Title
Disparities in Diffusion: Impacts on Smartphone Dependency and Universal Connectivity

Author
Criste, Michael

Publication Date
2022

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Disparities in Diffusion:

Impacts on Smartphone Dependency and Universal Connectivity

A thesis submitted in partial satisfaction

of the requirements for the degree Master of Urban and Regional Planning

by

Michael Criste

2022

ABSTRACT OF THESIS

Disparities in Diffusion:

Impacts on Smartphone Dependency and Universal Connectivity

by

Michael Criste

Master of Urban and Regional Planning

University of California, Los Angeles, 2022

Professor Paavo Monkkonen, Chair

In this thesis, I demonstrate how digital inequality is the latest layer in the web of social, cultural, and economic exclusions. Previous research has shown that individual characteristics impact internet and communication technology (ICT) access and adoption. I utilize Van Dijk's four forms of access to move past the binary of the digital divide. Using the 2019 American Community Survey Public Use Microdata Sample (5 year estimates), I develop two logistic regression models that incorporate individual and community-level factors to predict the likelihood of a resident achieving universal connectivity or being smartphone dependent. The findings indicate that there is a polarity between those who have universal connectivity versus those who are smartphone dependent. Wealthier, more educated residents have the highest rates of obtaining a universal connection. Inversely, residents with lower incomes, with less than a college education are increasingly smartphone dependent.

The thesis of Michael Criste is approved.

Jose Loya

Todd Franke

Paavo Monkkonen, Committee Chair

University of California, Los Angeles

2022

TABLE OF CONTENTS

DISPARITIES IN DIFFUSION:

Impacts on Smartphone Dependency & Universal Connectivity

1. INTRODUCTION

Digital inequality is the latest layer in the 20th Century's web of social, cultural, and economic exclusions to be carried over into the 21st Century. The ability to take advantage of the benefits and opportunities afforded by universal connectivity, defined as having both a fixed and mobile broadband connection speeds, became more severe during the COVID-19 pandemic. Some workers and students were able to successfully transition to remote settings, while others endured increasingly dangerous conditions. The diffusion of internet and communication technologies (ICT) has followed previous patterns of exclusion due to the high costs of implementation, subscriptions, and devices in addition to the reliance on the private market to install critical infrastructure. In addition to the gap in material access, the compounding forces of exclusion impact the ability to gain the skills necessary and the usage opportunities of ICT to increase educational, employment, and economic outcomes.

Policymakers and researchers have made the case that the adoption of a smartphone and mobile data plan create access to opportunities afforded by an internet connection (Prieger, 2013). In contrast to this perspective, researchers have made the case that fixed and mobile broadband are not substitutes for each other and that relying solely on a mobile device does not offer the same opportunities and economic benefits due to the inconsistent speed quality, gaps in coverage area, and limited capabilities of devices (Wulf et al., 2013). In this paper I add necessary granularity to previous literature, moving past the binary lens of the digital divide to include those who are smartphone dependent. Differentiating between universal connectivity and smartphone dependency, policymakers can better address the different needs of unconnected or under connected urban and rural residents.

In this thesis I utilize Van Dijk's four forms of access to move past the binary of the digital divide and demonstrate how social and economic differences impact the likelihood of a resident's ability to adopt ICT (2003). The framework examines how ongoing forms of exclusion based on race, gender, and immigration status impact the adoption of broadband in Los Angeles County. By using the 2019 American Community Survey Public Use Microdata Sample (5 year estimates), I develop two logistic regression models that incorporate individual and community-level factors to predict the likelihood of a resident achieving universal connectivity or being smartphone dependent.

My findings indicate that there is a polarity between those who have universal connectivity versus those who are smartphone dependent. Wealthier, more educated, English speaking white residents have the highest rates of obtaining a universal connection. Inversely, residents of color, with lower incomes, with less than a college education, who may speak a language other than english at home or not speak english at all are increasingly smartphone dependent. The community-level variables of median community income, percent of the community that identify as non-Hispanic White, and density demonstrate how the desire for profit from private market actors isolates specific groups from opportunities afforded by ICT. For ease of interpretation, I report the results in odds ratios that indicate the probability of an individual's likelihood of being smartphone dependent or achieving universal connectivity Following the two logistic regression models, I report the marginal effects for individuals with a specific characteristic or set of characteristics to demonstrate the compounding effects of exclusion. For example, there is a 24 percentage point difference in the likelihood of an individual obtaining a universal connection between respondents who earn less than $50,000 and those who earn more than $100,000

The analysis portrays the great levels of disparity in access to ICT, for example non-Hispanic White individuals who did not earn a high school degree are 72 percent likely to obtain a universal connection compared Black individuals who did complete high school, who are only

69 percent likely to achieve the same connectivity status. The disparity is greater as educational attainment increases, non-Hispanic White individuals are 85 percent likely to obtain universal connectivity but their Black counterparts with that same level of education are five percentage points less likely to achieve universal connectivity. By measuring and visualizing the interactions between digital and ongoing forms of exclusion across space, a more holistic approach to policy making can be taken to inform future implementation of interventions addressing the gaps in resources necessary to use ICT and the opportunities to harness the benefits of adoption. By conducting two models that differentiate between the level of connectivity I am able to demonstrate how systematic forms of exclusion force individuals to rely on an inferior form of internet access due to their limited economic resources and lower levels of educational attainment in addition to a combination of social factors.

To begin my analysis, a short review of the previous research in digital inequality and how social and economic factors impact an individual's ability to obtain an internet connection. Next, I introduce a framework for access and evaluating the diffusion of adoption. Then, I explain the setting, data source of the study, and methods used. Finally, I report the results and expand on the conclusions drawn from the analysis.

2. LITERATURE ON DIGITAL INEQUALITY AND EXCLUSION

Brief History of Policy and Infrastructure Investments

Over the last 20 years broadband access expanded quickly through public and private investments. A large sum of investment has come from four major pieces of federal legislation: the Communications Act of 1996, the Farm Security and Rural Investment Act of 2002, the American Recovery and Reinvestment Act of 2009, and the Coronavirus Aid, Relief, and Economic Security Act of 2020 (Blackwater, 2020). The largest investment into broadband access came in 2021 with the passage of the Infrastructure Investment and Jobs Act, which allocated $65 billion aimed at expanding infrastructure deployment and lowering the cost of services ("President Biden's Bipartisan Infrastructure Law").

After the Communications Act of 1934, the first major update came with the Communications Act of 1996. This policy codified the guiding principle of the Federal Communication Commision (FCC), the right to universal service, through the creation of the Universal Service Fund and the its four mechanisms: high cost support for providers, low income support for individuals, rural healthcare, and support for schools and libraries through the E Rate program ("Universal Service Fund"). The two key programs are Lifeline, which provides a $34.25 monthly discount and a one time $100 discount for set up for residents on tribal lands, and E Rate, due to its ability to connect schools and libraries and makes the internet publicly available. While the intent of the act was to increase competition, the policies and regulations resulted in 85 percent of cable lines being owned by the four largest providers – up from less than 50 percent before the Act was passed (Blackwater, 2020)

The Farm Security and Rural Investment Act of 2002, as known as the "Farm Bill," enabled the USDA Rural Utilities Service to provide loans to cover the cost of construction, improvement, and acquisition of facilities and equipment for expanding broadband into eligible communities (Blackwater, 2020). After the great recession, the American Recovery and Reinvestment Act of 2009 provided $7.2 billion to be distributed through the National Telecommunications and Information Administration (NTIA) and USDA Rural Utilities Service (RUS). $3.9 billion was allocated to the Broadband Technologies Opportunity Program (BTOP), which included 233 projects aimed at increasing public access and increasing skill levels to help workers to transition to the new economy. The remaining $3.6 billion was distributed through the Broadband Infrastructure Program (BIP) to fund grants, loans, and a combination of the two specifically to rural communities through the RUS. (*Broadband Infrastructure Programs in the American Recovery and Reinvestment Act*, 2011).

With the onset of the COVID19 pandemic, congress passed the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) which established the Emergency Broadband Benefit

(EBB) which granted recipients a discount of $50 on their mobile or fixed subscriptions, and a $75 discount for residents on tribal lands. Additionally, the Coronavirus Relief Fund was able to help state and local governments navigate the changes of the pandemic, a number of which used this funding opportunity to expand public wifi, distance learning tools, and expand telehealth (*States Tap Federal CARES Act to Expand Broadband*, 2020).

The recently enacted Infrastructure Investment and Jobs Act has allocated $65 billion to expand broadband service allowing more residents to participate and partake in the economic benefits of the new, knowledge-based, economy. The largest portion, $42.5 billion will be issued as block grants to extend the necessary infrastructure to unconnected and under connected communities. $14.2 billion will transition EBB to become a permanent program, now known as the Affordable Connectivity Program (ACP). The ACP also increases program eligibility to households within 200 percent of the poverty line. $2.75 billion is proportioned to the NTIA and will be invested in inclusion initiatives to increase skill level and support so residents can take advantage of the new technology. The NTIA will receive an additional $2 billion to extend the Tribal Connectivity Program. $1 billion will be distributed by the NTIA to create a grant program to expand access to “middle mile” infrastructure. The USDA’s ReConnect Loan and Grant Program will receive $2 billion focused on deployment in rural areas. Lastly, $600 million will finance private activity bonds to support public-private partnerships (Casper, 2021)

Critiques of the Digital Divide

The term digital divide rose in popularity in the 1990s as the federal government began to recognize the value in investing in internet communication technologies. The term gained popularity when the National Information Technology Administration used the phrase in two reports: Falling Through the Net II: New Data and Digital Divide (1998) and Falling Through the Net: Defining the Digital Divide (1999), but Lloyd Morrisett is credited with conceiving the idea of digital haves and have-nots in 1996 (Hoffman et al., 2000; Eubanks, 2011). It is the definition of “haves versus have-nots” that scholars have come to criticize as disparities in the diffusion of ICT has persisted. Digital inequality is not an isolated occurrence but reproduces, reinforces, and exacerbates existing social inequalities because they carry over preexisting differences into a digital setting (DiMaggio & Garip, 2012).

An early scholar to critique the false dichotomy of the digital divide was Kvansy who in 2006 proposed the term digital inequality. They argue "unlike the digital divide, which is concerned with access to computing artifacts, digital inequality is concerned with the equitable access to the benefits derived from internet and computer use." By using Bourdieu's theory of cultural reproduction as a foundation she argues that "ICT is deeply implicated because it provides a highly efficient and cost-effective mechanism for perpetuating systems of power and privilege on a global scale. This temporal aspect ties well to critical research which posits that social reality is historically constituted, and produced and reproduced by people." Where Bourdieu’s theory is limited to class-based factors of income, education, and occupation; Kvansy expanded the lens to include social-based aspects of exclusion including race and ethnicity, gender, and age.

Later scholars repeat the call to widen the scope of sources causing digital inequalities. Through focusing solely on material goods, the root causes of structural racism, unequal distribution of income, and class dynamics are left unaddressed. This further limits any potential interventions to focus on an individual level and places the responsibility in the hands of private entities. When the scope is widened to account for marginalization, exploitation, isolation, and other forms of systemic oppression; the scale of solutions grows to accommodate specific social groups and communities (Eubanks, 2011). When digital inequality is held alongside historic forms of inequality, it becomes increasingly clear that an individual’s ability to access and adopt ICT plays a key role in a diverse range of outcomes including educational attainment, labor and economic success, civic participation, and even quality of health (Robinson et al, 2015).

