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Intersectional analysis of sociodemographic factors and values influencing internet usage in the United States

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Abstract

This study examines how sociodemographic variables (age, gender, education, and race/ethnicity) and beliefs in unifying societal values interact to influence internet usage in the U.S. Employing data from the Pew Research Center's 2024 National Public Opinion Reference Survey (N = 5,626), the study combines multivariate regression and two-step cluster analyses to identify both direct and intersectional effects. Statistical analysis reveals meaningful interactions between age, gender, education, race/ethnicity, and unity beliefs, accounting for about 24% of the variation in how frequently people use the internet. To enhance our understanding, we conducted cluster analysis alongside regression, identifying distinct user groups and providing deeper insights into how demographic factors and belief in unifying values combine to influence online behavior. The results emphasize the importance of approaches that address multiple factors when developing strategies to bridge the digital divide, a multifaceted societal problem rooted in both structural and perceptual disparities in digital access and engagement. Policies and interventions to minimize the digital divide should consider the intersectionality among factors rather than focusing on individual factors alone.

Keywords: digital divide, internet usage, intersectionality, multivariate regression, cluster analysis

Introduction

The digital divide in America goes beyond just having internet access. It is about whether people can use digital tools, participate online, and improve their lives using technology (Greenstein et al., 2024; Sadun & Greenstein, 2025). While more Americans can get online now, many communities still face real obstacles – from limited high-speed internet options to affordability issues – that keep them disconnected from the digital world (Pew Charitable Trusts, 2024). These gaps hit certain groups harder: older people, those with lower incomes, and racial or ethnic minorities (Pew Charitable Trusts, 2024; Fang et al., 2024). For example, senior citizens, especially minorities with limited financial resources, often struggle the most with accessing and using digital technology (Fang et al., 2024; Yang et al., 2024). To build an equitable society, we must ensure historically underserved groups have meaningful digital access and overcome barriers to both connectivity and usage, enabling full participation in civic, economic, and educational life**.** Not doing so risks worsening existing inequalities (Pew Charitable Trusts, 2024; Fang et al., 2024).

The digital divide is not just about physical access to technology; it is also shaped by individuals' attitudes and perceptions toward digital tools. Even in places where the internet is available, underserved communities often face invisible barriers related to culture and mindset that keep them from participating in the digital world (Nittas et al., 2024; Cui et al., 2024). These obstacles often come from broader social and cultural issues - like websites lacking culturally relevant content or not being available in multiple languages - making it harder for vulnerable groups to use digital technologies (Raihan et al., 2024). Rural Americans face a stubborn digital divide due to spotty internet service and inconsistent tech training. With unreliable connections and few resources to build digital skills, people from rural regions risk being left behind as everyday life increasingly moves online (Raihan et al., 2024). While internet access has been shown to improve many aspects of life, such as access to education, health information, and civic resources, this is not universally experienced, and benefits vary by individual context, perceived usefulness, and ability to engage meaningfully.

Efforts to bridge the digital divide have typically focused on subsidizing broadband access and providing digital literacy training (National League of Cities, 2021; Pew Research Center, 2021; Ragnedda & Mutsvairo, 2022; Scheerder et al., 2017). However, these initiatives often overlook important factors such as users' perceptions of inclusivity and optimism about technology's potential to connect communities (Robinson et al., 2020). Studies show that when people feel good about digital tools, they are more likely to use them and work together online, and this is especially true for communities that have traditionally been left out of the conversation. Creating a positive vibe around technology can help bring more diverse voices into our digital spaces (Ragnedda & Mutsvairo, 2022; Robinson et al., 2020).

This study explores how interactions among sociodemographic factors such as age, education, gender, race/ethnicity, and beliefs about national unity influence digital engagement. Findings from this research provide valuable guidance for developing inclusive strategies that ensure equitable access to digital opportunities.

Literature Review

Research shows that age, education level, gender, and racial or ethnic background strongly influence internet use. While young people tend to be more comfortable online, seniors frequently find themselves at a disadvantage regarding technology. Many older adults have not developed the digital know-how to use websites and applications comfortably, leaving them hesitant or frustrated (Arcury et al., 2020; Eurostat, 2024). Interestingly, this age gap in digital skills suggests that simply providing access is not enough - there are other important factors beyond having an internet connection that determine how and whether people engage with digital technology (Sycamore Institute,2024; Sen et al., 2024).

Educational attainment is another critical factor that influences internet use. Individuals with advanced degrees are likelier to engage in diverse online activities, including e-learning and professional development. The relationship between education and digital engagement appears bidirectional, as digital skills increasingly determine educational and career advancement opportunities in the modern economy (Scheerder et al., 2017).

Research shows that gender influences internet use. Men tend to spend their online time focused on work and entertainment, while women are more likely to use digital tools for connecting with others socially and seeking health information (Bünning et al., 2023; Kontos et al., 2014). These differences reflect broader societal gender roles but may be evolving as digital platforms become increasingly integrated into daily life across demographic boundaries.

Racial and ethnic disparities in broadband access and internet usage are closely tied to systemic inequities such as income, geographic location, and educational opportunities (Li et al., 2023; Singh et al., 2020).

