I, Kelli R Chapman, hereby submit this original work as part of the requirements for the degree of:
Master of Arts
in Sociology
It is entitled:
Mannheim in the Digital Age: Assessing Generational Effects on Internet Use

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5/24/2010
Mannheim in the Digital Age:
Assessing Generational Effects on Internet Use

A thesis submitted to the
Graduate School
of the University of Cincinnati
in partial fulfillment of the
requirements for the degree of

Master of Arts

in the Department of Sociology
of the College of Arts and Sciences
by

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June 2007

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ABSTRACT: While research has consistently revealed unequal patterns of Internet use by age, race, sex, community type, education and income (Bimber, 2000; Park, 2009; Jones, Johnson-Yale and Millermaier, 2009; Zillien and Hargittai, 2009; and Wilson, Wallin and Reiser, 2003), research has yet to reveal the generational effect on Internet use. Previous research has assumed that Internet use decreases consistently with age. However, this assumption is problematic as Mannheim's theory of generational cohorts indicates that cohorts, created during major shifts in the social structure, think and act differently. Data from the Pew Internet & American Life Project reveal significant differences in the rates of Internet use of three different generations; digital natives, digital immigrants, and digital aliens. These differences are further structured by race, sex, community type, education and income. Results support Mannheim's theory and provide a more accurate picture of Internet use in America. In this paper, I discuss the results and implications of the generational effect on Internet use.
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Introduction

Karl Mannheim (1997) provides a unique way of understanding generational cohorts as groups of individuals who share similar thoughts and behaviors because of their common age, social location, and position in relation to events of social change. Mannheim argues that generations are not simply biological or social, but rather a combination of the two. Distinctions between the behaviors of different generations are formed during times of social change. As change occurs, generations experience the shift in the social structure differently, resulting in distinct differences between generations.

One recent example of a social change that would greatly influence the thoughts and behaviors of each generation is the development of the Internet. The Internet has undoubtedly changed our society in many ways. We now have access to news and information online, the ability to communicate through instant messaging and email, and has cause drastic changes in our political, education and governmental systems. However, the Internet has not changed all of our lives in the same way as research has consistently revealed unequal patterns of Internet use by age, race, sex, community type, education and income.

Previous research on this digital divide, however, has not adequately assessed the generational effects on the use of the Internet because of two flawed assumptions. First, most research assessing the digital divide has assumed that Internet use decreases consistently with age. This assumption is problematic as Mannheim's theory indicates that generational cohorts will behave differently. As the Internet is clearly a major shift in the social structure, it is essential to reveal the generational effect on Internet use in order to assess how these inequalities differ by generation. Second, previous research that has included generational effects has only made a distinction between two generations, those born after the emergence of the Internet and
those born before. While this approach is better, this assumption is also problematic as those born before the digital age cannot all be analyzed as one generation. According to Mannheim, those who were younger at this time will have a very different experience than those who were older when the Internet emerged.

In this paper I analyze the ways in which race, sex, community type, education, and income influence the Internet use of three different generational cohorts. This reveals important differences in how socio-demographic characteristics influence who does and who does not use the Internet. Bringing Mannheim's theory of generational cohort formation to this analysis provides a better understanding of how these characteristics influence generations in different ways.

Literature Review

*Mannheim's Theory of Cohort Formation*

Karl Mannheim (1997) argues that generations are a combined result of biological, social, and historical processes that have a direct effect on the experience and thought of that generation. Mannheim defined generational cohorts as groups of individuals who all share being born into the same socially and historically significant context. Because a generation is situated within a historical process, Mannheim believed that generations are structured as a social location, similar to a class position. This social location becomes a common lens through which that generation sees the world.

[Belonging to one generation] limit[s] [individuals] to a specific range of potential experience, predisposing them for a certain characteristic mode of thought and experience, and a characteristic type of historically relevant action (Mannheim 1997:291)
However, Generations are not simply based on age and social location. Generations are also formed in direct relation to events of social change. According to Mannheim, the element of social change is key to understanding generational effects. When social change occurs, groups of individuals born around the same time will be exposed to this social change in a similar manner. Exposure of different cohorts to social changes results in generations with different thoughts and behaviors, thus reinforcing the cohesion of the cohort. One recent social change with the capacity to create such generational differences has been the development of computers and associated forms of electronic communication.

