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Digital inequality in the Appalachian Ohio: Understanding how demographics, internet access, and skills can shape vital information use (VIU)

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ABSTRACT

Access to information and resources via the Internet is an increasingly vital dimension of contemporary life. However, there can be several impediments to optimal Internet utilization in the form of access, skills, and motivation. Even when access is available, several digital inequalities arise as citizens often lack the skills and motivations to pursue those vital uses through the Internet to the best of their advantage. Digital inequalities in the hills of the Appalachian area of Ohio are often manifested in terms of social, cultural and geographic divides. Not only do the hills block wireless signals and make cables expensive to install, but regional poverty also drives away telecom investment. We conducted a survey of Appalachian Ohio to explore digital inequity issues and the determinants of online participation for things that matter. Through a number of analyses, we explore how Internet access and digital skills impact online contribution to the community in terms of services and resources considered to be basic social needs: health, employment, education, and social media. These social needs, what we have called Vital Internet Use (VIU) can determine citizens' political and civic participation, societal contribution, and overall benefit to their communities. Centered on the concepts of digital access, Internet skills, and benefit outcomes, we extend knowledge in this domain and propose a comprehensive framework of VIU.

1. Introduction

The Internet is one of the most revolutionizing technologies in the world, that brings with it a great deal of optimism for the betterment of humanity. In the information age, access to the Internet and the ability to use it effectively have become increasingly important for a person's economic, political, and social wellbeing. Individuals use the Internet to not only connect to each other, but also educate themselves, share and receive information, engage in monetary transactions, entertain, and do just about everything that online communication affords.

While the availability of the Internet has indeed transformed the lives of individuals, the direction and the extent of its impact

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remain debatable. Over the years, a great deal of emphasis has been placed on making the Internet available to everyone. While access to Internet has greatly improved in the developed world (despite the persistence of rural-urban internet access divide in some areas), the focus shifted towards Internet skills (DiMaggio and Hargittai, 2001), and more recently towards beneficial outcomes of Internet use (Wei et al., 2011).

Around the world, individuals are faced with Internet-related challenges of various types, ranging from unequal access, differences in skills, and the varied capabilities to reap beneficial outcomes. Such differences have resulted in undesirable inequalities. Such inequalities or gaps have been referred to as the "digital divide" (DiMaggio and Hargittai, 2001; Selwyn, 2004). For purposes of this research, we use the term *digital inequality* instead of digital divide because we find it more explanatory of the dynamic social causes and consequences of inadequate Internet access and skills that determine obtaining the best benefits from its usage.

Digital inequality can take various forms (Pearce and Rice, 2013), and is prevalent in various parts of the United States (U.S.). However, digital inequality is more acute in the rural areas of the country like the Appalachian region. According to the U.S. Census Bureau, in the year 2015, about one-fifth of Americans did not have broadband Internet at home (Ryan and Lewis, 2017); and nearly one-third of Ohioans in rural counties do not have broadband Internet access (Wedell, 2018). This translates into a wide access gap in terms of poor Internet quality, which in turn impacts Internet access, usage, levels of service adoption and utilization of beneficial outcomes.

Motivations for Internet use are varied. People use the Internet to seek information, educate and entertain themselves, connect and communicate with others, and to engage in work, commerce, and financial transactions (Papacharissi and Rubin, 2000; Kalmus et al., 2011). Van Deursen and Helsper (2017) outline how engagement with the Internet leads to various economic, social, cultural, and political outcomes. The kind of activities people engage in online and the type of skills they have are important for the kind of outcomes gained for their communities (Van Deursen and Helsper, 2017).

Among other things, the internet affords certain important or vital uses according to the degree of their necessity to an individual. Through the use of the internet that requires access, media literacy, and efficient utilization, a person is able to fulfill his or her wellbeing needs, informational or learning needs, economic needs, and social connectivity needs. We are more interested in understanding vital uses of the internet that include goal-oriented activities that lead to tangible beneficial outcomes instead of purposeless time-wasting activities (Selwyn et al., 2005). We therefore introduce the concept of Vital Internet Use (VIU) to understand the factors that lead to beneficial outcomes of Internet use. VIU can be defined as the use of Internet services that are related to basic social needs such as health, education, job search, and information search. VIU also includes the use of social media as it can open doors for social and informational resources. The concept of VIU is based on the premise that even when Internet access is available, increased Internet use does not always translate into beneficial outcomes from its use. The extent of utilization of these services can potentially determine the citizens' participation in their communities as well as the citizens' rights acknowledgment and exercising.