Living in the countryside still means struggling with internet access in ways urban populations do not experience. As Tassinari, Kleine-Rueschkamp, and Veneri (2024) discovered, people in rural areas are not getting online as much, mainly because the high-speed internet infrastructure is not there. This research highlights why we need specific plans to bring reliable internet to country communities and tackle their unique challenges (Sadun & Greenstein, 2025). Despite significant research documenting these sociodemographic patterns, questions remain about how these factors interact in contemporary contexts and their relative importance in predicting digital engagement.

The Role of Non-Structural Barriers

Non-structural barriers, including attitudes, cultural norms, and perceptions of technology, are critical but often overlooked factors in the digital divide. In their literature review, Vassilakopoulou and Hustad (2021) indicate that motivation to use digital content and personality traits, alongside physical access, can significantly impact digital engagement. Related research using web tracking data has found that even when good internet service is available, a community's attitudes and cultural expectations can strongly influence how its members use digital tools (Kacperski et al., 2025). These studies suggest that social and cultural factors meaningfully shape who gets online and how they participate in the digital world.

Interventions focusing solely on improving access and affordability are unlikely to achieve meaningful digital inclusion without addressing adoption barriers beyond accessibility. For example, a study found that the digital divide will not close without addressing access and the behavioral, psychological, and social factors influencing adoption (Boston Consulting Group, 2022). Users of digital services have reported that psychological and lifestyle factors, such as motivation, time, and routine, significantly influence technology adoption (Borghouts et al., 2021). These studies indicate that psychological and cultural factors must be included in addressing the digital divide alongside structural improvements.

Non-structural barriers, such as ageism, attitudes, cultural norms, and perceptions of technology, are critical factors impacting the digital divide. Ageism is a socially constructed phenomenon influenced by social expectations, cultural norms, and lived experiences that could threaten elders' successful engagement with digital technologies (Mannheim et al., 2024; Köttl & Mannheim, 2021). The World Economic Forum’s Digital Trust Initiative (2021) highlights that mistrust in digital content and technologies can further exacerbate disparities in digital engagement. Despite growing recognition of these non-structural barriers, questions remain about how they interact with sociodemographic factors and their relative impact on different types of digital engagement.

Belief in Unifying Values and the Digital Divide

Studies show that how people engage with technology significantly influences their sense of social connection and unity and social connection, though this relationship works in multiple, complicated ways. Digital platforms serve as significant forums for dialogue where people can securely express their viewpoints and personal stories, fostering greater understanding among different communities (Social Connection Guidelines, 2024; Üblacker et al., 2024). The capacity of digital platforms to bring together individuals from varied backgrounds to online environments could potentially cultivate collective identity and shared principles (Üblacker et al., 2024; Kann et al., 2023).

Digital media serves as "an important tool for national unity through messages highlighted in the medium," it simultaneously presents risks that can exacerbate divisions when misused (Hendrix, 2023; Rachmawati et al., 2023; Üblacker et al., 2024). This two-sided nature of technology shows why we need to pay attention to how people's online habits might either strengthen or weaken our sense of shared values and togetherness, especially as our communities become more divided and fragmented.

Digital platforms with features and algorithms to promote social connection have shown real potential for strengthening unity in online spaces (Üblacker et.al., 2024; Social Connection Guidelines, 2024). However, significant implementation gaps exist, evidenced by research showing that while "63% of consumers believe companies should use marketing to encourage national unity," approximately "57.4% of marketers indicated that their companies are doing nothing on this front" (Moorman & American Marketing Association, 2021; The CMO Survey, 2021). Though many studies have documented the enabling potential of internet access, a growing body of research also emphasizes potential negative impacts, such as screen fatigue, misinformation exposure, and digital exclusion of those unable or unwilling to adopt new technologies (Kbaeir et.al., 2024; Seifert et.al., 2021; Zablotsky et.al., 2024).

Despite growing interest in how digital media shapes national identity and unity, there remains a notable lack of cross-cultural empirical studies examining the mechanisms by which digital programs influence people's views and behaviors related to national values. There is a limited understanding of whether individuals who strongly believe in unifying values engage differently online than to those who do not. The present study addresses this research gap by investigating how demographic factors and beliefs about unity relate to internet use and engagement patterns.

Research Questions

This research is guided by the following questions:

- **RQ1**: *How does age influence the frequency and types of internet usage among U.S. residents?*
- **RQ2**: *To what extent do gender differences affect internet usage patterns and activity types?*
- **RQ3**: *What is the relationship between educational attainment and internet usage levels?*
- **RQ4**: *Do racial/ethnic disparities persist in internet usage, and how do socioeconomic and infrastructural factors influence them?*
- **RQ5:** *Does a strong belief in unifying values correlate with higher internet engagement?*

This study uses data from Pew Research Center's 2024 National Public Opinion Reference Survey (NPORS) to examine how age, gender, education, race/ethnicity, and beliefs in unifying values influence internet usage among U.S. residents. Multivariate regression analysis identifies direct effects and interactions between these factors, while a complementary cluster analysis explores latent user profiles, providing a comprehensive view of the digital divide's determinants.