*Researching the Digital Divide*

The advent of the Internet has markedly reshaped our society. E-communities have changed the way we develop social capital (Boggs, 2001; Scott and Johnson, 2005); Facebook has modified our understanding of social networking (Boyd, 2008; Boute and Laurier, 2009; Rainie, Horrigan, Wellman and Boase, 2006); and cyber-activism has altered how we participate in politics (Banaji, 2008; Juris, 2009). However, the diffusion of the Internet has not occurred equally across socio-demographic lines. Many researchers have demonstrated unequal access and use based on age, race, gender, education, income, and community type (Park, 2009; Jones, Johnson-Yale and Millermaier, 2009; Zillien and Hargittai, 2009; and DiMaggio, Hargittai, Neuman and Robinson, 2001).

Studies conducted by the National Telecommunications and Information Administration have shown that inequalities in access to the Internet have favor whites, men, urban residents, and those with college educations (NTIA 1998, 1999, 2000). Race plays an interesting role in Internet use because, although whites are more likely to be Internet users and have Internet
access at home, African-Americans are more likely to know where to find public access sites to use the Internet (Wilson, Wallin and Reiser, 2003).

Research has shown that, overall, women use the Internet at lower rates than men (Ono and Zavodny, 2003; Bimber, 2000; OECD, 2001). In comparing the gender gap in access to the Internet and the gender gap in use of the Internet, Bimber (2000) found that, while access differences can be explained by socioeconomic differences such as level of education and income, the gender gap in the use of the Internet is a result of both socioeconomic influences and unexplained gender specific reasons. However, as socioeconomic differences between men and women are slowly decreasing, the gender gap in access and use is also decreasing (Bimber, 2000).

Community types also have a significant influence on Internet use. Many rural areas remain cut off from access to high-speed Internet, leaving rural dwellers at a great disadvantage (NTIA, 2004). Public access to the Internet, frequently found in libraries, is also far more available in urban settings than rural (Bertot & McClure, 1999). Public access sites play an important role in the diffusion of Internet to otherwise disadvantaged groups. Urban libraries, which are almost three times more likely to have high-speed Internet connections than rural libraries, frequently serve urban poor populations, giving them an advantage over rural poor populations (Bertot & McClure, 1999).

As education and income are closely related, they affect Internet use in similar ways. Both education and income are positively related to higher levels of Internet use (OECD, 2001). There is some contention as to the mechanism of this relationship. Some studies have found that income is the important variable; households making over $50,000 are significantly more likely to have Internet access in the home than lower income families (Crews & Feinberg, 2002;
Looker & Thiessen, 2003). Other studies, though, have found that education has twice the predictive power on Internet use as income (Robinson, Kestnbaum, Neustadtl and Alvares, 2000).

Despite these findings, previous research has failed to capture the effects of the cohorts formed by this dramatic change in society. By including generational effects, this paper analyses the ways in which education, income, and the other control variables influence generational cohorts differently, revealing important differences in how socio-demographic characteristics influence who does and who does not use the Internet.