The over simplification of the digital divide also penetrates how scholars have approached research and analysis. Gunkel (2003), was one of the earliest scholars to identify the assumptions made by centering technological determinism, researchers often leave preconditions unexamined. Since then, scholars have moved to directly criticize methodological approaches, specifically how often bivariate analyses are used to measure adoption over multivariate models, compound indices, and time-distance methodologies (Vehover et al., 2007). The difference between monotopical and comprehensive analyses is in the purpose of the tool, level of observation, and approach to the data that allow policymakers to understand digital inequality in connection to other forms of social exclusion. While encouraging the use of integrative indices, it should be noted that they include more risk and require more robust scientific methods (Barzilai-Nahon 2007).

A Dimensional Framework for Understanding Access

Building off of the critiques of the digital divide, multiple scholars have proposed more nuanced frameworks to define access and understand connectivity. DiMaggio & Hargittai proposed five dimensions of digital inequality: equipment, autonomy of use, skills, social support, and purpose of use (2001). Mossberger and colleagues distinguish between four divides: access divide, skills divide, economic opportunity divide, and democratic divide (2003). The most cited and utilized framework is Van Dijk’s four forms of access: motivational access, material access, skills access, and usage access (2005).

Van Dijk’s four successive forms of access more accurately depict the process of adopting a new technology, see figure 1. The sequence allows scholars to pinpoint where society or research subjects are in the adoption cycle to more accurately evaluate the current circumstances. At the foundation of the framework is the difference in categorical inequalities in society that produce an unequal distribution of resources. This unequal distribution of resources causes unequal access to digital technologies. The unequal access of digital technologies causes unequal participation in society, which then reinforces the categorical inequalities at the core. These categorical inequalities include personal and positional properties like age, sex, and race. In his book The Deepening Divide, Van Dijk demonstrates how those in dominant positions in society extend their own access to ICT and limit others in society from the benefits of adopting technology (2005).

The sequence begins with motivational access, which is an individual's desire to obtain a new technology. In the early 2000s when households and workplaces were just implementing computers, motivational access was a topic of discussion given individuals questioning the benefit of ICT use in their personal lives. This phase is defined by the split between the early adopters and the want-nots of a new technology. The next phase of the sequence is material access. Once an individual has the motivation to adopt a technology, they face a new challenge of acquiring the necessary devices and subscriptions required to utilize the technology. The majority of research and policy is focused on this form of access, often citing that once an individual obtains a computer and a reliable connection the digital divide will be closed. Many of the scholars who critique the technocentric approach to the digital inequalities encourage researchers and policy makers to move beyond this singular vision of access (Eubanks, 2011; Mossberger et al., 2013; Greene, 2021).

Van Dijk posits that society will gradually shift from the first two phases of access to second two. Once the majority of the motivational and material access has been addressed the divide will persist between digital skills and usage opportunities (1999, 2000, 2003). Skills access encompases the necessary education to operate devices and the skill to "search, select, process, and apply information from a superabundance of sources and the ability to strategically use this information to improve one's position in society." Usage access is the last phase of the sequence which is defined as the "need, occasion, obligation, time, and effort" to utilize ICT. Van Dijk further explains that usage access has multiple characteristics that support or impede usage access: complexity, expense, network effects, approachability, culture and language to name a few (2005).

A strength of Van Dijk's framework is that multiple forms of technology can be evaluated along the same cycle. They point out how after diffusion of computers and narrow band internet connections, the diffusion of broadband faced challenges in material and usage access, due to increased cost and personal availability, but motivational and skills access was less of a barrier (2005). A more contemporary example of this cycle would be the adoption of smartphone and mobile broadband either after, in conjunction with, or even before fixed broadband access. Mobile and fixed broadband have reached their respective highest rates of diffusion but are not direct substitutes due to limitations of the devices and quality of connection (Perrin, 2021). These two forms of ICT are compliments, each filling a gap left by the other allowing for universal connectivity for those who have means to adopt both (Mossberger et al., 2013). Furthermore, due to limitations of mobile devices, usage has been differentiated by production and consumption. While users of both forms of connectivity are able to produce and consume knowledge, content, and goods, smartphones are more likely to enable individuals to consume rather than produce (Wolfson et al., 2017).

Economic, Social, and Geographic Influences on Internet Access

The primary barrier to adopting any and multiple internet connections is cost. To adopt any form of internet, a resident must be able to pay the upfront costs of a device and installation and the recurring costs for monthly service (Powell, Bryne, & Dailey, 2010; West, 2015, Bach et al., 2018). Cost has been proven to have a cyclical impact on adoption, those with higher earnings are more likely to use computers intensely and be rewarded accordingly, while those with less income experience the reverse effect (Flamm & Chaudhuri, 2007; DiMaggio & Bonikowski, 2088; Witte & Mannon, 2009). Van Dijk applied Robert Merton's (1968) Matthew Effect to describe this phenomenon, where those with the greatest access to ICT will be the ones to see the most benefits which allows them to consume newer forms of technology. The same effect is a continuing topic of discussion due to the pace of automation and the potential impact to reshape the economy. Digital skills will only become more essential for workers to compete and reap greater rewards in the future (Brynjolfsson & McAfee, 2014). It is also important to understand that internet adoption is precarious, and households can be pushed into a phase of “un-adoption” due to limits on income but can become connected again once financial constraints have been removed (Powell, 2010; Van Dijk 2005). Human capital factors, primarily educational attainment, are positively associated with internet use. This is due to the increased economic opportunities of highly educated individuals who are exposed to new ICT uses in the workplace and can afford a connection at home (Fuchs, 2009; Mesch & Talmud, 2011).

Given the history and the ongoing legacy of white supremacy in the United States, individuals of different racial groups experience different levels of exclusion to resources required to participate in society. By acknowledging this pattern in society, scholars have demonstrated the link between ICT access and the differences in outcomes and opportunities (Mesch, Mano, & Tsamir, 2012; Chen, 2013). Within the body of research between internet access and race, there are two main hypotheses: stratification hypothesis and normalization or diversification hypothesis (Robinson et al., 2015). The stratification hypothesis follows Kvansy’s framework by viewing online outcomes as an extension of offline opportunities due to factors in human capital that carry over into new spaces (DiPrete et al., 2011; DiMaggio & Grip, 2012). The normalization or diversification hypothesis stands in contrast to the previously mentioned hypothesis because it asserts that ICT adoption and usage can create new sources of opportunity. While this hypothesis runs the risk of being a techno-centric solution to poverty and inequality (Green, 2021), there is evidence that while internet use is lower among non-White racial and ethnic groups in the United States (Anderson, 2019), Black and Latinx residents report creating more content for social media (Correra et al. 2010). Wolfson et al, take this a step further and propose the analytical framework of emancipatory adoption (2017). Collectively, they charge readers and other scholars to move past the false borders of the digital divide, allowing further research beyond cost and skills, and finally allowing space for alternative strategies for broadband adoption centered around political empowerment and collective identity building.

Additional social factors such as age and gender have demonstrated an impact on internet adoption. Older adults have consistently lagged behind in adopting the ICT, this is thought to be an outcome of a lack of interest or lack of opportunity due to the constraint of their employment and social networks (Van Dijk, 2005). Views on the differences between the sexes and ICT have evolved. Earlier research posited that women lack opportunities to use technology because of gendered social hierarchies where women's roles were more routine and did not require a formal education (Van Dijk, 2005; Brynin, 2006). More recent research has found that the gap between men and women has closed (Blank & Groselj, 2014). By moving beyond the gap, scholars have begun to focus on the outcomes of ICT use among women. Hargittai & Shaw found that women with strong digital skills often underestimated their abilities compared to men (2015). Furthermore, the gender composition of the information technology industry is heavily dominated by men, limiting the leadership opportunities and economic gains that come with the industry, a trend which is likely to continue (Shade, 2014).

Geography has also been found to be a determining factor for achieving universal connectivity. Those in urban and suburban areas can readily and more affordably obtain an internet connection as opposed to those who live in rural areas due the prohibitive cost and diminishing returns of building the necessary infrastructure in sparsely populated places (Pereira, 2016; Reddick et al., 2020). Beyond the difference in availability, the quality of the service can vary further limiting the usefulness of a connection (Riddlesden & Singleton, 2014). Rural residents are often older, have a lower economic status furthering their ability to pay for a quality connection (Oyana, 2011).

Scholars who have proposed adjusting how digital inequalities are viewed often refocus the lens on ongoing forms of exclusion, this should include the experience of immigrants. While a substantial body of research has focused on the opportunities available to different ethnic groups, more limited research has been concerned with the difference between native born and forign born residents. As the composition of the United States is changing it is critical to understand the experience of new residents who have less education, limited English ability, and often lack financial resources (Quian and Lichter, 2007). The limited studies found that immigrants are less likely to obtain an internet connection compared to native born residents, and that English ability is a contributing factor to the difference (Ono & Zavodny, 2008). A study focused on Spanish-dominant Latinx residents, demonstrated a lower probability of internet use compared to English-speaking Latinx residents, .35 probability compared to .5 when controlling for other factors (Mossberger et al., 2013).

Some may champion mobile devices and wireless internet as the solution to digital inequality (Prieger, 2013), others have criticized it as a second-class form of access (Crawford, 2011). By distinguishing between fixed and mobile broadband connections, scholars have demonstrated that people of color, lower income, and less educated individuals are more likely to be smartphone dependent (Mossberger et al., 2013; Tsetsi & Rains, 2017). Specifically Black and Latinx residents are more likely to depend on a smartphone to access the internet compared to white (Mossberger et al., 2013; Vogels, 2017; Anderson, 2019; Perrin, 2021). Furthermore, mobile broadband suffers from inconsistent speeds and many individuals are limited by data caps (Anderson & Horrigan, 2016).

3. METHODS

In order to answer the question of which factors impact an individual's ability to obtain an internet connection, I test Van Dijk's broad framework of access which includes material, skills, categorical, and usage access; I conducted two separate logistic regressions. Since the United

States is at an advanced stage of ICT adoption, the dependent variable in each regression represents usage access, the last form of access, measured by the level of connectivity, either smartphone dependent (only mobile broadband adoption) or universal connectivity (mobile and fixed broadband adoption). The independent variables include the forms of access that are necessary to reach differences in usage access. The primary independent variable, median family income, represents material access. Educational attainment and English ability measure skills access. Lastly, categorical access I will examine race and ethnicity, age, sex, and place of birth. By creating a unified analysis, I am able to demonstrate which foundational forms of access have the greatest impact on usage access and level of connectivity across individuals and social groups.

Data

The following analysis relies on the 2019 American Community Survey (5 year estimate) Public Use Microdata Samples (PUMS), accessed through the University of Minnesota's IPUMS USA. The American Community Survey (ACS) provides yearly socioeconomic statistics about households across the nation. Utilizing the data at the individual level as opposed to aggregated household data more accurately predicts the interaction between variables. The dataset has consistently provided demographic and economic data, the survey began including questions regarding internet and computer access in 2013 (Census, n.d.). The sample used in this analysis includes respondents over 18 living in Los Angeles County with complete responses to the questions included in the logistic regression, this yields a sample size of 368,425 observations. The results are weighted by using the ACS person population weights for accuracy compared to the actual population.

Methods in Use

Using two logistic regressions, I examine factors that impact an individual's ability to gain and maintain internet access; including income, educational attainment, race, age, sex, nativity status, and english abililty. Many of these variables have been researched at length with the exception of those relating to immigration, nativity status and English ability. The dependent variable in each regression is a different level of usage access: universal connectivity and smartphone dependency. Depending on the model, respondents will receive a code of 1 if they meet the usage access criteria or 0 otherwise. The primary independent variable in the analysis is total family income, additional covariates are included to account for social and cultural determinants to connectivity. For ease of interpretation, the results are reported in odds ratios. Ratios greater than 1 indicate the variable is more likely to contribute to obtaining the type of access in question, or less than 1 the variable is likely to impede on gaining the type of access.