Methodology

Data were collected from a nationally representative Pew Research Center survey (Feb–June 2024; N=5,626; response rate=32%) conducted online, via mail, and by phone in English and Spanish, weighted to match U.S. Census benchmarks. The dependent variable was internet usage frequency; independent variables included Age, gender, education level, race/ethnicity, and beliefs about national unity. Survey items used in this study are presented in Appendix A.

We employed two complementary analytical approaches, multivariate regression and cluster analysis, to examine relationships among sociodemographic variables and internet usage. The regression analysis tested direct effects and interactions among age, education, gender, race/ethnicity, and unity beliefs on internet usage frequency. The hypotheses were evaluated at a significance level of 0.05 (two-tailed). The regression model, incorporating main effects and interactions (e.g., age × education, unity × gender), produced nationally representative estimates using survey weights.

$$Internet\ Usage = \beta0 + \beta1*(AGE) + \beta2*(EDUCATION) + \beta3*(GENDER) + \beta4*(RACE) + \beta5*(UNITY) + \beta6*(AGE\times EDUCATION) + \beta7*(UNITY\times GENDER) + \ldots + \epsilon$$

Additionally, a two-step cluster analysis identified natural groupings of respondents based on internet usage frequency and sociodemographic attributes. The optimal number of clusters was determined using Bayesian Information Criterion (BIC), with cluster quality assessed via silhouette coefficients (Eligüzel et al., 2023). Combining these methods provided both quantitative validation of relationships (regression) and descriptive insights into distinct user profiles (clustering), offering a comprehensive perspective on the digital divide.

Results

The multivariate regression model was statistically significant ($F=3.440$, $p<.001$), indicating the examined sociodemographic variables collectively explained about 24% of variance (adjusted $R^2=0.17$) in internet usage frequency. In social and behavioral sciences, regression models typically yield lower R^2 values (around 0.10–0.30) due to the complexity and variability of human behavior; thus, even modest variance explained, such as 24%, is considered meaningful and practically significant (Cohen, 1988; Abelson, 1985). Consequently, statistical significance of key predictors is generally regarded as more important than achieving a high R^2 value in these contexts (Abelson, 1985; Cohen, 1988).

Table 1 summarizes the main effects of each independent variable on internet usage from the regression analysis and Appendix B summarizes significant interaction effects from the regression analysis, highlighting complex interdependencies among age, gender, education, race/ethnicity, and beliefs about societal unity.

Table 1. Regression analysis of key predictors of internet usage frequency (main effects)

Predictor	F-value	p-value	Significant?
Age (AGECAT)	7.734	< .001	Yes – younger use more
Belief in Unifying Values (UNITY)	2.864	.091	No (ns)
Gender (GENDER)	3.546	.029	Yes – men use slightly more
Race/Ethnicity (RACETHN)	1.413	.227	No (ns)
Education (EDUCATION)	5.091	< .001	Yes – higher ed use more

Overview of Cluster Analysis Findings

Cluster analysis identified 11 distinct user groups based on internet usage frequency and sociodemographic attributes, including age, race/ethnicity, gender, education level, and beliefs about national unity, as summarized in Table 2 and detailed in Appendix C. The algorithm's determination of 11 clusters was based on statistical criteria (with diminishing model fit improvements beyond 11 clusters). The average silhouette coefficient for the clustering solution was approximately 0.2, indicating that some clusters are not sharply separated.

While higher silhouette scores (~1) indicate clear cluster separation, lower scores (~0.2–0.3), though suboptimal, can still provide meaningful insights in exploratory analyses, especially in complex datasets with overlapping clusters (Rousseeuw, 1987). While the silhouette coefficient of ~0.2 indicates only modest cluster separation, this is common in social science applications involving multidimensional survey data. In such contexts, even low silhouette scores can yield useful typological distinctions and hypothesis-generating insights (Kaufman & Rousseeuw, 2009).

Table 2. Summary of identified user clusters (profiles from two-step cluster analysis)

Cluster (#)	Typical Internet Use	Avg. Age (approx)	Predominant Race/Ethnicity	Gender Mix	Education Level	Unity Belief Attitude
1	Multiple times/day	~60 (older)	Majority White	More male	College graduate	Most **do not** believe united
2	Multiple times/day	~55 (older)	Majority White	More female	College graduate	Most **do not** believe united
3	Constantly online	~32 (young adult)	Predominantly non-White (Hispanic & Asian)	~50/50 gender	College graduate	Very few believe united
4	>1 time/day	~62 (older)	Predominantly non-White (Black & Hispanic)	More female	Some college	Most **do not** believe united
5	Multiple times/day	~52 (middle-aged)	Predominantly White	Gender balanced	Some college	**Believes country is united**
6	Multiple times/day	~54 (middle-aged)	Predominantly White	~50/50 gender	Some college	Most **do not** believe united
7	~Once per day	"Older" (65+)	Predominantly White	~50/50 gender	High school	Most **do not** believe united
8	Almost constantly	~28 (very young)	Mixed (no single majority)	More female	HS or some college	Some believe (most do not)
9	Multiple times/day	~57 (older)	Predominantly White	~50/50 gender	College graduate	Most **do not** believe united
10	Frequently (daily)	~37 (young adult)	Predominantly White	More female	College graduate	Most **do not** believe united
11	Constantly online	~33 (young adult)	Predominantly White	More male	College graduate	Most **do not** believe united

Integrated Results

We present the findings for each research question (RQ) by integrating insights from the multivariate regression and the two-step cluster analysis. For each RQ, the regression results and cluster results are discussed side-by-side to highlight how they align or differ. Summary Table 3 compares the two approaches for each factor.