*Mannheim in the Digital Age*

Mannheim's theory of generational cohort formation hinges on moments of social change. These moments create the bond within a generation and shape their experiences, thoughts, and behaviors. One such defining moment is 1983 – the date frequently cited for the birth of the Internet (Segaller, 1998). Individuals' social locations and ages at this time will determine which generation they belong to. Previous research that has included these generational divisions has distinguished only two groups -- digital natives and digital immigrants (Prensky, 2001; Palfrey and Gasser, 2008). Loosely, these terms refer to those born into the digital age, digital natives, and those born prior to it, digital immigrants. An important third group is left out of this division. Not all of those born before the digital age were the same age or in the same social location at its inception. Just as there is a generational divide between these natives and immigrants, there should also be a divide within those previously termed immigrants between those who were younger and therefore in one social location in 1983 and those who were older and in a different social location. I term this third oldest group "digital aliens".
First is the generation born in 1983 or later. Borrowing the term from Prensky (2001), I call this group the “digital natives.” There is a fundamental difference between the youngest generation who are all “native speakers of the digital language” and the adults in their lives (Prensky, 2001:1). Digital natives are fluent in this new technological language. Being a digital native grants membership in a unique culture (Palrey and Gasser, 2008). Digital natives think differently, act differently, and live differently, relying on technology in all facets of life from school, to work, to social interactions. Seemingly everything in the life of a digital native is mediated by digital technology. They do not distinguish between online and offline identities. They are always connective to their friends through instant messaging, cell phones and social networking sites, and information is always accessible with a single click of the mouse (Palrey and Gasser, 2008). In contrast, older generations, while they may adapt to its use, will always retain their pre-digital “accent.”

Almost all research on Internet use demonstrates that digital natives outpace older generations in many online activities. For example, 54% of all bloggers are under the age of 30 (Lenhart and Fox, 2006) despite the fact that 18-34 year olds are only 23.1% of the population (U.S. Census Bureau). Digital Natives also use social networking sites, such as Facebook and MySpace, at much higher rates than those only a few years older. Of online adults, 75% of 18 to 25 have a profile on a social networking site while only 57% of Internet users age 25-34 years olds. This continues to decrease as only 30% of online 35-44 year olds, 19% of 45-54 year olds, 10% of 55-64 and only 7% of those 65 and older have profiles on a social networking site (Lenhart, 2009). The digital generation shares a bond of digital behavior and knowledge. Because these digital natives have grown up in and live in a fully digital world, education, income, and other socio-demographic characteristics will have little influence on Internet use.
The second generational cohort is the “digital immigrants”, a term also coined by Prensky (2001). Digital immigrants were born into a non-digital world. However, as the Internet has drastically changed the workplace, the education system and our daily lives, many digital immigrants have had to learn this new world as it developed. Unlike natives, immigrants do not share the same online behaviors and digital knowledge. And, while sometimes being fully proficient in the digital world, digital immigrants never appear to be as fully integrated as the digital natives.

Typically digital immigrants are thought to be those born anytime before 1982. But this group, which includes workers, both early and late in their careers, as well as retirees, undoubtedly contains individuals who have experienced the digital revolution quite differently. Digital immigrants, born between 1943 and 1982, include anyone born into the non-digital world but who was not older than 40 in 1983. In 1983, many of these digital immigrants would either have been in the educational system or the early stages of their careers. As the Internet spread and revolutionized both schools and the workforce, the social location of the digital immigrants will greatly influence their adoption. In 1983, those with higher socio-economic status would be attending wealthier schools with more resources to adapt to this technological change. Similarly, those with higher socio-economic status would have higher incomes, giving them the personal resources to bring the Internet into their homes as it developed. For this group, education, income, and other socio-demographic characteristics will have great influence on who does and does not use the Internet. However, these digital immigrants will have much higher usage rates than the generation older than them, having spent the majority of their adult lives in the digital world.
The eldest generation -- the “digital aliens” -- were 40 years or older in 1983, when the Internet was forming. At this age, digital aliens would have been at or past the midpoint of their careers and well-established in the non-digital workforce. By the early 1990s, when computers and the Internet became widespread, the youngest of the digital aliens were even closer to retirement and the older digital aliens would have been at or beyond retirement age. Each of these groups would have been much less likely to adapt to this new technology at late stages in their careers. The digital aliens would, mostly, have completed their education by 1983, and many would have seen little need for using personal resources to invest in this new technology.

As a result, digital aliens will most likely have significantly lower rates of Internet use than either digital natives or immigrants. However, this is not to say that no digital aliens are online. Research has shown that senior citizens have not been entirely left out of this technological transformation (National Telecommunications and Information Administration, 2000). Rather, because they do not have the same dependency on technology as digital natives and digital immigrants, education, income, and other socio-demographic characteristics will have a strong influence on which aliens have adopted to the Internet and which have not.