The logistic regressions include a second mode which includes community level factors by aggregating individual level factors to the community level. Since the analysis utilizes PUMS data, communities are defined by the Public Use Microdata Areas (PUMAs). PUMAs are roughly areas containing 100,000 residents. Los Angeles County contains 69 PUMAs that closely align with city limits, but not exactly. This scale of measurement allows for better comparison across communities within the county as opposed to relying exclusively on city limits, zip codes, or electoral boundaries. The aggregated variables are median family income of the community, to determine impact of communities economic status; percent of the community that is non-Hispanic White, to measure the impact of racial segregation; and the population density, to understand impacts of urban and rural communities on individuals.

Construction of Variables

Many of the variables included in the 2019 ACS do not require further construction for analysis, like age, sex, years of education, language spoken, and nativy status. Others, including the dependent variables of connectivity and the independent variables of total family income and race, needed to be generated by combining responses for specific questions.

This was critical when developing the connectivity variables. Much of the research into digital inequality that utilizes the ACS, relies on the question that asks, “do you or any member of this household have access to the internet?” Respondents are allowed to select the following answers: 1) “Yes, by paying a cell phone company or Internet service provider,” 2) “Yes, without paying a cell phone company or Internet service provider,” 3) “No access to the Internet at this house, apartment, or mobile home.” Given the differences in speed and reliability between fixed and mobile connectivity and the difference in device capabilities between computers and smartphones, this question does not allow for a deeper analysis between those who have universal connectivity and those who are smartphone dependent. This question was utilized as the foundation for determining access, but the connectivity variable was constructed by conjoining two other questions: specifically in regards to high speed broadband connection and mobile data plan. Through disaggregating by type of connectivity, we can identify those respondents who have both a fixed and mobile connection and those reliant only on mobile broadband from the previous “Yes, by paying a cell phone company or Internet service provider.” The type and number of devices a respondent has was considered in the development process, but ultimately the collinearity of connection and type of device was too strong and did not add any further nuance to the analysis.

The second variable to be constructed was race and ethnicity to add a more detailed understanding of the different groups in Los Angeles County. The ACS relies on two separate questions to determine race and ethnicity, namly hispanic origin. For this analysis, it was important to include the Latinx population along with other races. Additionally, since digital inequality is tied to other forms of oppression it was critical to separate non-Hispanic Whites to more accurately measure the effects of segregation and racial hierarchy. Lastly, total family income was aggregated by $10,000 to allow more meaningful interpretation of the logistic regression

To understand how community factors influence the level of internet connectivity, three variables were aggregated to the PUMA level: median family income of the community, density of the community, and percent of the community that identifies as non-Hispanic White. To generate the median family income at the community level, the median of the individual results were calculated by PUMA, then quartiles were calculated from the distribution. The lowest quartile include median family income at the community level under $59,341 and the highest quartile include median family income at the community level over $90,691. The lowest quartile was assigned a code of 0 and the highest quartile was assigned a code of 2, with the middle 50 percent coded as 1. These codes were applied to the individual responses through a many to one merge based on the resident's PUMA. A similar process was utilized to develop the percent of the community that identifies as non-Hispanic White. The percentage of non-Hispanic White residents within each PUMA was calculated by dividing the non-Hispanic White respondents by the total number of respondents for each PUMA. Again, quartiles were calculated and applied to individual respondents. The lowest quartile includes communities with non-hispanic Whites representing 12 percent or less of the total population, while the highest quartile includes PUMAs with over 50 percent of the respondents identifying as non-Hispanic White. There were no PUMAs that were 100 percent non-Hispanic White, the highest percentage of non-Hispanic White was 84 percent for an individual PUMA. These results were coded as 0 to the lowest quartile, 2 to the highest, and 1 to the middle 50 percent and reapplied to individual level responses by PUMA. Lastly, the density of the PUMA was used to represent if the community was urban, suburban or rural. Density is calculated as the average local population density among residents for each PUMA, measured in persons per square mile. Density is reported in a population-weighted average rather than the density of the entire PUMA due to better representation of the density experienced by residents. The most dense quartile represents urban communities and is coded with 0, while the least dense quartile represents rural communities and is coded 2, and the middle 50 percent represents suburban communities and is coded 1.

Descriptive Statistics

By disaggregating the total sample of 368,425 respondents, differences in connectivity can be more clearly assessed. Analyzing those who are connected (in any form) versus those who are not connected, the sample would be split 90 percent to 10 percent. This division demonstrates that Los Angeles County is slightly less connected than the United States overall (Anderson, 2019). By considering the full spectrum of digital inequality over the dichotomy of the digital divide, separating the 12 percent of respondents who only have a mobile data plan from the 78 percent with universal connectivity we can begin to measure the differences between levels of connectivity. See Table 9 in Appendix for Complete Descriptive Statistics.

The median family income for the entire sample in Los Angeles County is $74, 242. When disaggregating between the levels of access, the median family income for those who are considered unconnected earn less than half the median family income of the sample at $32,373. Those who are considered smartphone dependent have median family income that is two-thirds the sample's median family income at $57,193. The only group to have a median family income greater than the sample's median are those considered to be universally connected, earning $85,249.

Age is often cited as a critical predictor of internet access. The median age of the entire sample is 47 years old, the only group to have a meaningfully different median age are those who lack any internet connection with a median age of 56. Looking beyond the median age at each level of connectivity, we can apply a cohort or generational lens to the group of respondents. The oldest cohort, defined at 65 years and older, represent 20 percent of the entire sample, but account for over double that amount among those who are not connected at all, 40 percent. This cohort is slightly underrepresented in smartphone dependency and universal connectivity. The middle cohort, which accounts for 52 percent of the sample, are underrepresented in those who lack connectivity completely, but more accurately account for those who are smartphone dependent and have complete connectivity. The youngest cohort, 18 to 34 year olds, represents 28 percent of respondents who are accurately represented in smartphone dependency and universal connectivity, and underrepresented in lacking connectivity all together.

The racial composition of the sample comprises 43 percent Lantinx and/or Hispanic identifying, 31 percent of Non-Hispanic Whites,18 percent Asian and/or Pacific Islander, 7 percent Black, 0.55 percent American Indian or Alaskan Native, and 0.37 identify as other. Latinx and/or Hispanic respondents are over represented in lacking a connection and being smartphone dependent, 56 percent and 55 percent respectively, and underrepresented in universal connectivity, 38 percent. Non-Hispanic Whites are accurately represented in universal connectivity, at 34 percent, but underrepresented in smartphone dependency and lacking access all together. Asian or Pacific Islander respondents are slightly overrepresented in universal connectivity, at 20 percent, and slightly underrepresented in smartphone dependency, 15 percent, and more so underrepresented in lacking connectivity all together, 12 percent. The experience is different for Black respondents, who are over represented at 10 percent of respondents lacking any form of connectivity, seven percent of respondents being smartphone dependent, and more accurately represented in universal connectivity at six percent. While those who identify as American Indian, Alaskan Native or Other represent a small portion of the sample, they are accurately represented in all levels of connectivity.

Table 1: Distribution of Race and Ethnicity in Sample

	Entire Sample	Lacks Any Connection	Smartphone Dependent	Universal Connection
White NH	31	21	21	34
Black	7	10	7	6
Asian/PI	18	12	16	20
AI/AN	<1	<1	<1	<1
Latino/Hispanic	43	56	55	39
Other Race	<1	<1	<1	<1

Those who have identified as male represent 48 percent of respondents and those who have identified as female represent 52 percent of respondents. Overall, both sexes are fairly distributed across the levels of connectivity with the exception of female respondents being slightly over represented in those who lack connectivity, at 54 percent.

When comparing levels of educational attainment, 16 percent of respondents lack a highschool diploma, 29 percent of respondents have completed highschool but have not pursued any higher education, 23 have a highschool diploma and attempted some college or professional training, and 33 percent have completed a Bachelor's degree or more. Those who lack a high school diploma are overrepresented, over double, in those who lack any form of connectivity, 35 percent, and are slightly over represented in smartphone dependency, at 22 percent. This translates to being underrepresented in those who are universally connected, at 12 percent. Respondents who have completed high school but did not attempt any further education are also over represented in lacking connectivity and smartphone dependency, 36 percent and 34 percent respectively. This group is only slightly underrepresented in universal connectivity at 26 percent. The ratio is flipped for those who have completed high school and attempted further education, being underrepresented at 17 percent of those who lack connectivity and being more accurately represented in smartphone dependency and universal connectivity, at 22 percent and 24 percent respectively. The respondents who have a college education or more are slightly over represented in universal connectivity at 38 percent, underrepresented in smartphone dependency at 22 percent, and significantly underrepresented amongst those who lack connectivity completely at 11 percent.

Table 2: Distribution of Educational Attainment of Sample

	Entire Sample	**Lacks Any Connection**	**Smartphone Dependent**	**Universal Connection**
Less than High School	16	36	22	12
Completed High School	29	36	34	27
Some College	23	18	22	24
Completed Bachelors or more	33	11	22	38

Los Angeles County is a prime setting to study the difference in nativity status given that 42 percent of the sample is foreign-born and 58 percent is native born. Those who are foreign-born are overrepresented in lacking connectivity at 53 percent, slightly over represented in being smartphone dependent at 50 percent, and slightly underrepresented in achieving universal connectivity at 40 percent. Conversely, those who are native born to the United States are underrepresented in lacking connectivity and smartphone dependency, at 47 percent and 50 percent respectively, but slightly overrepresented in universal connectivity at 60 percent.

Table 3: Distribution of Nativity Status Across the Sample

	Entire Sample	**Lacks Any Connection**	**Smartphone Dependent**	**Universal Connection**
Native Born	58	47	50	60
Foreign Born	42	53	50	40

Lastly, the diverse composition of the County allows for a meaningful analysis of the impacts of English ability on digital inequality. 45 percent of respondents speak only English, 51 percent speak a language other than English at home, and five percent of respondents don't speak English at all. Respondents who only speak English are underrepresented in lacking connectivity and smartphone dependency at 35 percent and 34 percent respectively, and over represented in universal connectivity at 48 percent. Respondents who speak a language other than English at home are more accurately represented in lacking connectivity, at 53 percent, and universal connectivity, at 49 percent, but over represented in smartphone dependency 59 percent. Respondents who do not speak any English, account for 12 percent of those who lack connectivity, more than three times their percentage of the sample. They are slightly over represented in smartphone dependency at six percent, and slightly underrepresented in universal connectivity at three percent.

Table 4: Distribution of English Ability Across Sample

	Entire Sample	**Lacks Any Connection**	**Smartphone Dependent**	**Universal Connection**
Speaks only English	45	35	34	48
Speaks a language other than English at home	51	53	59	49
Speaks no English	5	12	6	3

Looking at the distribution of income and the racial composition across the PUMAs demonstrates the correlation between wealth and Whiteness, see figures 2 and 3 in the appendix. The western side of Los Angeles County is both the wealthiest and the whitest, as depicted by the deep purple in both diagrams. Conversely, the communities in Central Los Angeles County have significantly less income and overwhelmingly communities of color. The largest PUMA in the northern half of the County is the least dense, but is largely white and has a median family income that is above the median of the entire sample. The exceptions are the PUMAs that represent Lancaster, CA and Palmdale, CA.These communities lack the same financial resources as the community surrounding them and are less White. The southeastern portion of the county is more diverse in both racial composition and in distribution of median family income.