Table 3. Summary of effects of key predictors from regression and cluster analyses (RQ1)

Regression Findings	Cluster Analysis Findings
Age: Younger respondents report significantly more frequent internet use ($F = 7.734$, $p < .001$). Even after controlling for other variables, age remained a strong predictor, indicating a clear trend of declining usage with increasing age.	**Age:** The user segments with the highest internet usage were those with younger average ages. The least-active user segment was the oldest group (primarily seniors). Notably, the cluster with the lowest usage was composed of older adults (65+) with lower education, illustrating that advanced age – especially when coupled with low education – corresponds to very low internet engagement.
Gender: A modest gender gap in usage frequency: men use the internet slightly more often on average than women ($F = 3.546$, $p = .029$). Significant interactions (e.g., gender × age, gender × unity) suggest that gender differences in usage depend on other factors (age, attitudes), rather than being uniform across the board.	**Gender:** No cluster showed an extreme gender divide in internet use. High-usage clusters included men and women — some were slightly male-dominated, others slightly female-dominated. The lowest-usage cluster had an even gender split, indicating that both genders are represented among the least frequent users. Overall, men and women are similarly present in the frequent-user groups, implying minimal disparity in basic access and frequency of use.
Education: Higher educational attainment is associated with significantly more frequent internet use ($F = 5.091$, $p < .001$). Education also moderates other effects: for instance, the age × education interaction ($F = 2.575$, $p < .001$) indicates that older individuals with lower education are much less frequent users than younger or better educated.	**Education:** The lowest-usage user segment had the lowest education levels (the majority had only a high school education, and they were often older individuals). By contrast, every high-usage cluster featured a high proportion of individuals with at least some college education. In essence, no cluster with predominantly low-education members achieved high internet use. This clustering pattern confirms that low education — often combined with older age — corresponds to markedly reduced online engagement.
Race/Ethnicity: No significant main effect of race on usage frequency when other variables are controlled ($p > .05$). However, race does play a role via interactions: for example, race × age ($F = 4.687$, $p < .001$) and race × education was significant, indicating that the impact of race is conditional on a person's age or education level.	**Race/Ethnicity:** No user group (cluster) was a "low-use minority" group. A predominantly non-White cluster was among the highest-frequency users, and the lowest-frequency cluster was predominantly White (older individuals with low education). Minority users were present across various usage levels. For instance, minority seniors with some college education belonged to a moderate-use cluster rather than the lowest-use cluster, highlighting that factors like education and age differentiate usage more than race alone. These cluster patterns illustrate that race/ethnicity is not an independent determinant of frequent internet use, but intersects with other factors.

Regression Findings	Cluster Analysis Findings
Unity Belief: No significant overall effect of believing in national "unity" on internet use ($p > .05$). People with strong unity beliefs were not broadly more active online than those who feel the country is divided. However, belief in unity showed effects in specific subgroups: for example, a significant unity × gender interaction indicated that unity belief correlates with higher usage particularly among women (especially younger women, as seen in a three-way interaction with age).	**Unity Belief:** Only one out of 11 user clusters combined widespread internet use with a strong belief that the country is united. In that "optimistic, high use" cluster, members were mostly middle-aged and did believe in national unity. By contrast, most other high-usage clusters had no such unifying belief (many members perceived the country as divided). Thus, an optimistic unity belief characterizes a specific high-use segment but is uncommon across all heavy internet users. Overall, clusters show that cultural outlooks like unity optimism are not a defining factor for most frequent internet users.

Age and Internet Usage (RQ1): Both analyses confirmed younger age as a significant predictor of higher internet usage (Regression: $F = 7.734$, $p < .001$). Clusters reinforced this, showing younger groups as the most active, while older adults, particularly those with low education, had minimal engagement (Table 1).

Gender and Internet Usage (RQ2): Gender had a modest, though significant, effect in regression ($F = 3.546$, $p = .029$), indicating slightly higher male usage. However, cluster analysis revealed gender- balanced representation across all usage categories, suggesting minimal overall gender disparities in internet use frequency.

Education and Internet Usage (RQ3): Both methods confirmed education as strongly predictive of internet use. Regression analysis indicated significantly higher usage among more educated respondents ($F = 5.091$, $p < .001$). Cluster analysis vividly illustrated this relationship, with low-education clusters less active online, especially among older adults.