Bringing Mannheim's theory of generational cohort formation to this analysis provides a better understanding of how the social structural locations influence access to important new technologies. It is in this context that I examine the unequal patterns of Internet use and assess how cohort location moderates the influence of other socio-demographic factors.
Data and Methods

Data

I use data from the Pew Internet & American Life Project, which Princeton Survey Research Associates International collected via telephone interviews between April and May 2008. The survey covers the topics of Internet use, political participation and attitudes, the use of social networking sites, the use of cloud computing applications, as well as demographic characteristics of respondents. The sample was selected using random digit dialing from telephone exchanges in the United States yielding a final sample of 2,251 adults age 18 and older who were interviewed (Pew Internet & American Life Project). The data were then weighted in accordance with the population parameters set forth in the Census Bureau's March 2007 Annual Social and Economic Supplement (weighted n=6,894) (Pew Internet & American Life Project). Respondents used in my analyses have valid scores on all variables (weighted n= 5,336). The percentages, means and standard deviates for each variable discussed below are shown in Table 1.

Dependent Variable

The dependent variable in this analysis is Internet use. The Pew Internet & American Life Project asked respondents two separate questions that were combined to create this variable. The first question asked respondents if they go online at least occasionally. Over seventy-one percent of respondents answered that they use the Internet at least occasionally. The second asked if they use email at least occasionally. Over sixty-five percent of respondents use email at least occasionally. Respondents who answer yes to either of these questions are categorized as an
Internet user. Of those categorized as Internet users, two percent of respondents answered yes to using email and no to using the Internet. I have included these respondents because using email requires the respondent to go online. Seventy-three percent of respondents are Internet users (n=5,041) and twenty-seven percent non-users (n=1,853). This variable is dummy coded, 1 = Uses Internet, 0 = Does not use Internet.

Table 1. Frequencies of all variables including mean (std. deviation) and category percentages.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Categories</th>
<th>Mean</th>
<th>n</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet Use</td>
<td>Internet User</td>
<td>0.73</td>
<td>5041</td>
<td>73.1</td>
</tr>
<tr>
<td></td>
<td>Not a User</td>
<td>0.443</td>
<td>1853</td>
<td>26.9</td>
</tr>
<tr>
<td>Digital Cohort</td>
<td>Natives</td>
<td>------</td>
<td>833</td>
<td>12.4</td>
</tr>
<tr>
<td></td>
<td>Immigrants</td>
<td>0.399</td>
<td>4798</td>
<td>71.4</td>
</tr>
<tr>
<td></td>
<td>Aliens</td>
<td>0.500</td>
<td>1088</td>
<td>16.2</td>
</tr>
<tr>
<td>Race</td>
<td>White</td>
<td>0.80</td>
<td>5353</td>
<td>80.1</td>
</tr>
<tr>
<td></td>
<td>Non-White</td>
<td>0.399</td>
<td>1328</td>
<td>19.9</td>
</tr>
<tr>
<td>Sex</td>
<td>Male</td>
<td>0.48</td>
<td>3315</td>
<td>48.1</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>0.500</td>
<td>3578</td>
<td>51.9</td>
</tr>
<tr>
<td>Community Type</td>
<td>Urban/Suburban</td>
<td>0.81</td>
<td>5598</td>
<td>81.2</td>
</tr>
<tr>
<td></td>
<td>Rural</td>
<td>0.391</td>
<td>1295</td>
<td>18.9</td>
</tr>
<tr>
<td>Education</td>
<td>Less than High School</td>
<td>2.70</td>
<td>912</td>
<td>13.2</td>
</tr>
<tr>
<td></td>
<td>High School degree</td>
<td>1.019</td>
<td>2150</td>
<td>31.2</td>
</tr>
<tr>
<td></td>
<td>Technical training/Some College</td>
<td>1848</td>
<td>26.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bachelor's/Post-graduate degree</td>
<td>1904</td>
<td>27.6</td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>Less than $20,000</td>
<td>2.8</td>
<td>970</td>
<td>17.6</td>
</tr>
<tr>
<td></td>
<td>$20,000 to under $50,000</td>
<td>(1.364)</td>
<td>1914</td>
<td>34.7</td>
</tr>
<tr>
<td></td>
<td>$50,000 to under $75,000</td>
<td></td>
<td>873</td>
<td>15.8</td>
</tr>
<tr>
<td></td>
<td>$75,000 to under $100,000</td>
<td></td>
<td>780</td>
<td>14.1</td>
</tr>
<tr>
<td></td>
<td>$100,000 or more</td>
<td></td>
<td>976</td>
<td>17.7</td>
</tr>
</tbody>
</table>
Independent Variables