Interactions Between Independent Variables

Understanding that digital inequalities are an outcome of compounding influences of ongoing oppression and exclusion. To understand these interactions it was essential to quantify the relationships between the independent variables before conducting an analysis of connectivity. As the literature suggests, income and educational attainment are likely to be the biggest determinants of obtaining a universal connection. By illustrating the interaction of these two variables with social factors that impact an individual's ability to participate in society, such as race or immigration status, I can then form a more nuanced foundation to understand the interactions of all the variables together.

Median family income ranges dramatically when comparing groups within the other independent variables. The largest difference in median family income exists between non-Hispanic Whites, earning $93,864, compared to that of Blacks, earning $59,826. Individuals who identify as Asian or Pacific Islander have a median family income of $87,947; American Indians or Alaska Natives have a median earning of $71,066; Latinx/Hisanic respondents earn only $61,800; and those identified as Other have a median family income of $75,500. The median family income of individuals who have earned a bachelor's degree or more is over double that of individuals with less than a highschool degree, $109,000 compared to $45,815. The median family income for those who have completed highschool earn $62,000 and those who have pursued some college earn $74,149. Individuals who are native born have a median family income of $82,012 compared to $63,938 of foreign born individuals. Those who speak only

English earn over double that of those who do not speak English at all, $86,438 compared to $41,717. Those who speak a language other than English have a median family income of $68,716. Lastly, when comparing between age groups, individuals who are between the ages of 35 to 64 years old have the median family income of $82,885 compared to $68,214 for 18 to 34 year olds and $62,105 for those over 65 years old.

Table 5: Median Income of Sample by Race and Ethnicity

	Median Income ($)
White NH	93,864
Black	59,826
Asian/PI	87,947
AI/AN	71,066
Latino/Hispanic	61,800
Other Race	75,500

Levels of educational attainment alter dramatically between groups. Non-Hispanic White and Asian or Pacific Islander have the highest proportion of respondents who have earned a bachelor’s degree or more, 50 percent and 51 percent respectively. Non-hispanic Whites without a high school degree are the lowest, at three percent, among all racial groups. Respondents who have completed high school and have not pursued college represent 23 percent of non-Hispanic whites and those that have pursued further education without completing a Bachelor's degree also represent 23 percent. Similarly, 20 percent of Asian or Pacific Islander respondents have completed some college and an additional 20 percent have completed high school but have not pursued any college. Nine percent of Asian or Pacific Islander respondents have not completed high school. 27 percent of Black respondents have completed a Bachelor’s degree or more, while 33 percent have attempted some level of higher education. An additional 33 percent have completed high school but have not attempted further education and six percent have less than a high school education. Latinx/Hispanic respondents have the lowest proportion of those who have completed a bachelor's degree or more at 13 percent, 22 percent have completed high school and attempted some form of higher education, while 36 percent have completed high school and have not pursued further levels of education. 30 percent have not completed high school. Of American Indian and Alaska Native respondents, 32 percent have completed a Bachelor's degree or more, 33 percent have attempted some college, 30 percent have complete high school but did not pursue higher education and six percent have not completed high school Among the respondents who have identified as Other, 42 percent have completed a Bachelor's degree or more, 24 percent have attempted higher education, 27 percent have only completed high school and seven percent have not completed high school.

Table 6: Distribution of Educational Attainment of Sample by Race and Ethnicity

	Less Than High School	**Completed High School**	**Some College**	**Completed College or More**
White NH	3	23	23	50
Black	6	33	33	27
Asian/PI	9	20	20	51
AI/AN	6	30	33	32
Latino/Hispanic	30	36	22	13
Other Race	7	27	24	42

Given the portion of the sample that identify as immigrants, it is vital to disaggregate between place of birth and English ability between racial groups. 82 percent of Non-Hisanic Whites are native born compared to 18 percent that are forign born. Similarly 82 percent speak only english, 18 percent speak a language other than English at home, and less than one percent doesn't speak english. 91 percent of Black respondents are native born compared to eight percent who are forign born. 92 percent speak only English, eight percent speak a different language other than English at home and less than one percent speak no English. Conversely two groups, Asian or Pacific Islander and Lantix/Hispanic respondents are majority forign born and more likely to speak two or more languages. Respondents who identified as Asian or Pacific Islanders are only 27 percent native born compared to 73 percent forign born. Furthermore, only 24 percent only speak English, the majority, 72 percent speak a language other than English at home and less than five percent do not speak English at all. For Latinx/Hispanic respondents, 53 percent are forign born and 47 percent are native born. Only 18 percent of Latinx/Hispanic respondents only speak English, while 74 percent speak a language, other than English, and eight percent speak no English. While a significantly small portion of the population, those who identify as American Indian and Alaska Natives are 95 percent native born and 86 percent speak only English, while 13 percent speak a language other than English at home. Those respondents who identify as Other, 60 percent are native born compared to 40 percent that are forign born. 56 percent speak only English, 47 percent speak a language other than English at home and roughly one percent do not speak English at all.

Table 7: Distribution of Nativity Status of Sample by Race and Ethnicity

	Native Born	**Foriegn Born**
White NH	82	18
Black	92	8
Asian/PI	27	73
AI/AN	95	5
Latino/Hispanic	47	53
Other Race	60	40

Levels of educational attainment also vary amongst native and foreign born respondents and among differences in English ability. The portion of native born respondents to complete a Bachelor’s degree or more is 38 percent compared to 27 percent of foreign born respondents. There is a large difference between these groups when comparing the proportion of respondents who have not completed high school, five percent for native born respondents compared to 30 percent of foreign respondents. The proportion of respondents who have completed high school but did not attempt further education are similar, 29 percent for native born and 28 percent for foriegn born. 28 percent of native born respondents have completed some college compared to 16 percent of foriegn born. Amongst respondents who only speak English, 43 percent completed college, 26 percent have completed some college, 27 percent have completed high school but have not pursued higher education, and four percent have not completed high school. For respondents who speak a language other than English at home, 26 percent have completed a Bachelor’s or more, 22 percent have completed some college, 31 percent have only completed high school and 20 percent have not completed high school. The rates of educational attainment for those who do not speak English are the inverse of the previous two groups discussed, four percent have completed college, four percent have attempted college, 20 percent have completed high school and 72 percent have less than a high school education.

Table 8: Distribution of Educational Attainment of Sample by English Ability

	Less Than High School	**Completed High School**	**Some College**	**Completed College or More**
Only Speaks English	4	27	26	43
Speaks a Language Other Than English at Home	20	31	22	26
Speaks No English	72	20	4	4

4. RESULTS

The results of the logistic regressions confirmed much of the previous literature. Respondents who are wealthier, identify as non-Hispanic White, more educated, or speak only English are more likely to achieve universal access to ICT. Conversely those with lower incomes, people of color, less educated, or immigrants are less likely to achieve universal connectivity and more likely to be smartphone dependent. Sex was not statistically significant in either regression. While race and ethnicity are critical in both models, those who identified as American Indian or Alaskan Native did not yield statistically significant results, this is likely due to the small sample size within the larger Los Angeles County sample. The median family income of the community and percent of the community who identify as non-Hispanic White were statistically significant in both regressions, while density was only statistically significant in regards to universal connectivity.

Logistic Regression: Universal Connectivity

The results of the first logistic regression, Table 10 in the appendix, are concerned with universal connectivity, indicating that with every increase in $10,000 in total family income, an individual will be six percent more likely to achieve universal access. Individuals who are 65 and older are 45 percent less likely to be considered universally connected compared to those under 65. When comparing racial and ethnic groups, only those who identify as Asian or Pacific Islander are more likely to have a higher rate of universal connectivity than non-Hispanic Whites, by six percent. Every other racial group is less likely to be universally connected when compared to their non-Hispanic White counterparts: Blacks are 41 percent less likely, Latinx and/or Hispanics are 22 percent less likely; and individuals who identify as Other are 36 percent less likely. While those who identify as American Indians or Alaskan Natives are 18 percent less likely than non-Hispanic Whites, the results are not statistically significant. Individuals who identify as female are nine percent more likely than males to achieve universal connectivity, but the results are not statistically significant at conventional levels.

The impacts of educational attainment are some of the most severe when compared to the reference category, in this case those who have a Bachelor’s degree or more. Individuals with less than a high school diploma are 61 percent less likely to achieve universal connectivity. Those with a high school diploma and no education beyond that are 48 percent and those with less than a bachelor's degree are 28 percent less likely to be universally connected.

Immigration in relation to achieving universal connectivity is less severe but still statistically significant. Those who are foreign-born are five percent less likely to be universally connected compared to those who are native born. The impacts of English ability are more drastic than place of birth, with those who do not speak any English being 39 percent less likely to be connected compared to those who only speak english. Those who speak a language other than English at home are 18 percent less likely to obtain universal connectivity.

When including the community level variables, many of the results hold consistent with few exceptions. The likelihood of Asian or Pacific Islander increases to 13 percent more likely than non-Hispanic Whites; while the likelihood of Black and Latinx or Hispanic respondents increases by nearly ten percentage points each. The impact of having less than a high school diploma increases by three percentage points to 58 percent less likely. Respondents who are in the lowest quartile of median family income by community are 17 percent less likely to be universally connected to ICT than those in the middle 50 percent. While not statistically significant, those in the highest quartile of median family income by community are three percent more likely than those in the middle 50 percent. Interestingly, respondents in the lowest and highest quartiles of density are more likely than those in the middle 50 percent to achieve universal connectivity, by eight and six percent respectively. The community factor with the greatest impact was percent of community population identifying as non-Hispanic White. Communities in the highest quartile, those being the whitest, are 20 percent more likely to be universally connected compared to the middle 50 percent; conversely individuals living in the lowest quartile, those being the least white, are 13 percent less likely than those in the middle two quartiles.

Logistic Regression: Smartphone Dependency

The second logistic regression, Table 11 in the appendix, is used to determine the likelihood of smartphone dependency among residents in Los Angeles County. The outcomes of these models demonstrate an inverse effect compared to universal connectivity. For every $10,000 increase in total family income, the likelihood of being smartphone dependent declines by nearly three percent. Furthermore, those who are over 65 years of age are 12 percent less likely to depend on smartphones to access the internet. Black and Latinx/Hispanic individuals are 46 percent and 38 percent more likely to be smartphone dependent when compared to non-Hispanic Whites. Asian, Pacific Islander, American Indian, Alaskan Native, and individuals who identify as Other are also more likely to be smartphone dependent than non-Hispanic Whites, but these results are not statistically significant. Additionally, there is no statistically significant difference between individuals who identify as women or men.

Like race, educational attainment follows the reverse trend of universal connectivity. Individuals with less than a high school diploma are 50 percent more likely to rely only on a smartphone than those who have completed an undergraduate degree or more. High school graduates who did not pursue further education are 43 percent more likely and high school graduates who did pursue higher education but have not completed college are 20 percent more likely to be smartphone dependent. The results between native born and foreign born respondents is statistically significant, but only a seven percent increase in the likelihood of smartphone dependency. When considering English ability, those who speak a language other than English at home are 20 percent more likely to be smartphone dependent. While individuals who speak no English are 25 percent more likely than those who only speak English to be smartphone dependent.

When including the community level variables, some results see an improvement. Most notably the likelihood of Black individuals being smartphone dependent decreases to 26 percent from 46 percent. Latinx/Hispanic individuals also experience a decline from 38 percent to 25 percent. The effect of educational attainment sees more modest declines, those with no high school education experience a decline of nine percentage points. Both individuals with a high school degree that did and did not pursue higher education experience a decline of two percentage points and five percentage points, respectively. Foriegn born individuals are the only group to see an increase in the likelihood of being smartphone dependent in the second model, but the increase is only one percentage point. Like previous variables, English ability sees a decline in the likelihood of being smartphone dependent, 16 percent for those who speak a language other than English at home and 18 percent for those who speak no English at all.