***Race/Ethnicity and Internet Usage (RQ4)*:** Race/ethnicity alone did not significantly predict internet use, but regression identified significant interactions (race × age, $F = 4.687$, $p < .001$), indicating intersectional influences. Cluster analysis similarly showed racial diversity across high-usage clusters, emphasizing that race-related disparities emerge mainly in conjunction with socioeconomic factors rather than independently.

Belief in Unifying Values and Internet Usage (RQ5): Unity beliefs showed limited direct influence in regression analyses ($F = 2.864$, $p = .091$), significant only through interactions (e.g., unity × gender, $F = 6.033$, $p = .002$). Cluster analysis confirmed that strong beliefs in national unity characterized only a minority of frequent internet users, which suggests unity-based outreach may benefit specific subgroups rather than general populations.

Together, regression and cluster analyses provided clear, intersectional insights. Age and education emerged as critical predictors, whereas gender, race, and societal values had more subtle, contextual impacts. This combined methodological approach clarified patterns, enabling effective targeted strategies for addressing the digital divide without redundant details.

Discussion and Implications

This research offers a fresh perspective on digital participation. It utilizes regression and cluster analyses to examine the relationship between demographic factors and national unity beliefs. Although our findings generally confirm previous research, we discovered several unexpected and counterintuitive results that provide important guidance for developing focused policy solutions. It is also important to acknowledge that internet access does not automatically equate to improved well-being for all individuals. For some, especially those with limited digital literacy or trust in online systems, increased connectivity may bring risks or anxieties. This study focused on structural and attitudinal enablers of digital engagement, but it is equally important to consider potential downsides of increased internet usage, particularly among novice users. Risks such as exposure to misinformation, privacy concerns, and tech fatigue may affect digital well-being, and future research should explore how these factors influence adoption and engagement.

Age and Education: Our results align with previous studies showing younger and more educated individuals as frequent internet users, whereas older adults with limited education remain digitally marginalized (Arcury et al., 2021; Park & Feng, 2023; Li et al., 2023). Our analysis shows a significant interaction of educational attainment moderating the age-related digital engagement. Specifically, elderly individuals with higher educational credentials maintain considerable digital participation levels, contradicting the prevailing assumption that advancing age uniformly diminishes internet utilization. Our result implies that rather than implementing very general policies for improving digital skills for all older adults, interventions should be tailored specifically for seniors with lower levels of education.

Gender: Minimal Differences Contrary to Common Assumptions: Our findings regarding gender differences diverged notably from previous studies, indicating pronounced gendered usage patterns (Bünning et al., 2023; Kontos et al., 2014). Prior research emphasizes distinct gender-based preferences, with men favoring professional and entertainment activities and women engaging more in social networking. However, our analysis revealed a negligible influence of gender on internet usage frequency across all demographic clusters. This result indicates that digital access and frequency of online engagement have mostly equalized between men and women. As a result, policy approaches should move away from targeting gender differences and instead focus on creating inclusive initiatives that appeal to a wide range of online interests.

Race/Ethnicity: Intersectionality Rather than Direct Effect: Contrary to many studies highlighting direct racial and ethnic disparities in internet usage (Singh et al., 2020; Li et al., 2023), our findings revealed no significant independent racial or ethnic effects once socioeconomic and educational factors were accounted. Rather than race and ethnicity as key drivers of digital inequality, our findings show these factors primarily affect digital engagement through their interactions with age, education level, and economic status. Practical approaches must consider how these factors intersect and overlap to create meaningful reductions in digital disparities.

Beliefs in National Unity: A particularly non-intuitive finding was the limited and highly selective impact of beliefs about national unity on internet usage, contrary to literature suggesting a broader influence of cultural values and optimism on digital engagement (Ahmed & Rahman, 2022; Garcia & Lee, 2021; Johnson, 2023). Our regression analyses indicated that believing in national unity only modestly influenced digital engagement, and even cluster analyses revealed that such optimistic beliefs characterized only a minority of frequent internet users. Thus, while valuable, optimism or cultural cohesion messaging may not be a universally effective strategy for promoting digital inclusion. As a result, policymakers are advised to strategically use culturally tailored messaging in communities where beliefs about unity hold significant meaning.

Using the insights from this study, we recommend the following targeted, multi-dimensional strategies to overcome the digital divide within the United States:

- ***Prioritize Seniors with Limited Education***: Develop specialized digital skills development initiatives and reduce the cost of internet access specifically for older adults with limited formal education.
- ***Inclusive, Rather than Gender-Specific Outreach***: Develop broadly appealing digital training resources emphasizing diverse interests, reflecting the minimal gender differences identified in fundamental usage frequency.
- ***Intersectional Interventions for Minority Populations***: Combine broadband infrastructure improvements with culturally responsive, multilingual educational programs addressing underlying socioeconomic and educational inequities rather than race alone.
- ***Selective Use of Community Values Messaging***: Apply unity-oriented digital engagement strategies selectively in communities where optimism about societal cohesion resonates and as needed to complement structural interventions rather than relying on them exclusively.
- ***Holistic, Evidence-Based Digital Inclusion Strategies***: Coordinate infrastructure development, affordable access, targeted education, culturally sensitive outreach, and continuous evaluation to systematically address intersecting barriers.