The primary independent variable in this analysis is generational cohort. For this analysis, I establish three generational cohorts -- digital natives, digital immigrants, and digital aliens. Using 1983 as the reference point for generational cohort formation, respondents who are 18-25 are coded digital natives (1), respondents 26-65 are coded as digital immigrants (2) and those 66 or older are coded digital aliens (3). The sample is 12.4% digital natives (n=833), 71.4% digital immigrants (n=4,798), and 16.2% digital aliens (n=1,088). Table 2 provides the distribution of each of the variables discussed below for each generation.

Table 2. Distribution and column percentages of independent variables by generational cohort.¹

<table>
<thead>
<tr>
<th></th>
<th>Natives</th>
<th>Immigrants</th>
<th>Aliens</th>
<th>sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>545</td>
<td>3789</td>
<td>933</td>
<td>0.000</td>
</tr>
<tr>
<td>Non-White</td>
<td>275</td>
<td>891</td>
<td>121</td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>444</td>
<td>2338</td>
<td>458</td>
<td>0.000</td>
</tr>
<tr>
<td>Female</td>
<td>390</td>
<td>2460</td>
<td>630</td>
<td></td>
</tr>
<tr>
<td>Community Type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban/Suburban</td>
<td>717</td>
<td>3889</td>
<td>842</td>
<td>0.000</td>
</tr>
<tr>
<td>Rural</td>
<td>116</td>
<td>909</td>
<td>246</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than HS</td>
<td>192</td>
<td>427</td>
<td>275</td>
<td>0.000</td>
</tr>
<tr>
<td>HS degree</td>
<td>277</td>
<td>1457</td>
<td>393</td>
<td></td>
</tr>
<tr>
<td>Technical training/Some College</td>
<td>288</td>
<td>1324</td>
<td>201</td>
<td></td>
</tr>
<tr>
<td>Bachelor's/Post-graduate degree</td>
<td>56</td>
<td>1586</td>
<td>204</td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than $20,000</td>
<td>134</td>
<td>551</td>
<td>267</td>
<td>0.000</td>
</tr>
<tr>
<td>$20,000 to under $50,000</td>
<td>295</td>
<td>1316</td>
<td>290</td>
<td></td>
</tr>
<tr>
<td>$50,000 to under $75,000</td>
<td>64</td>
<td>708</td>
<td>93</td>
<td></td>
</tr>
<tr>
<td>$75,000 to under $100,000</td>
<td>74</td>
<td>672</td>
<td>28</td>
<td></td>
</tr>
<tr>
<td>$100,000 or more</td>
<td>80</td>
<td>845</td>
<td>47</td>
<td></td>
</tr>
</tbody>
</table>

¹Significance levels are from chi-square
Race is a dummy variable of white (coded 1) and non-white (coded 0). The categories African American, Hispanic, Asian, Pacific Islander, mixed race and other are collapsed into the category non-white. The sample is 80.1% white and 19.9% non-white. Sex is also a dummy variable of female (coded 1) and male (coded 0). The sample is 51.9% female and 48.1% male. Community type represents the respondents area of residence, either urban, suburban or rural. Pew derived the community categories, rural, urban, or suburban from the United States Census Bureau’s categorization of zip codes (Pew Internet & American Life Project). Community type is also a dummy variable, coded suburban or urban = 1 versus rural = 0. As rural areas are disadvantaged in access to the Internet, the urban and suburban categories are collapsed into one group. The sample is 81.2% urban and suburban and 18.9% rural.