The lowest quartile of median family income by community is nine percent more likely than the middle 50 percent to be smartphone dependent. While the top 25 percent is six percent less likely to be, the result is not statistically significant. Comparing the lowest density quartile and the highest density quartile to the middle 50 percent, did not yield any statistically significant results. Segregation, measured by the level of the community that identifies as no-Hispanic White is a significant predictor of smartphone dependency. Individuals who live in communities with the lowest quartile are 22 percent more likely to be smartphone dependent, while those who live in the whitest communities are 12 percent less likely to be smartphone dependent than those in the middle 50 percent.

Marginal Effects

Following the logistic regressions, I obtained the predictive margins to further demonstrate the differences in likelihood of achieving universal connectivity and smartphone dependency. By holding each variable at the mean, the inverse relationship between the two levels of connectivity and the independent variables is clearly demonstrated in Table 12 (see appendix). Due to lack of statistical significance the variable of sex has been omitted from the predictive margins.

Median family income and educational attainment had the greatest difference in universal connectivity, 26 percentage points and 13 percentage points respectively. Race and ethnicity followed with eight percentage points between the highest group to achieve universal connectivity, Asian or Pacific Islander, and the lowest groups, Black and Other. There was also an eight percentage point difference between those under and over 65. There is a seven percentage point difference between those who only speak English and those who speak no English. Place of birth only resulted in a difference of one percentage point. For the community level variables, percent of community that identifies as non-Hispanic White had a difference of six percentage points, median family income of the community had a difference of four percentage points, and density has only a single percentage point difference.

Similar to the predicted margins of universal connectivity, smartphone dependency saw the largest difference between income levels, with a seven percentage point difference. Educational attainment follows with a 4 percentage point difference. There is a three percentage point difference between racial and ethnic groups. English ability follows with a two percentage point difference. Lastly, age and place of birth only demonstrate one percentage point difference. The community level factors for smartphone dependency are less severe than universal connectivity. The percentage of the community that identifies as non-Hispanic White demonstrates a three percentage point difference between the lowest and highest quartiles. Median family income by community demonstrates a two percentage point difference, and density experiences no difference among quartiles for smartphone dependency.

To further understand the compounding effects related to an individual's ability to adopt mobile and fixed broadband connections, predictive margins can be developed by crossing multiple independent variables while holding all other variables constant at the means. Given the significance of median family income and educational income, I began this stage of the analysis with these two variables, see Tables 13 in the appendix. Individuals with a family income below $50,000 and lack any formal education are only 59 percent likely to obtain a universal connection compared to those who make over $100,000 and have a Bachelor’s degree or more have a 90 percent likelihood of obtaining both fixed and mobile broadband. Comparing these two groups and the likelihood of being smartphone dependent, the weather and more educated groups is half as likely compared to those with less education and less income, eight percent to 16 percent respectively.

To measure the compounding impacts of family income and race, see Table 14 in the appendix. Non-Hispanic Whites who have a family income of less than $50,000 are 70 percent likely to achieve a universal connection, while non-Hispanic Whites who earn more than $100,00 or more are 17 percentage points higher. Black respondents who earn less than $50,00 are only 62 percent likely to obtain universal connectivity, but their likelihood increases by 20 percentage points for those who have a family income of $100,000 or more. latinx/Hispanic respondents experience a similar jump in connectivity to Black respondents, from 67 percent to 85 percent between levels of income. When comparing these groups across smartphone dependency, non-Hispanic White respondents' likelihood decreases by a third from 12 percent to eight percent from those who earn less than $50,000 to those who earn more than $100,000. Black and Latinx/Hispanic respondents also see a decrease of a third from 15 percent to ten percent as their incomes increase.

Table 15 demonstrates the effects of educational attainment and race. Non-Hispanic Whites who lack a high school education are 72 percent likely to achieve a universal connection, while non-Hispanic Whites with a four year degree or more are 13 percentage points higher. Black respondents who lack a high school diploma are only 65 percent likely to obtain universal connectivity, but their likelihood increases by 15 percentage points for those who have completed college or more. latinx/Hispanic respondents experience a similar jump in connectivity to Black respondents, from 69 percent to 83 percent between levels of educational attainment. Black and Latinx/Hispanic respondents have a higher likelihood of smartphone dependency at all levels of education when compared to non-Hispanic White respondents.

Comparing immigration across race, Tables 16 and 17 demonstrate the impacts of place of birth and English ability across race and ethnicity. Across all races, place of birth only made a single percentage point difference between native and foreign born respondents, with the exception of Asian or Pacific Islander respondents who were consistent at 80 percent for universal connectivity and 11 percent for smartphone dependency regardless of place of birth. While there was little variation between respondents, the effect of social exclusion based on race is demonstrated, as Black respondents regardless of place of birth had the lowest likelihood of obtaining a universal connection. Black and Latinx/Hispanic respondents had the same rates of smartphone dependency regardless of place of birth. Comparing English ability across and race had more variability and impact on the level of connectivity compared to place of birth. Given the large portion of respondents who are immigrants, the difference in social and economic exclusion is demonstrated between Asian and Pacific Islander and Latinx/hispanic respondents. Asian or Pacific Islander respondents of all English abilities have the highest rates of universal connectivity and the second lowest rates of smartphone dependency, behind non-Hispanic Whites. Conversely, Latinx/Hispanic respondents lag behind Asian and Pacific Islander respondents at all levels of English proficiency in terms of universal connectivity; five percentage points for those who only speak English, four percentage points for those who speak a language other than English at home, and six percentage points for those who don’t speak any English. Asian and Pacific Islander respondents were consistently two percentage points less likely to be smartphone dependent than Latinx/Hispanic respondents at all levels of English ability.

Lastly, Table 18 demonstrates the impact on an individual's level of connectivity by percent of the community that identifies as non-Hispanic White and race or respondent. Regardless of race, all respondents experience an increase in universal connectivity as the percentage of individuals who identify as non-Hispanic White increases, and the inverse is true for smartphone dependency. For Black respondents, those who live in the lowest quartile (being the least White) and those who live in the highest quartile (the most White) experience a six percentage point difference in universal connectivity and a four percentage point difference in smartphone dependency. In each quartile, Black respondents lag non-Hispanic White respondents by six percentage points in universal connectivity and lead non-Hispanic White respondents by three percentage points in smartphone dependency. Respondents who identify as latinx/Hispanic are three to four percentage points more likely than Black respondents to obtain a universal connection, but have the same rates of smartphone dependency regardless of the community's quartile. Asian and Pacific Islander respondents are one to two percentage points more likely to have a universal connection compared to non-Hispanic White respondents regardless of their community's quartile, but consistently one point more likely to be smartphone dependent.

Limitations

A primary concern is the opportunity to create false statistically significant results due to the large size of the sample. Therefore, my results may not be generalizable to smaller counties or populations. The large sample size made it more difficult to interpret meaningful results about smaller populations, such as those who identify as American Indian or Alaskan Native. Another limitation is the creation of the smartphone dependent variable. Since I used data provided by the American Community Survey, I relied on defining smartphone dependency as a respondent who has a mobile data plan and no fixed broadband access. In future studies it would be advantageous to directly ask a repsonsdent if they are limited to using a smartphone to access the internet.

Additional limitations relating to the construction of variables include how immigrants are defined and the use of density to represent the urban, suburban, and rural divide. I used a similar approach as Ono and Zavodny (2008) by utilizing English ability and place of birth. Their study used the additional variables of year of entry into the United States and whether the survey was conducted in English or Spanish to add further analysis to the experiences of immigrants.

When it came to determining whether a community was defined as a ubran, suburban, or rural, I initially followed the methods of Mossberger, Tolbert, and Franko (2013). Their study utilized the ‘METRO’ variable provided by the American Community Survey and differentiated between urban communities, defined as “in central/principal city,” suburban as “central/principal city status indeterminable (mixed),” and rural as “not in central/principal city.” This yielded an inaccurate distribution of Los Angeles County, which has large suburban areas that fall within the “central/principal city.” Due to this, I relied on density as the proxy. This resulted in statistically significant results despite what previous literature and common knowledge suggests about the differences between urban and rural communities opportunities to access ICT. This lack of difference could also be attributed to Los Angeles County being considered a metropolitan county A single county may not be the appropriate setting to generalize the differences between urban and rural communities; future research may need to use an entire state to make meaningful comparisons.

5. CONCLUSION

In this paper I have examined the differences in universal connectivity and smartphone dependency across Los Angeles County using individual survey responses to the 2019 American Community Survey. By expanding the scope of digital inequalities beyond the limitations of the digital divide, we can more accurately depict how a larger framework of exclusion impacts an individual's ability to obtain an internet connection and take advantage of the economic and social opportunities. Working from Van Dijk's four forms of access, I utilized two separate regressions to measure the likelihood of achieving universal connectivity and smartphone dependency in relation to social and economic factors.

As the literature has indicated, income and educational attainment has the largest impact on the level of connectivity for an individual. An increase in income positively affects an individual's ability to obtain a universal connection and lessens the likelihood of being smartphone dependent. Similarly, the greater level of education achievement the more likely they are to be universally connected while those with less education are more likely to be smartphone dependent. Social factors including race, age and immigration status negatively impacted the likelihood of obtaining a universal connection. In contrast to much of the early ICT literature, sex was not statistically significant when determining an individuals likelihood to be smartphone dependent or universally connected. This is likely due to the level of diffusion of ICT in personal and work spaces in the United States.

Community level factors had more mixed outcomes compared to individual level factors. A community's median family income was only statistically significant for the lowest quartile of respondents. This supports the criticism in the literature that private actors are less likely to build the necessary infrastructure in low-income areas due to the limited return of investment in these communities. This criticism is further supported by the results of the percent of the community's population that identifies as non-Hispanic White variable. Respondents of any race who lived in communities with the lowest percentage of non-Hispanic Whites are 13 percent less likely to be universally connected but 22 percent more likely to be smartphone dependent. Conversely, respondents who live in communities with the highest percentage of non-Hispanic White are 20 percent more likely to be universally connected and 12 percent less likely to be smartphone dependent regardless of race or ethnicity.

The results of this study can help inform how policymakers address digital inequality by understanding its place within the larger system of ongoing inequalities and exclusion. Given the United States high level of diffusion for traditional computing and smartphones, little research is needed on motivational access, that should be reserved for emerging technologies. Much of the current research and interventions focus on addressing Van Dijk's first two forms of access, material and skills. Future research should dig deeper into usage access and opportunities to apply ICT skills in employment and social settings, or demonstrate the differences in resources across space, for example the cost of service in neighborhoods, the distribution of infrastructure like cell towers or lines of fiber, and reliability and quality of service within communities of color versus predominately non-Hispanic White communities.