The focus of our research is to better understand the remaining dimensions of digital inequality among community members in Appalachia. We hope to gain new insights into how digital access varies, and how social structural differences within this understudied population may be shaping the vital uses they pursue. Through a survey, we explored digital inequalities in counties of south eastern Appalachian Ohio. We propose a comprehensive framework whereby access is understood in terms of physical Internet access (infrastructure, hardware, software), and Internet usage skills (operational, technical, navigational, cognitive-creative, and social skills) to achieve beneficial outcomes or Vital Information Use (VIU).

2. Literature review

The digital divide is a complex and evolving phenomenon (Van Dijk and Hacker, 2003). Although, inequalities in terms of Internet access have significantly lessened in the developed countries (Barnidge et al., 2018) such as the U.S., gaps still exist both in terms of access, usage (Hilbert, 2016), and beneficial outcomes (Wei et al., 2011). Research literature reveals three levels of digital divide that amount to different levels of digital inequality: (i) "first-level" digital divide or "haves" versus "have-nots" approach to Internet access (Attewell, 2001; Van Dijk, 2005; Van Deursen and van Dijk, 2009; Campos-Castillo, 2015); (ii) second-level digital divide comprised of differences in Internet skills or capability and usage (Hargittai, 2002; Selwyn, 2004); and (iii) third-level digital divide or the inequality of outcomes or productivity (Wei et al., 2011).

Besides access and skills, our study concentrates on outcomes whereby the individual needs to gain important benefits from Internet (Scheerder et al., 2017). This also applies to the use of mobile Internet which may be available to a vast number of people (such as in Appalachian Ohio); however, users may not gain potential benefits of the Internet because they do not engage in many important activities (Pearce and Rice, 2013).

2.1. Access divide

2.1.1. Physical access

Internet access can prove beneficial and is thus essential in almost every aspect of life including job searching, connecting on social media, seeking information on health and education, and for entertainment (Van Deursen et al., 2014; Vargas, 2015). Differential access in terms of computer hardware and Internet infrastructure (Attewell, 2001; Hargittai, 2002; Selwyn, 2004; Van Dijk, 2005), opportunity of access due to differences in socioeconomic status (Bucy, 2000; Talukdar and Gauri, 2011), and race (Campos-Castillo, 2015) are some of the areas where the first-level digital divide has been studied. In a study done in the Netherlands, Van Deursen et al. (2014) showed that Internet access correlated with economic participation (people finding jobs via Internet, buying or selling products; with social participation (people finding friends or groups of interest); political participation (people finding political parties or voicing opinions); cultural participation (people finding educational and entertainment resources and opportunities); and institutional participation (people finding health services and information resources). Research has shown that mobile devices aid in reducing the access gaps over time and enable a broad range of useful Internet activities (Pearce and Rice, 2013). However, there are factors that have the potential to inhibit the benefits of mobile Internet. For example, a research study by Gonzales (2016) based on seventy two interviews in a US metropolitan city and a medium-sized midwestern town revealed that Internet access amongst the poor is characterized by instability and frequent disconnections, which in turn limits access to health, employment and other affordances.

The degree of physical access usually mirrors income and education status in society, which in turn "reinforces social inequalities" (Helsper, 2012). Physical access usually correlates with demographics such as income, education, age, ethnicity, and gender (Bonfadelli, 2002). For example, Atkinson et al. (2009) indicate that older women with high literacy are more likely to access the Internet for vital use including seeking information on health. Furthermore, those using the Internet for a longer period of time are also likely to be those who have greater Internet skills (Hargittai, 2002).

2.1.2. Internet reliability

An important aspect of physical access divide is the reliability and the quality of the connection. Quality Internet access made possible through wired broadband is vital in fulfilling everyday tasks that are fundamental to economic development, social inclusion, people empowerment, and democratization of information (Norris, 2001; Selwyn, 2004). According to the 2016 Broadband Progress Report by the Federal Communication Commission (FCC), close to 39% Americans, especially in rural areas, still lack access to high-speed Internet access (25 Mbps download/3 Mbps upload) that allows for "high-quality voice, data, graphics and video offerings" (FCC, 2016). This also impacts the type and extent of social media use, which depending on the platform, use, and skills, can lead to a set of beneficial outcomes.