Respondent’s education is indicated by the highest level of school completed. The response options are coded 1 - less than high school (13.2%), 2 – high school degree (31.2%), 3 – technical training or some college (26.8%), and 4 – bachelors or post-graduate degree (27.6%). The mean education for the sample is 2.7, corresponding with technical training or some college.

Income is measured based on annual household income for the previous year. The categories are coded 1 – less than $20,000 (17.6%), 2 - $20,000 to under $50,000 (34.7%), 3 - $50,000 to under $75,000 (14.1%), 4 - $75,000 to under $100,000 (14.1%), and 5 - $100,000 or more (17.7%). The mean income for the sample is 2.8, corresponding with $50,000 to under $75,000. Notably, 1,381 respondents (20% of the sample) refused to provide their income.

Analysis

Because Internet use, the dependent variable, is dichotomous, I use a binary logit model to assess the effect of generational cohort while controlling for socio-demographic
characteristics. The binary logit model allows me to assess the odds of using the Internet, the impact of the independent variables, as well as the change in probability given differing values of the independent variables. To derive predicted probabilities, I use the following equation:

\[
\Pr(y = 1) = \frac{\exp(\beta)}{1 + \exp(\beta)}
\]

where \(\beta=\)logit coefficient (Long, 1997). The models were estimated using SPSS 16.0 software.

Findings & Discussion

Table 3 provides the bivariate relationships between all of the independent variables and Internet use. All variables, except gender, show a significant relationship with Internet use. As previous research has demonstrated, whites, urban or suburban residents and those with higher levels of education and income are more likely to use the Internet. Non-white respondents are only 18% of all Internet users yet 26% of non-users. Rural residents are 14% of all Internet users and 26% of non-users. As levels of education and income increase, the probability of being an Internet user also increases. Those with less than a high school education are only 8% of all Internet users yet 28% of all non-users and those with a bachelors or post-graduate degree are 35% of all Internet users and only 9% of non-users. Similarly, those earning less than $20,000 are only 10% of users and 41% of non-users while those earning over $100,000 are 22% of Internet users and only 4% of non-users.

Table 4 presents the exponentiated betas from four logit regression models that explore the additive effects of generational cohort and other explanatory variables on use of the Internet. Model 1 regresses generational cohort on Internet use. Model 2 includes race, sex and community type to the regression. Model 3 adds the education and income variables and, finally, model 4 includes the interactions of generation with both education and income.
The exponentiated betas in table 5 show that, for models 1 through 3, all independent variables are statistically significant. When controlling for generation, sex, community, education and income, the odds of using the Internet are increased by a factor of 2.223 by being white rather than non-white. Men, when controlling for all other variables, are .571 less likely to use the internet than women and urban and suburban residents are 1.602 times more likely than
rural residents to use the Internet. Each increase in level of education or income is associated with being almost twice as likely to use the Internet. The predictive power of the models increases dramatically from a beginning Nagelkerke $r^2$ of .163 to a .415 in model 3.