6. APPENDIX

FIgure 1: Van Dijk's Framework for Access

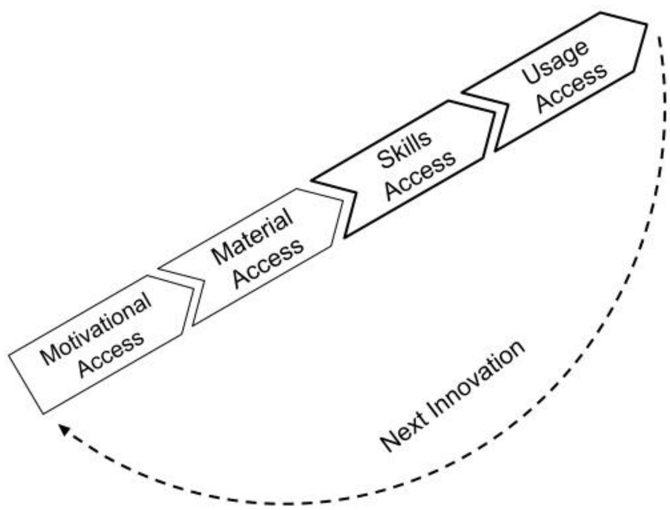

Figure 2: Median Family Income by Los Angeles County PUMA

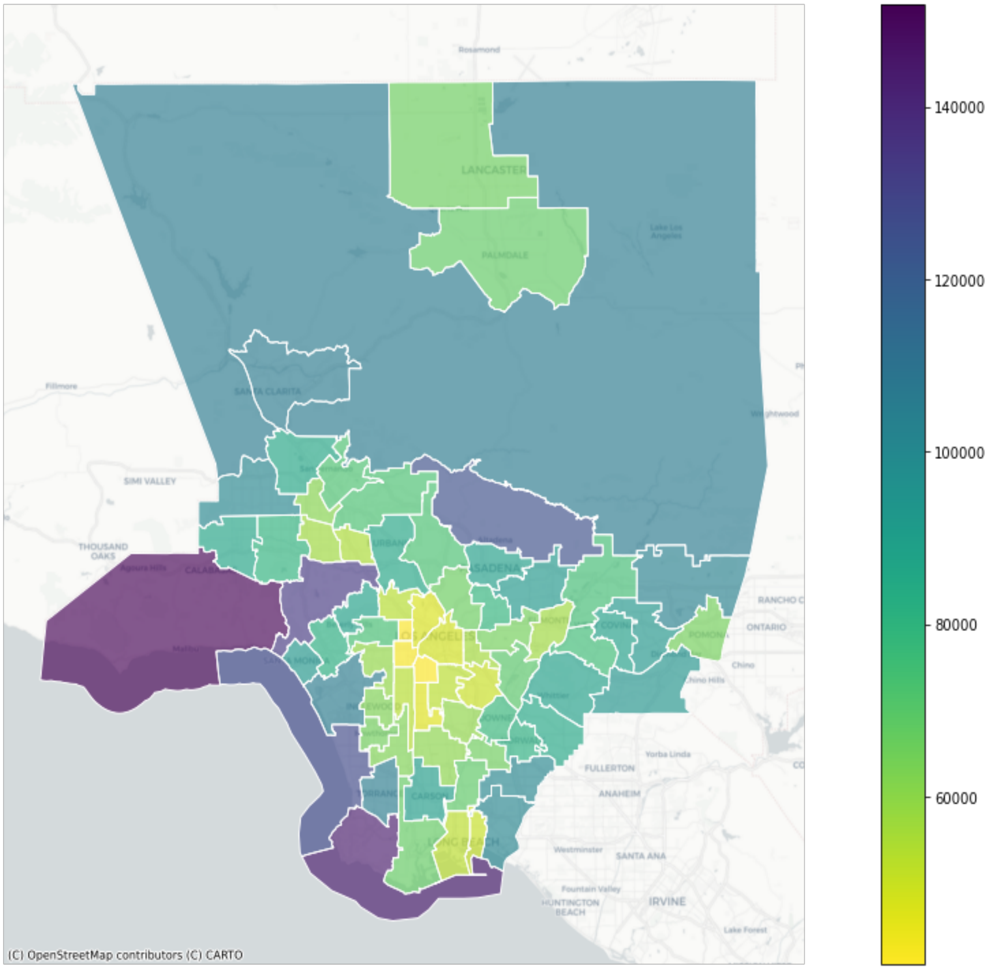

Figure 3: Percent of Los Angeles County PUMA That Identifies as Non-Hispanic White

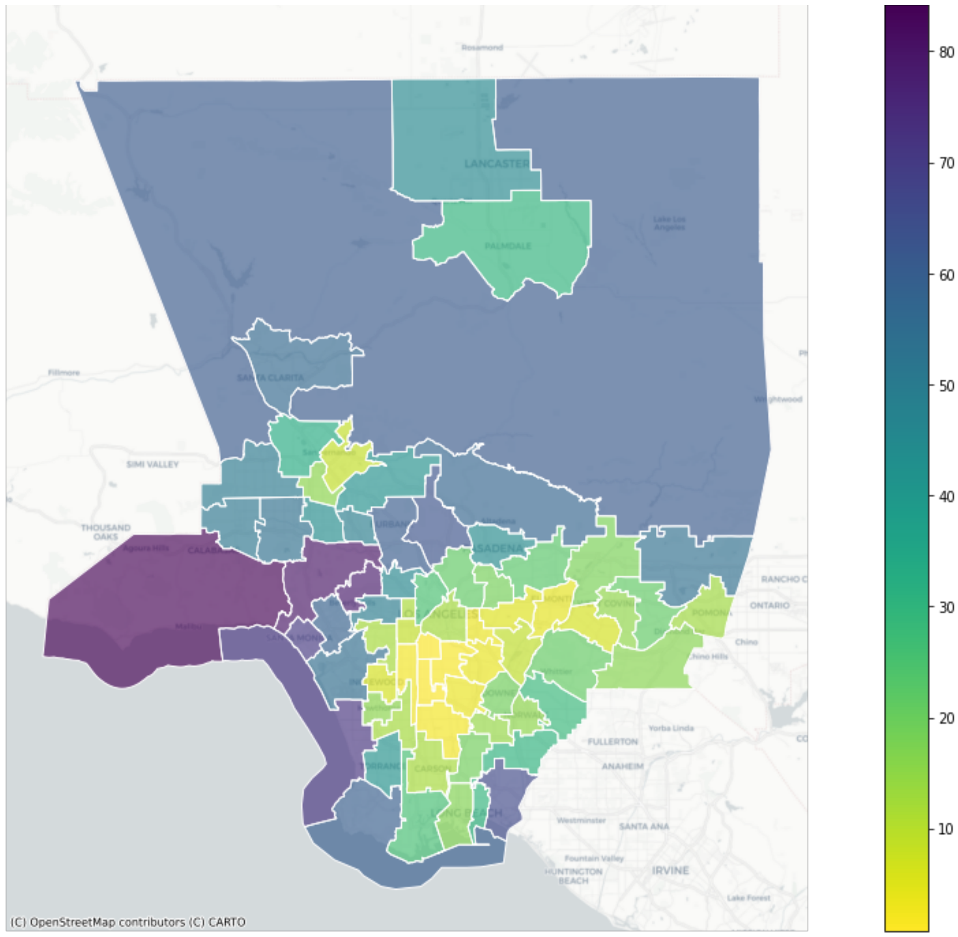

Table 9: Descriptive Statistics of Los Angeles County Sample

	Entire Sample	Lacks Any Connection	Smartphone Dependent	Universal Connection
Respondents (n/percent)	368,425 / 100	37,832/ 10	45,050 / 12	285,543 / 78
Median Family Income	$74,242	$32,373	$57,193	$85,249
Age				
Median Age (years)	47	59	47	46
18-34	28	19	30	29
35-64	52	41	52	53
65 and Older	20	40	19	17
Race				
White NH	31	21	21	34
Black	7	10	7	6
Asian/PI	18	12	16	20
AI/AN	<1	<1	<1	<1
Latino/Hispanic	43	56	55	39
Other Race	<1	<1	<1	<1
Sex				
Male	48	46	47	48
Female	52	54	53	52
Education				
Less than High School	16	36	22	12
Completed High School	29	36	34	27
Some College	23	18	22	24
Completed Bachelors or more	33	11	22	38
Nativity Status				
Native Born	58	47	50	60
Foreign Born	42	53	50	40

English Ability				
Speaks only English	45	35	34	48
Speaks a language other than English at home	51	53	59	49
Speaks no English	5	12	6	3

Percent unless otherwise noted.

Table 10: Logistic Regression for Universal Connectivity

	Individual Model	**Individual & Community Model**
Total Family Income ($10,000 increments)	1.064* (0.001)	1.061* (0.001)
65 & Older (ref: under 65)	0.557* (0.007)	.546* (0.007)
RACE (ref: white)		
Black	0.587* (0.012)	0.695* (0.015)
Asian or Pacific Islander	1.059* (0.019)	1.134* (0.021)
American Indian or Alaskan Native	0.823 (0.055)	.881 (0.059)
Latino/Hispanic	0.780* (0.012)	.875* (0.014)
Other Race	0.636* (0.053)	0.689* (0.057)
Female (ref: male)	1.009 (0.009)	1.005 (0.01)
EDUCATION (ref: Bach or more)		
Less than High School	0.399* (0.007)	0.424* (0.008)
Completed High School	0.522* (0.008)	0.539* (0.008)
Some College	0.720* (0.011)	0.733* (0.011)
Foriegn Born (ref: native born)	0.955* (0.012)	0.949* (0.012)

ENGLISH ABILITY (ref: Speaks only english)		
Speaks a Language Other Than English at Home	0.821* (0.012)	0.856* (0.013)
Speaks No English	0.613* (0.015)	0.660* (0.016)
Median Family Income of Community (ref: middle 50%)		
Lowest 25%	-	0.832* (0.013)
Highest 25%	-	1.031 (0.017)
Density of Community (ref: middle 50%)		
Lowest 25%	-	1.083* (0.016)
Highest 25%	-	1.066* (0.016)
Percent of Community that Identifies as Non-Hispanic White (ref: middle 50%)		
Lowest 25%	-	0.872* (0.011)
Highest 25%	-	1.204* (0.019)

Standard errors in parentheses, *p<0.05

Table 11: Logistic Regression of Smartphone Dependency

	Individual Model	**Individual & Community Model**
Total Family Income ($10,000 increments)	0.976* (0.001)	0.978* (0.001)
65 & Older (ref: Under 65)	0.887* (0.014)	0.895* (0.014)
RACE (ref: white)		
Black	1.467* (0.038)	1.268* (0.035)
Asian or Pacific Islander	1.075 (0.024)	1.016 (0.022)
American Indian or Alaskan Native	1.101 (0.098)	1.04 (0.094)

Latino/Hispanic	1.387* (0.026)	1.258* (0.025)
Other Race	1.396 (0.144)	1.310 (0.135)
Female (ref: male)	1.003 (0.012)	1.006 (0.012)
EDUCATION (ref: Bach or more)		
Less than High School	1.502* (0.033)	1.417* (0.022)
Completed High School	1.432* (0.025)	1.381* (0.024)
Some College	1.207* (0.022)	1.181* (0.022)
Foriegn Born (ref: native born)	1.077* (0.017)	1.086* (0.017)
ENGLISH ABILITY (ref: Speaks only english)		
Speaks a Language Other Than English at Home	1.207* (0.022)	1.164* (0.021)
Speaks No English	1.258* (0.039)	1.185* (.037)
Median Family Income of Community (ref: middle 50%)		
Lowest 25%	-	1.090* (0.020)
Highest 25%	-	0.949 (0.019)
Density of Community (ref: middle 50%)		
Lowest 25%	-	0.996 (0.017)
Highest 25%	-	0.942 (0.016)
Percent of Community that Identifies as Non-Hispanic White (ref: middle 50%)		
Lowest 25%	-	1.224* (0.018)
Highest 25%	-	0.882* (0.017)