Conclusion

This study underscores the complexity of the digital divide, revealing how sociodemographic factors and cultural attitudes intersect to shape internet usage patterns. By applying multivariate regression and cluster analysis to a large, recent dataset, we verified classic determinants (age, education) of digital engagement. We identified specific user profiles and subtle attitudinal influences that enrich our understanding. The critical comparison of the two methods demonstrates that a mixed-method analytical strategy can yield a deeper, more nuanced perspective than either method alone.

For practitioners and policymakers, our findings emphasize that closing the digital divide requires targeted, intersectional approaches: initiatives must consider the multifaceted nature of disadvantage. Infrastructure investment and affordability programs remain vital (especially for rural and low-income communities). However, they should be coupled with training and outreach tailored to the needs and mindsets of specific groups, whether it is boosting digital literacy among older adults, designing inclusive content and services that appeal across gender and cultural lines, or instilling optimism and trust in technology's benefits for those wary of it.

By aligning strategies with the distinct "clusters" of the left-behind population, we can make digital inclusion efforts more efficient and effective. Ultimately, ensuring equitable internet use is not just about technology deployment but about understanding people, their demographics, values, and communities, and meeting them where they are. The combined insights from our regression and cluster analyses provide a roadmap for such understanding and, thus, for bridging the remaining divides in our increasingly digital society.

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APPENDIX A
Survey Questions from the National Public Opinion Research Survey (Pew Research Center, 2024)

UNITY. Which statement comes closer to your own view, even if neither is exactly right? [PN: IF CATI:] (READ LIST) 1 Americans are united when it comes to the most important values 2 Americans are divided when it comes to the most important values 98 [PN: IF CATI:] (DO NOT READ) Don't know 99 [PN: IF CATI:] (DO NOT READ) Refused / [PN: IF WEB:] Web blank

INTFREQ. About how often do you use the internet? [PN: IF CATI:] (READ LIST) 1 Almost constantly 2 Several times a day 3 About once a day 4 Several times a week 5 Less often 98 [PN: IF CATI:] (DO NOT READ) Don't know 99 [PN: IF CATI:] (DO NOT READ)

RACE and ETHNICITY: What is your race or origin? [PN: IF CATI: You can select as many as apply.] [PN: IF WEB:] [Check all that apply.] [PN: IF CATI:] (READ LIST) 1 White 2 Black or African American 3 Asian or Asian American 4 American Indian or Alaska Native 5 Native Hawaiian or other Pacific Islander 6 Some other race or origin (please specify): [PN: INSERT TEXT BOX] 98 [PN: IF CATI:] (DO NOT READ) Don't know 99 [PN: IF CATI:] (DO NOT READ) Refused / [PN: IF WEB:] Web blank

GENDER: Do you describe yourself as a man, a woman, or in some other way? 1 A man 2 A woman 3 In some other way 98 [PN: IF CATI:] (DO NOT READ) Don't know 99 [PN: IF CATI:] (DO NOT READ) Refused / [PN: IF WEB:] Web blank

EDUC: What is the highest degree or level of school that you have completed?

Value	Label
1	College graduate+
2	Some College
3	H.S. graduate or less
99	Refused

AGE: What is your age?

Value	Label
1	18-29
2	30-49
3	50-64
4	65+
99	Refused

APPENDIX B
Multivariate Regression Analysis Results

Dependent Variable: Frequency of internet use					
Source	Type III Sum of Squares	df	Mean Square	F	Significance: p
Corrected Model	104079.595[a]	450	231.288	3.440	<.001
Intercept	1682.434	1	1682.434	25.025	<.001
AGECAT	1559.822	3	519.941	7.734	<.001
UNITY	192.526	1	192.526	2.864	.091
GENDER	476.778	2	238.389	3.546	.029
RACETHN	379.970	4	94.993	1.413	.227
EDUCATION	2053.429	6	342.238	5.091	<.001
AGECAT * UNITY	205.664	3	68.555	1.020	.383
AGECAT * GENDER	818.572	5	163.714	2.435	.033
AGECAT * RACETHN	3781.485	12	315.124	4.687	<.001
AGECAT * EDUCATION	3115.763	18	173.098	2.575	<.001
UNITY * GENDER	811.130	2	405.565	6.033	.002
UNITY * RACETHN	317.619	4	79.405	1.181	.317
UNITY * EDUCATION	684.942	6	114.157	1.698	.117
GENDER * RACETHN	81.208	8	10.151	.151	.997
GENDER * EDUCATION	2194.809	10	219.481	3.265	<.001
RACETHN * EDUCATION	4320.477	24	180.020	2.678	<.001
AGECAT * UNITY * GENDER	528.296	3	176.099	2.619	.049
AGECAT * UNITY * RACETHN	1988.105	12	165.675	2.464	.003
AGECAT * UNITY * EDUCATION	778.715	17	45.807	.681	.824
AGECAT * GENDER * RACETHN	461.522	14	32.966	.490	.940
AGECAT * GENDER * EDUCATION	5441.326	19	286.386	4.260	<.001
AGECAT * RACETHN * EDUCATION	14819.809	61	242.948	3.614	<.001
UNITY * GENDER * RACETHN	671.958	4	167.990	2.499	.041
UNITY * GENDER * EDUCATION	4815.882	6	802.647	11.939	<.001
UNITY * RACETHN * EDUCATION	4645.362	21	221.208	3.290	<.001
GENDER * RACETHN * EDUCATION	6741.503	23	293.109	4.360	<.001
AGECAT * UNITY * GENDER * RACETHN	510.838	10	51.084	.760	.668
AGECAT * UNITY * GENDER * EDUCATION	5061.185	17	297.717	4.428	<.001
AGECAT * UNITY * RACETHN * EDUCATION	6300.646	40	157.516	2.343	<.001
AGECAT * GENDER * RACETHN * EDUCATION	4491.812	43	104.461	1.554	.012
UNITY * GENDER * RACETHN * EDUCATION	6214.477	15	414.298	6.162	<.001
AGECAT * UNITY * GENDER * RACETHN * EDUCATION	3965.271	14	283.234	4.213	<.001
Error	330230.690	4912	67.229		
Total	471861.000	5363			
Corrected Total	434310.286	5362			
a. R Squared = .240 (Adjusted R Squared = .170)					