Table 4. Exponentiated Betas from logistic Regression of Internet Use on independent variables. (n=5336)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Immigrants</td>
<td>0.509 ***</td>
<td>0.415 ***</td>
<td>0.242 ***</td>
<td>0.052 ***</td>
</tr>
<tr>
<td>Aliens</td>
<td>0.07 ***</td>
<td>0.048 ***</td>
<td>0.042 ***</td>
<td>0.019 ***</td>
</tr>
<tr>
<td>White</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>2.83 ***</td>
<td>2.223 ***</td>
<td>2.162 ***</td>
<td></td>
</tr>
<tr>
<td>Urban or Suburban</td>
<td>2.279 ***</td>
<td>1.602 ***</td>
<td>1.585 ***</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td>1.935 ***</td>
<td>0.926</td>
</tr>
<tr>
<td>Income</td>
<td></td>
<td></td>
<td>1.988 ***</td>
<td>2.387 ***</td>
</tr>
<tr>
<td>Immigrant*Education</td>
<td></td>
<td></td>
<td></td>
<td>2.46 ***</td>
</tr>
<tr>
<td>Alien*Education</td>
<td></td>
<td></td>
<td></td>
<td>1.643 **</td>
</tr>
<tr>
<td>Immigrant*Income</td>
<td></td>
<td></td>
<td></td>
<td>0.809</td>
</tr>
<tr>
<td>Alien*Income</td>
<td></td>
<td></td>
<td></td>
<td>0.899</td>
</tr>
<tr>
<td>Constant</td>
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<td>2.92</td>
<td>0.291</td>
<td>1.023</td>
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<tr>
<td>Nagelkerke $R^2$</td>
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<td>0.217</td>
<td>0.415</td>
<td>0.423</td>
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</table>

*** Significant at the .001 level  
** Significant at the .01 level

Model 4 includes the interaction effects of generation and education and income. While the interaction of generation and education is statistically significant, it barely increases the predictive power of the model. Because the interactions do not improve the percentage of correct classification, I will focus my analysis and this discussion on model 3.
For all generations, white females living in urban or suburban settings have the highest probability of being an Internet user and non-white males living in rural areas have the lowest. However the predicted probabilities by race, sex and community type, shown in table 5, reveal three important generational effects. First, it is clear the predicted probabilities for natives always surpass both the immigrants and natives. For all combinations of race, sex and community type, digital natives score between 3% and 13% higher than immigrants and between 52% and 70% higher than aliens. However, table 5 also reveals that the immigrants and aliens have drastically different predicted probabilities, supporting the hypothesis that these are two significantly

<table>
<thead>
<tr>
<th></th>
<th>Natives</th>
<th>Immigrants</th>
<th>Aliens</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Non-White Female Rural</td>
<td>0.877</td>
<td>0.782</td>
<td>0.184</td>
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</table>
different groups. Digital immigrants score between 48.2% and 59.8% higher than aliens, a difference which cannot be ignored.

Finally, comparing the range of predicted probabilities within each cohort show different levels of racial, sex, and residential benefits. The predicted probabilities of natives only increase from 80.2% to 96.2%, a 16% increase. The range for immigrants however, shows a 25.6% increase, from 67.2% to 92.8%. Aliens have the largest increase, from 11.4% likelihood to 44.6%, an increase of 33.2%. These ranges reveal that the benefits of race, sex, and community type vary by generation. While a white female urban resident who is a digital alien only has a 44.6% probability of using the Internet, compared to a 96.2% probability if she were a digital native, race, sex and community type provide a greater increase for digital aliens than digital natives.

*Race, Sex and Community Type*

Comparing the predicted probabilities shown in Table 5 reveals that all of the included independent variables affect the dependent variable in different ways. However, race, sex and community type are far more influential for digital aliens than either digital natives or immigrants. As shown in Figure 1, controlling for gender, community type, and setting education and income at the cohort means, white digital natives have a predicted probability of using the Internet of .946 while non-white digital natives have a predicted probability of .888, a race gap of 6%. For digital immigrants, the predicted probability for whites is .899 and for non-whites is .800, a gap of 11%. For digital aliens, whites have a predicted probability of .363 and .204 for non-whites, a race gap of 44%.
Controlling for race, community type, and setting education and income at the cohort mean, sex has a similar effect on the different generational cohorts as race, as shown in Figure 2. Female digital natives have a predicted probability of using the Internet of .948 while males have a predicted probability of .911, a gap of 4%. Female and male digital immigrants have a predicted probability of .909 and .852, respectively. Digital immigrants have a 6% sex gap. For digital aliens, women have a predicted probability of .398 and men have .274, a sex gap of 31%.
Community type also affects digital aliens far more than either digital natives or digital immigrants (see Figure 3). Holding constant race, sex, and setting education and income at the cohort means, digital natives who live in urban or suburban communities have a predicted probability of .935 while their rural counterparts have a predicted probability of .899, a 4% difference. Digital immigrants who live in urban or suburban areas and those who live in rural areas have predicted probabilities of .893 and .839, respectively. Community type accounts for a 6% gap for digital immigrants. For digital aliens, living in an urban or suburban area gives a predicted probability of .368 and living in a rural area gives a predicted probability of .266, a 28% gap.