Standard errors in parentheses, *p<0.05

Table 12: Margins for Universal Connectivity and Smartphone Dependency

	Margin of Universal Connectivity	Margin of Smartphone Dependency
Income		
Less than $50,000	68 (0.001)	14 (0.001)
$50,000 to $100,000	79 (0.002)	13 (0.001)
Over $100,000	86 (0.002)	9 (0.001)
Race/Ethnicity		
Non-Hispanic White	78 (0.002)	11 (0.001)
Black	72 (0.003)	13 (0.003)
Asian or Pacific Islander	80 (0.002)	11 (0.002)
American Indian or Alaskan Native	76 (0.011)	11 (0.009)
Latinx/Hispanic	76 (0.001)	13 (0.001)
Other	72 (0.015)	14 (0.012)
Age		
Under 65 Years Old	76 (0.001)	12 (0.001)
Over 65 Years Old	68 (0.002)	11 (0.001)
Educational Attainment		
Less than High School	69 (0.002)	14 (0.002)
Completed High School	74 (0.002)	13 (0.001)
Completed High School and Some College	79 (0.002)	12 (0.001)

Completed Bachelors or More	84 (0.002)	10 (0.001)
Place of Birth		
Native Born	77 (0.001)	12 (0.001)
Foriegn Born	76 (0.001)	13 (0.001)
English Ability		
Speaks Only English	78 (0.002)	11 (0.001)
Speaks a Language Other Than English at Home	76 (0.001)	13 (0.001)
Speaks No English	71 (0.004)	13 (0.003)
Median Family Income of Community		
Lowest Quartile (Under 25%)	74 (0.002)	13 (0.001)
Middle Quartiles (25% to 75%)	77 (0.001)	12 (0.001)
Highest Quartile(Over 75%)	78 (0.002)	11 (0.002)
Density of Community		
Lowest Quartile (Under 25%)	77 (0.002)	12 (0.001)
Middle Quartiles (25% to 75%)	76 (0.001)	12 (0.001)
Highest Quartile(Over 75%)	77 (0.001)	12 (0.001)
Percent of Community that Identifies as Non-Hispanic White		
Lowest Quartile (Under 25%)	74 (0.001)	14 (0.001)
Middle Quartiles (25% to 75%)	77 (0.001)	12 (0.001)
Highest Quartile(Over 75%)	80 (0.002)	11 (0.001)

Table 13: Predicted Margins for Universal Connectivity and Smartphone Dependency by Median Family Income and Education

	Margin of Universal Connectivity	**Margin of Smartphone Dependency**
Less Than $50,000		
Less Than High School Education	59 (0.003)	16 (0.002)
Completed High School	64 (0.002)	16 (0.002)
Completed Some College	70 (0.002)	14 (0.002)
Completed Bachelor’s or More	77 (0.02)	12 (0.002)
$50,000 to $100,000		
Less Than High School Education	71 (0.003)	14 (0.002)
Completed High School	76 (0.002)	14 (0.002)
Completed Some College	81 (0.002)	12 (0.002)
Completed Bachelor’s or More	85 (0.02)	11 (0.002)
More Than $100,000		
Less than High School Education	80 (0.002)	11 (0.002)
Completed High School	83 (0.002)	10 (0.001)
Completed Some College	87 (0.002)	9 (0.001)
Completed Bachelor’s or More	90 (0.01)	8 (0.001)

Table 14: Predicted Margins for Universal Connectivity and Smartphone Dependency by Median Family Income and Race

	Margin of Universal Connectivity	**Margin of Smartphone Dependency**
Less Than $50,000		
Non-Hispanic White	70 (0.003)	12 (0.002)
Black	62 (0.004)	15 (0.003)
Asian or Pacific Islander	72 (0.003)	13 (0.002)
American Indian or Alaskan Native	67 (0.014)	13 (0.010)
Latinx/Hispanic	67 (0.002)	15 (0.002)
Other	62 (0.019)	16 (0.013)
$50,000 to $100,000		
Non-Hispanic White	80 (0.003)	11 (0.002)
Black	74 (0.004)	14 (0.003)
Asian or Pacific Islander	82 (0.003)	11 (0.002)
American Indian or Alaskan Native	78 (0.014)	12 (0.009)
Latinx/Hispanic	78 (0.002)	14 (0.002)
Other	74 (0.015)	14 (0.012)
More Than $100,000		
Non-Hispanic White	87 (0.002)	8 (0.001)
Black	82 (0.003)	10 (0.002)
Asian or Pacific Islander	88 (0.002)	8 (0.001)

American Indian or Alaskan Native	85 (0.008)	9 (0.007)
Latinx/Hispanic	85 (0.002)	10 (0.001)
Other	82 (0.012)	11 (0.009)

Table 15: Predicted Margins for Universal Connectivity and Smartphone Dependency by Race and Educational Attainment

	Margin of Universal Connectivity	**Margin of Smartphone Dependency**
Less Than High School		
Non-Hispanic White	72 (0.003)	12 (0.002)
Black	65 (0.005)	15 (0.004)
Asian or Pacific Islander	74 (0.003)	12 (0.002)
American Indian or Alaskan Native	69 (0.013)	12 (0.010)
Latinx/Hispanic	69 (0.002)	15 (0.002)
Other	64 (0.018)	15 (0.014)
Completed High School		
Non-Hispanic White	76 (0.002)	12 (0.002)
Black	69 (0.004)	15 (0.003)
Asian or Pacific Islander	77 (0.003)	12 (0.002)
American Indian or Alaskan Native	73 (0.012)	12 (0.010)
Latinx/Hispanic	73 (0.002)	14 (0.002)
Other	69	15

	(0.017)	(0.013)
Completed High School and Some College		
Non-Hispanic White	80 (0.002)	10 (0.002)
Black	75 (0.004)	13 (0.003)
Asian or Pacific Islander	82 (0.002)	11 (0.002)
American Indian or Alaskan Native	78 (0.011)	11 (0.009)
Latinx/Hispanic	78 (0.002)	13 (0.002)
Other	74 (0.015)	13 (0.012)
Completed Bachelor's Degree or More		
Non-Hispanic White	85 (0.002)	9 (0.001)
Black	80 (0.003)	11 (0.002)
Asian or Pacific Islander	86 (0.002)	9 (0.002)
American Indian or Alaskan Native	83 (0.009)	9 (0.007)
Latinx/Hispanic	83 (0.002)	11 (0.002)
Other	79 (0.013)	11 (0.010)

Table 16: Predicted Margins for Universal Connectivity and Smartphone Dependency by Race and Place of Birth

	Margin of Universal Connectivity	**Margin of Smartphone Dependency**
Non-Hispanic White		
Native Born	79 (0.002)	10 (0.002)
Foriegn Born	78	11

	(0.002)	(0.002)
Black		
Native Born	73 (0.004)	13 (0.003)
Foriegn Born	72 (0.004)	14 (0.003)
Asian or Pacific Islander		
Native Born	80 (0.002)	11 (0.002)
Foriegn Born	80 (0.002)	11 (0.002)
American Indian or Alaskan Native		
Native Born	77 (0.011)	11 (0.009)
Foriegn Born	76 (0.011)	12 (0.009)
Latinx/Hispanic		
Native Born	76 (0.002)	13 (0.013)
Foriegn Born	75 (0.002)	14 (0.014)
Other		
Native Born	72 (0.015)	13 (0.011)
Foriegn Born	72 (0.015)	14 (0.012)

Table 17: Predicted Margins for Universal Connectivity and Smartphone Dependency by English Ability and Race

	Margin of Universal Connectivity	**Margin of Smartphone Dependency**
Speaks Only English		
Non-Hispanic White	80 (0.002)	10 (0.001)
Black	75	12

	(0.003)	(0.002)
Asian or Pacific Islander	82 (0.002)	10 (0.002)
American Indian or Alaska Native	78 (0.010)	10 (0.008)
Latinx/Hispanic	77 (0.002)	12 (0.002)
Other	74 (0.014)	13 (0.011)
Speaks a Language Other Than English at Home		
Non-Hispanic White	78 (0.002)	11 (0.002)
Black	72 (0.004)	14 (0.003)
Asian or Pacific Islander	79 (0.002)	12 (0.002)
American Indian or Alaska Native	75 (0.011)	12 (0.009)
Latinx/Hispanic	75 (0.001)	14 (0.001)
other	71 (0.015)	14 (0.012)
Speaks No English		
Non-Hispanic White	74 (0.002)	11 (0.003)
Black	67 (0.003)	14 (0.004)
Asian or Pacific Islander	76 (0.002)	12 (0.003)
American Indian or Alaska Native	71 (0.010)	12 (0.009)
Latinx/Hispanic	70 (0.002)	14 (0.003)
other	66 (0.014)	14 (0.013)

Table 18: Predicted Margins for Universal Connectivity and Smartphone Dependency by Race and Percent of Community Identified as Non-Hispanic White

	Margin of Universal Connectivity	**Margin of Smartphone Dependency**
Lowest Quartile		
Non-Hispanic White	76 (0.003)	12 (0.002)
Black	70 (0.004)	15 (0.003)
Asian or Pacific Islander	78 (0.003)	13 (0.002)
American Indian or Alaskan Native	74 (0.011)	13 (0.010)
Latinx/Hispanic	73 (0.002)	15 (0.002)
Other	69 (0.016)	16 (0.014)
Middle Quartiles		
Non-Hispanic White	78 (0.002)	10 (0.002)
Black	72 (0.004)	13 (0.003)
Asian or Pacific Islander	80 (0.002)	11 (0.002)
American Indian or Alaskan Native	76 (0.011)	11 (0.009)
Latinx/Hispanic	76 (0.002)	13 (0.001)
Other	72 (0.015)	13 (0.012)
Highest Quartile		
Non-Hispanic White	82 (0.002)	9 (0.002)
Black	76 (0.004)	11 (0.003)
Asian or Pacific Islander	83	9

	(0.003)	(0.002)
American Indian or Alaskan Native	80 (0.011)	10 (0.008)
Latinx/Hispanic	79 (0.002)	11 (0.002)
Other	76 (0.014)	12 (0.011)

7. REFERENCES

Anderson, Monica. "Mobile Technology and Home Broadband 2019." *Pew Research Center: Internet, Science & Tech*, 13 June 2019, https://www.pewresearch.org/internet/2019/06/13/mobile-technology-and-home-broadband-2019/.

Anderson, Monica, and John B. Horrigan. *Smartphones Help Those without Broadband Get Online, but Don't Necessarily Bridge the Digital Divide*. Oct. 2016. *policycommons.net*, https://policycommons.net/artifacts/618265/smartphones-help-those-without-broadband-get-online-but-dont-necessarily-bridge-the-digital-divide/1599208/.

Bach, Amy J., et al. "Poverty, Literacy, and Social Transformation: An Interdisciplinary Exploration of the Digital Divide." *Journal of Media Literacy Education*, vol. 10, no. 1, 2018, pp. 22–41. *DOI.org (Crossref)*, https://doi.org/10.23860/JMLE-2018-10-1-2.

Barzilai-Nahon, Karine. "Gaps and Bits: Conceptualizing Measurements for Digital Divide/s." *The Information Society*, vol. 22, no. 5, Dec. 2006, pp. 269–78. *Taylor and Francis+NEJM*, https://doi.org/10.1080/01972240600903953.

Blackwater, Darrah. "Broadband Internet Access: A Solution to Tribal Economic Development Challenges." *Indigenous Peoples' Journal of Law, Culture and Resistance*, vol. 6, 2020, pp. 93–116.