APPENDIX c
Two-Step Cluster Analysis Results

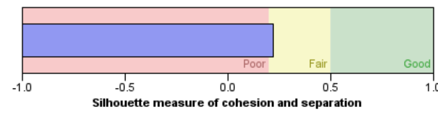
Cluster Distribution				
		N	% of Combined	% of Total
Cluster	1	485	9.4%	8.6%
	2	574	11.1%	10.2%
	3	461	8.9%	8.2%
	4	419	8.1%	7.4%
	5	730	14.1%	13.0%
	6	477	9.2%	8.5%
	7	389	7.5%	6.9%
	8	768	14.8%	13.7%
	9	284	5.5%	5.0%
	10	324	6.3%	5.8%
	11	272	5.2%	4.8%
	Combined	5183	100.0%	92.1%

Excluded Cases	443		7.9%
Total	5626		100.0%

Model Summary

Algorithm	TwoStep
Inputs	6
Clusters	11

Cluster Quality



Cluster Profiles

	Unity	IntFreq	Race		Age	Gender		Education	Unity	IntFreq	Race	Age	Gender	Education
1	1	4	White		3.507216	1.402062		3.917526	not united	MX Daily	White	60	More Male	C Grad
2	1	4.151568	White		3.238676	1.630662		3.543554	not united	MX Daily	White	55	More Fem	C Grad
3	0.87	4.761388	Non-White	Hisp/Asian	2.130152	1.546638	10 other	3.982646	mix not	Constant	Non-White	32	Even	C Grad
4	0.98	3.637232	Non-White	Black/Hisp	3.591885	1.670644		2.706444	not united,	> Once	Non-White	62	More Fem	S Coll
5	0	3.963014	White		3.193151	1.556164		3.141096	United	MX Daily	White	52	Even	S Coll
6	1	4	White		3.280922	1.551363		3	not united	MX Daily	White	54	Even	S Coll
7	1	3.570694	White		3.570694	1.544987		1.96401	not united,	> Once	White	62	Even	HS
8	0.8	4.565104	Mixed	Hisp	1.75	1.64974	other	2.605469	mix not	Constant	Mixed	28	More Fem	HS/S Coll
9	1	3.978873	White		3	1.549296		4	not united	MX Daily	White	57	Even	C Grad
10	1	4.641975	White		2	2		3.700617	not united	Constant	White	37	Female	C Grad
11	1	4.985294	White		2.165441	1.036765		4	not united	Constant	White	33	Male	C Grad

Hypothesis Test Summary				
	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Race-Ethnicity is the same across categories of TwoStep Cluster Number.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
2	The distribution of Age - 4 category is the same across categories of TwoStep Cluster Number.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
3	The distribution of GENDER. Do you describe yourself as a man, a woman, or in some other way? is the same across categories of TwoStep Cluster Number.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
4	The distribution of Education - 3 category is the same across categories of TwoStep Cluster Number.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
5	The distribution of UNITY. Which statement comes closer to your own view, even if neither is exactly right? is the same across categories of TwoStep Cluster Number.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
a. The significance level is .050.				
b. Asymptotic significance is displayed.				

Frequencies

UNITY. Which statement comes closer to your own view, even if neither is exactly right?

		Americans are united when it comes to the most important values		Americans are divided when it comes to the most important values	
		Frequency	Percent	Frequency	Percent
Cluster	1	0	0.0%	485	11.5%
	2	0	0.0%	574	13.6%
	3	60	6.3%	401	9.5%
	4	7	0.7%	412	9.7%
	5	730	76.6%	0	0.0%
	6	0	0.0%	477	11.3%
	7	0	0.0%	389	9.2%
	8	156	16.4%	612	14.5%
	9	0	0.0%	284	6.7%
	10	0	0.0%	324	7.7%
	11	0	0.0%	272	6.4%
	Combined	953	100.0%	4230	100.0%

INTFREQ. About how often do you use the internet?