Figure 2. Sex gap in predicted probabilities. Race, sex, education, and income all held at group means.
Figure 3. Community type gap in predicted probabilities. Race, sex, education, and income all held at group means.

Education and Income

To assess the different levels of educational effect on Internet use for each cohort, I have plotted the predicted probabilities of using the Internet for each cohort at each level of education (1-5) in Figure 4. The predicted probabilities for digital natives at each level of education are .855 at level 1, .920 at level 2, .957 at level 3, and .977 at level 4. The predicted probabilities for digital immigrants at each level of education are .693 at level 1, .814 at level 2, .894 at level 3, and .942 at level 4. Digital aliens score .180 at level 1, .298 at level 2, .451 at level 3, and .614 at level 4. Notably, a digital native without a high school degree has a greater likelihood of using the Internet than a digital alien with a post-graduate degree.
Figure 4. Change in predicted probabilities by education. Race, sex, community type, and income all held at group means.

The effects of income also vary for each cohort. As shown in Figure 5, each the slope of the line for each cohort is clearly different. Income ranges from 1-5 and digital natives predicted probabilities are .828 at level 1, .905 at level 2, .950 at level 3, .974 at level 4, and .987 at level 5. For digital immigrants the predicted probabilities are .661 at level 1, .795 at level 2, .885 at level 3, .934 at level 4, and .968 at level 5. The predicted probabilities for digital aliens at each level are .205 at level 1, .338 at level 2, .504 at level 3, .669 at level 4, .801 at level 5.
Conclusion

Mannheim argues that generations are a combined result of biological, social, and historical contexts that shape the ways each generation relates to social change. The most dramatic change in the last twenty years has been the rise of digital technology. As this analysis has shown, there are three distinct generational cohorts that are each structured differently by race, gender, community type, education, and income. While previous research has demonstrated the importance of these socio-demographic factors, this analysis clearly demonstrates the need to study such effects on three different generations.

Importantly, all of these factors have a much greater influence on digital aliens than either digital immigrants or digital natives. The gaps in using the Internet by race, gender, and
community type are much smaller for digital immigrants and natives than aliens. Overall, this analysis demonstrates that digital aliens have drastically smaller race, gender, community type, education, and income gaps. For those born into the digital era, these typically stratifying factors play a far less influential role in who uses the Internet than they do for the two older generations.

Of course, all analyses have limitations. Despite being a nationally representative sample, this is a cross-sectional analysis and cannot demonstrate how these effects have changed over time. And, while the data is from 2008, digital technologies are changing faster than data can be collected; and in the world of technological innovation, there could be many changes occurring over those two years.

While this study reveals important distinctions in how generations shape who uses the Internet, there are two important elements that should be considered for future research. Because of limitations in the data set, this analysis could not account for variation in work environment. One's occupation could have significant influence over whether one uses the Internet or not. This analysis relied on education and income as measures of socio-economic status, but was unable to capture the effect of occupation. As the U.S. employment sector has also undergone great changes over the last twenty years, a person's work history could reveal important distinctions about how work and industry also shape each generations relationship to emerging digital technologies.

Another avenue for future research to consider is how each generation, and each demographic group within each generation is using the Internet. While this analysis is limited to describing who does and who does not use the Internet, future research should consider the ways in which each group uses the Internet, and whether these generational cohorts are utilizing electronic resources differently. This research could reveal important differences in how sub-
groups within each generation are able to utilize digital technologies in ways which might benefit some groups within each generation over others.


