect is moderated by age, sex, and race. Age-based digital divides are particularly pronounced, as older adults remain significantly less likely to use the internet regardless of education level. Sex and race showcase moderating effects, indicating that while education broadly promotes internet adoption, its impact varies across social groups.

## CONCLUSIONS

The findings demonstrate that digital inequality is not solely about access but also about how social characteristics shape meaningful engagement with technology. Education strongly promotes internet adoption, yet older adults remain significantly less likely to use digital tools regardless of educational attainment, highlighting persistent age-based digital divides. Race and sex also moderate this relationship, with non-White respondents and men generally showing lower probabilities of use, even when controlling for education. These results align with prior research emphasizing the role of social and structural factors in shaping digital behavior, and they underscore the continued relevance of Bourdieu's forms of capital and Tichenor's knowledge gap hypothesis in understanding who benefits from technology.

Despite these insights, the study has several limitations. The General Social Survey (GSS) uses a simplified racial variable (White, Black, Other), which may obscure nuances among diverse groups, and sex is coded as a binary (Male, Female), excluding nonbinary identities. Internet use is measured dichotomously, so differences in skill, purpose, or intensity of use are not captured. Additionally, the GSS does not measure the quality or type of technology access, which could influence engagement. Future

research should explore digital capital in relation to emerging technologies, especially artificial intelligence, to understand how new tools may amplify or mitigate existing inequalities.

## REFERENCES

- DiMaggio, Paul, and Eszter Hargittai. 2001. “From the ‘Digital Divide’ to ‘Digital Inequality’: Studying Internet Use as Penetration Increases.” Princeton University Center for Arts and Cultural Policy Studies, Working Paper Series #15.
- Drufovka, Alina. 2015. “Inequality in the Information Age: From the Digital Divide to the Usage Divide.” Colorado College, December 2015. Senior Thesis.
- Gonzales, Amy L. 2016. “The Contemporary US Digital Divide: From Initial Access to Technology Maintenance.” *Information, Communication & Society* 19(2):234-248.
- Mirazchiyski, Plamen. 2024. “Digital Inequality Beyond Access: Engagement, Skills, and Social Factors.” *Journal of Digital Sociology* 2(1):45-63.
- Pew Research Center. 2022. “Internet/Broadband Fact Sheet.” Pew Research Center, Washington, DC.
- Tichenor, Philip J., George A. Donohue, and Clarice N. Olien. 1970. “Mass Media Flow and Differential Growth in Knowledge.” *Public Opinion Quarterly* 34(2):159-170.
- van Dijk, Jan A. G. M. 2020. *The Digital Divide*. 3rd ed. Cambridge, UK: Polity Press.