		Almost constantly		Several times a day		About once a day		Several times a week		Less often	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	0	0.0%	485	19.6%	0	0.0%	0	0.0%	0	0.0%
	2	383	18.4%	0	0.0%	112	38.5%	53	25.6%	26	20.6%
	3	365	17.6%	88	3.5%	2	0.7%	6	2.9%	0	0.0%
	4	72	3.5%	226	9.1%	40	13.7%	59	28.5%	22	17.5%
	5	218	10.5%	378	15.2%	63	21.6%	31	15.0%	40	31.7%
	6	0	0.0%	477	19.2%	0	0.0%	0	0.0%	0	0.0%
	7	50	2.4%	218	8.8%	56	19.2%	34	16.4%	31	24.6%
	8	513	24.7%	210	8.5%	16	5.5%	24	11.6%	5	4.0%
	9	0	0.0%	282	11.4%	0	0.0%	0	0.0%	2	1.6%
	10	208	10.0%	116	4.7%	0	0.0%	0	0.0%	0	0.0%
	11	270	13.0%	0	0.0%	2	0.7%	0	0.0%	0	0.0%
	Combined	2079	100.0%	2480	100.0%	291	100.0%	207	100.0%	126	100.0%

Race-Ethnicity

		White non-Hispanic		Black non-Hispanic		Hispanic		Other		Asian non-Hispanic	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	483	14.1%	0	0.0%	0	0.0%	2	1.1%	0	0.0%
	2	573	16.8%	0	0.0%	0	0.0%	0	0.0%	1	0.4%
	3	0	0.0%	102	19.4%	167	19.9%	47	27.0%	145	65.0%
	4	0	0.0%	203	38.6%	164	19.5%	38	21.8%	14	6.3%
	5	515	15.1%	63	12.0%	110	13.1%	17	9.8%	25	11.2%
	6	477	13.9%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	7	374	10.9%	1	0.2%	13	1.5%	0	0.0%	1	0.4%
	8	176	5.1%	139	26.4%	367	43.7%	60	34.5%	26	11.7%
	9	226	6.6%	18	3.4%	19	2.3%	10	5.7%	11	4.9%
	10	324	9.5%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	11	272	8.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	Combined	3420	100.0%	526	100.0%	840	100.0%	174	100.0%	223	100.0%

Age - 4 category

		18-29		30-49		50-64		65+	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	23	4.8%	85	5.5%	0	0.0%	377	21.9%
	2	77	16.0%	1	0.1%	204	14.3%	292	16.9%
	3	68	14.2%	287	18.5%	84	5.9%	22	1.3%
	4	0	0.0%	0	0.0%	171	11.9%	248	14.4%
	5	23	4.8%	150	9.7%	220	15.4%	337	19.5%
	6	0	0.0%	92	5.9%	159	11.1%	226	13.1%
	7	0	0.0%	0	0.0%	167	11.7%	222	12.9%

	8	251	52.3%	458	29.6%	59	4.1%	0	0.0%
	9	0	0.0%	0	0.0%	284	19.8%	0	0.0%
	10	0	0.0%	324	20.9%	0	0.0%	0	0.0%
	11	38	7.9%	151	9.8%	83	5.8%	0	0.0%
	Combined	480	100.0%	1548	100.0%	1431	100.0%	1724	100.0%

GENDER. Do you describe yourself as a man, a woman, or in some other way?

		A man		A woman		In some other way	
		Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	292	12.9%	191	6.6%	2	5.7%
	2	212	9.4%	362	12.5%	0	0.0%
	3	219	9.7%	232	8.0%	10	28.6%
	4	138	6.1%	281	9.7%	0	0.0%
	5	326	14.4%	402	13.9%	2	5.7%
	6	214	9.5%	263	9.1%	0	0.0%
	7	178	7.9%	210	7.3%	1	2.9%
	8	283	12.5%	471	16.3%	14	40.0%
	9	129	5.7%	154	5.3%	1	2.9%
	10	0	0.0%	324	11.2%	0	0.0%
	11	267	11.8%	0	0.0%	5	14.3%
	Combined	2258	100.0%	2890	100.0%	35	100.0%

Education - 3 category

		College graduate+		Some College		H.S. graduate or less		Refused	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	465	19.0%	0	0.0%	20	1.8%	0	0.0%
	2	314	12.9%	258	16.1%	2	0.2%	0	0.0%
	3	457	18.7%	0	0.0%	4	0.4%	0	0.0%
	4	70	2.9%	162	10.1%	181	16.4%	6	17.6%
	5	303	12.4%	231	14.4%	192	17.4%	4	11.8%
	6	0	0.0%	477	29.8%	0	0.0%	0	0.0%
	7	0	0.0%	0	0.0%	375	33.9%	14	41.2%
	8	0	0.0%	474	29.6%	285	25.8%	9	26.5%
	9	284	11.6%	0	0.0%	0	0.0%	0	0.0%
	10	276	11.3%	0	0.0%	47	4.2%	1	2.9%
	11	272	11.1%	0	0.0%	0	0.0%	0	0.0%
	Combined	2441	100.0%	1602	100.0%	1106	100.0%	34	100.0%