Blank, Grant, and Darja Groselj. "Dimensions of Internet Use: Amount, Variety, and Types." *Information, Communication & Society*, vol. 17, no. 4, Apr. 2014, pp. 417–35. *Taylor and Francis+NEJM*, https://doi.org/10.1080/1369118X.2014.889189.

Broadband Infrastructure Programs in the American Recovery and Reinvestment Act. https://www.everycrsreport.com/reports/R40436.html. Accessed 7 Mar. 2022.

Brynin, Malcolm. "Gender, Technology and Jobs." *The British Journal of Sociology*, vol. 57, no. 3, 2006, pp. 437–53. *Wiley Online Library*, https://doi.org/10.1111/j.1468-4446.2006.00119.x.

Brynjolfsson, Erik, and Andrew McAfee. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company, 2014.

Casper, Jericho. "A Community Guide to Federal Funding Opportunities for Broadband." *Institute for Local Self-Reliance*, 28 Sept. 2021, https://ilsr.org/a-community-guide-to-federal-funding-opportunities-for-broadband/.

Chen, Wenhong. "Internet Use, Online Communication, and Ties in Americans' Networks." *Social Science Computer Review*, vol. 31, no. 4, Aug. 2013, pp. 404–23. *SAGE Journals*, https://doi.org/10.1177/0894439313480345.

Correa, Teresa, et al. "Who Interacts on the Web?: The Intersection of Users' Personality and Social Media Use." *Computers in Human Behavior*, vol. 26, no. 2, Mar. 2010, pp. 247–53. *ScienceDirect*, https://doi.org/10.1016/j.chb.2009.09.003.

DiMaggio, Paul, and Bart Bonikowski. "Make Money Surfing the Web? The Impact of Internet Use on the Earnings of U.S. Workers." *2008*. https://journals.sagepub.com/doi/abs/10.1177/000312240807300203.

DiMaggio, Paul, and Filiz Garip. "Network Effects and Social Inequality." *Annual Review of Sociology*, vol. 38, no. 1, 2012, pp. 93–118. *Annual Reviews*, https://doi.org/10.1146/annurev.soc.012809.102545.

DiMaggio, Paul, et al. *From Unequal Access to Differentiated Use: A Literature Review and Agenda for Research on Digital Inequality*. p. 73.

DiPrete, Thomas A., et al. “Segregation in Social Networks Based on Acquaintanceship and Trust.” *American Journal of Sociology*, vol. 116, no. 4, Jan. 2011, pp. 1234–83. *journals.uchicago.edu (Atypon)*, https://doi.org/10.1086/659100.

Eubanks, Virginia. Digital Dead End: Fighting for Social Justice in the Information Age. United Kingdom, MIT Press, 2012.

FALLING THROUGH THE NET: A Survey of the “Have Nots” in Rural and Urban America | *National Telecommunications and Information Administration*. https://www.ntia.doc.gov/ntiahome/fallingthru.html. Accessed 13 Apr. 2022.

FALLING THROUGH THE NET II: NEW DATA ON THE DIGITAL DIVIDE | *National Telecommunications and Information Administration*. https://www.ntia.doc.gov/report/1998/falling-through-net-ii-new-data-digital-divide. Accessed 13 Apr. 2022.

Flamm, Kenneth, and Anindya Chaudhuri. “An Analysis of the Determinants of Broadband Access.” *Telecommunications Policy*, vol. 31, no. 6, July 2007, pp. 312–26. *ScienceDirect*, https://doi.org/10.1016/j.telpol.2007.05.006.

Fuchs, Christian. “The Role of Income Inequality in a Multivariate Cross-National Analysis of the Digital Divide.” *Social Science Computer Review*, vol. 27, no. 1, Feb. 2009, pp. 41–58. *SAGE Journals*, https://doi.org/10.1177/0894439308321628.

Greene, Daniel. The Promise of Access: Technology, Inequality, and the Political Economy of Hope. United States, MIT Press, 2021.

Gunkel, David J. “Second Thoughts: Toward a Critique of the Digital Divide.” *New Media & Society*, vol. 5, no. 4, Dec. 2003, pp. 499–522. *SAGE Journals*, https://doi.org/10.1177/146144480354003.

Hoffman, Donna L., et al. “The Evolution of the Digital Divide: How Gaps in Internet Access May Impact Electronic Commerce.” *Journal of Computer-Mediated Communication*, vol. 5, no. 3, Mar. 2000, p. JCMC534. *Silverchair*, https://doi.org/10.1111/j.1083-6101.2000.tb00341.x.

Hargittai, Eszter, and Aaron Shaw. “Mind the Skills Gap: The Role of Internet Know-How and Gender in Differentiated Contributions to Wikipedia.” *Information, Communication & Society*, vol. 18, no. 4, Apr. 2015, pp. 424–42. *DOI.org (Crossref)*, https://doi.org/10.1080/1369118X.2014.957711.

Merton, Robert King. The Matthew Effect in Science: The Reward and Communication Systems of Science Are Considered. N.p., n.p, 1968.

Mesch, Gustavo S., and Ilan Talmud. “Ethnic Differences in Internet Access.” *Information, Communication & Society*, vol. 14, no. 4, June 2011, pp. 445–71. *Taylor and Francis+NEJM*, https://doi.org/10.1080/1369118X.2011.562218.

Mesch, Gustavo, et al. “Minority Status and Health Information Search: A Test of the Social Diversification Hypothesis.” *Social Science & Medicine*, vol. 75, no. 5, Sept. 2012, pp. 854–58. *ScienceDirect*, https://doi.org/10.1016/j.socscimed.2012.03.024.

Mossberger, Karen, et al. *Virtual Inequality: Beyond the Digital Divide*. Georgetown University Press, 2003.

Mossberger, Karen, et al. Digital Cities: The Internet and the Geography of Opportunity. United Kingdom, OUP USA, 2013.

Ono, Hiroshi, and Madeline Zavodny. “Immigrants, English Ability and the Digital Divide.” *Social Forces*, vol. 86, no. 4, June 2008, pp. 1455–79. *Silverchair*, https://doi.org/10.1353/sof.0.0052.

Oyana, Tonny J. “Exploring Geographic Disparities in Broadband Access and Use in Rural Southern Illinois: Who’s Being Left Behind?” *Government Information Quarterly*, vol. 28, no. 2, Apr. 2011, pp. 252–61. *ScienceDirect*, https://doi.org/10.1016/j.giq.2010.09.003.

Pereira, João Paulo Ribeiro. "Broadband Access and Digital Divide." *New Advances in Information Systems and Technologies*, edited by Álvaro Rocha et al., Springer International Publishing, 2016, pp. 363–68. *Springer Link*, https://doi.org/10.1007/978-3-319-31307-8_38.

Perrin, Andrew. "Mobile Technology and Home Broadband 2021." *Pew Research Center: Internet, Science & Tech*, 3 June 2021, https://www.pewresearch.org/internet/2021/06/03/mobile-technology-and-home-broadband-2021/.

Powell, Alison, et al. "The Essential Internet: Digital Exclusion in Low-Income American Communities." *Policy & Internet*, vol. 2, no. 2, 2010, pp. 161–92. *Wiley Online Library*, https://doi.org/10.2202/1944-2866.1058.

"President Biden's Bipartisan Infrastructure Law." *The White House*, https://www.whitehouse.gov/bipartisan-infrastructure-law/. Accessed 7 Mar. 2022.

Qian, Zhenchao, and Daniel T. Lichter. "Social Boundaries and Marital Assimilation: Interpreting Trends in Racial and Ethnic Intermarriage." *American Sociological Review*, vol. 72, no. 1, Feb. 2007, pp. 68–94. *SAGE Journals*, https://doi.org/10.1177/000312240707200104.

Reddick, Christopher G., et al. "Determinants of Broadband Access and Affordability: An Analysis of a Community Survey on the Digital Divide." *Cities*, vol. 106, Nov. 2020, p. 102904. *ScienceDirect*, https://doi.org/10.1016/j.cities.2020.102904.

Riddlesden, Dean, and Alex D. Singleton. "Broadband Speed Equity: A New Digital Divide?" *Applied Geography*, vol. 52, Aug. 2014, pp. 25–33. *ScienceDirect*, https://doi.org/10.1016/j.apgeog.2014.04.008.

Robinson, Laura, et al. "Digital Inequalities and Why They Matter." *Information, Communication & Society*, vol. 18, no. 5, May 2015, pp. 569–82. *Taylor and Francis+NEJM*, https://doi.org/10.1080/1369118X.2015.1012532.

States Tap Federal CARES Act to Expand Broadband. https://pew.org/2GTWHKe. Accessed 7 Mar. 2022.

Shade, Leslie Regan. "Missing in Action: Gender in Canada's Digital Economy Agenda." *Signs: Journal of Women in Culture and Society*, vol. 39, no. 4, June 2014, pp. 887–96. *journals.uchicago.edu (Atypon)*, https://doi.org/10.1086/675542.

Tsetsi, Eric, and Stephen A. Rains. "Smartphone Internet Access and Use: Extending the Digital Divide and Usage Gap." *Mobile Media & Communication*, vol. 5, no. 3, Sept. 2017, pp. 239–55. *SAGE Journals*, https://doi.org/10.1177/2050157917708329.

van Deursen, Alexander J. A. M., and Jan A. G. M. van Dijk. "Using the Internet: Skill Related Problems in Users' Online Behavior." *Interacting with Computers*, vol. 21, no. 5–6, Dec. 2009, pp. 393–402. *Silverchair*, https://doi.org/10.1016/j.intcom.2009.06.005.

van Deursen, Alexander J. A. M., et al. "Development and Validation of the Internet Skills Scale (ISS)." *Information, Communication & Society*, vol. 19, no. 6, June 2016, pp. 804–23. *Taylor and Francis+NEJM*, https://doi.org/10.1080/1369118X.2015.1078834.

Van Dijk, Jan. The Deepening Divide: Inequality in the Information Society. United Kingdom, SAGE Publications, 2005.

van Dijk, Jan, and Kenneth Hacker. "The Digital Divide as a Complex and Dynamic Phenomenon." *The Information Society*, vol. 19, no. 4, Sept. 2003, pp. 315–26. *DOI.org (Crossref)*, https://doi.org/10.1080/01972240309487.

Vehovar, Vasja, et al. "Methodological Challenges of Digital Divide Measurements." *The Information Society*, vol. 22, no. 5, Dec. 2006, pp. 279–90. *Taylor and Francis+NEJM*, https://doi.org/10.1080/01972240600904076.

Vogels, Emily a. "Digital Divide Persists Even as Americans with Lower Incomes Make Gains in Tech Adoption." *Pew Research Center*, https://www.pewresearch.org/fact-tank/2021/06/22/digital-divide-persists-even-as-americans-with-lower-incomes-make-gains-in-tech-adoption/. Accessed 24 Oct. 2021.

West, Darrell M. *The Next Wave: Using Digital Technology to Further Social and Political Innovation*. Brookings Institution Press, 2013.

Witte, James C., and Mannon, Susan E.. The Internet and Social Inequalities. N.p., Taylor & Francis, 2010.

Wolfson, Todd, et al. “Emancipatory Broadband Adoption: Toward a Critical Theory of Digital Inequality in the Urban United States.” *Communication, Culture and Critique*, vol. 10, no. 3, Sept. 2017, pp. 441–59. *Silverchair*, https://doi.org/10.1111/cccr.12166.

Wulf, Jochen, et al. “Fixed and Mobile Broadband Substitution in the OECD Countries – A Quantitative Analysis of Competitive Effects.” *2013 46th Hawaii International Conference on System Sciences*, 2013, pp. 1454–63. *IEEE Xplore*, https://doi.org/10.1109/HICSS.2013.234.