2.1.3. Access location

Among other things, the location where an individual accesses the Internet makes a difference in terms of time extension and availability for its usage. Internet access through public libraries has played an important role in the development of communities (DeMaagd et al., 2013; Warf, 2013). For example, a program in rural Oklahoma enabled patrons to connect to the internet using personal smartphones, tablets, and laptops through cellular hotspots (Whitacre, 2019).

Internet access through public libraries can hold immense benefits. However, issues related to access times, availability of terminals, and possession of wireless technology that can connect to the internet at such locations can at times prove to be impediments to access. Therefore, Internet access at home is of vital importance as it is a significant indicator of equitable Internet access among groups (Atkinson et al., 2009). Kinney (2010) pointed out that "students with home computers perform higher on standardized tests; however, benefits of having a computer at home are greater for boys, white students, and students of higher socioeconomic status" (p.112). Home Internet access is also known to provide greater convenience and better accessibility to users and is predictive of academic collaboration in certain circumstances (Khan et al., 2014).

2.2. Skills divide

Since the binary way of portraying the digital divide in the form of "haves" and "have-nots" in the earlier stages of scholarly research in this area did not sufficiently explain the digital gap, digital skills were introduced as an additional concept to explain digital inequities. Hargittai (2002) referred to the skills divide as second-level divide, a divide that persists even after the first level of physical access has been attained.

Skills have been classified by scholars in various forms. Classified skills as medium related (e.g. operating a web browser) and content-related Internet skills (e.g. seeking information via search engines). Other classifications are proposed as information navigation skills, social skills, and creative skills (Van Deursen and van Dijk, 2009; Van Dijk, 2017; Scheerder et al., 2017). Information seeking or navigation skills provide "the ability to find, select, and evaluate sources of information on the Internet" (Scheerder et al., 2017, pp. 1608, 1609). Similarly, users also need information sharing skills or creative skills which are "needed to create different types of quality content and to publish or share this with others on the Internet." (Scheerder et al., 2017, p. 1609). Overall, individuals who possess higher Internet skills are advantaged in terms of being able to gain maximum benefit from Internet use (Dobransky and Hargittai, 2016).

2.3. Internet usage outcomes

The latest topic of digital inequities research is also known as the "third-level" digital divide, or the "digital outcome divide" (Wei et al., 2011, p.171). Internet or digital usage outcomes pertain to the consequences of Internet use and focuses on what users need in order to gain benefit from Internet usage and enjoy the best benefits (Scheerder et al., 2017). There are differences in how the Internet is utilized. A study by Selwyn et al. (2005) based on surveys and in-depth interviews found that Internet users from lower socioeconomic status were found to more likely be engaged in purposeless activities such as chatting and using bulletin boards rather than goal-oriented activities such as looking for "information for work, business or study" (p.12). We therefore believe that understanding digital inequality from an Internet usage outcome or VIU can prove more beneficial in understanding issues pertaining to the lack of optimal utilization of the Internet. This is in line with previous research by Ragnedda (2018), which views this from a "digital capital" perspective. Digital capital can be understood as an interaction of online competencies and digital technologies,

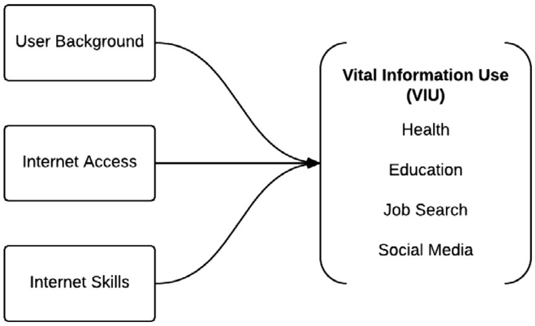

Fig. 1. VIU Research Model.

whereby inequalities emerge in the attainment of social benefits from Internet use (Ragnedda et al., 2019).

3. Conceptual model: vital information use (VIU)

Vital Internet Use (VIU) can be defined as the use of Internet services for useful online activities that are meaningful in the life of a person. Fig. 1 depicts the VIU framework, whereby factors for user background, Internet access, and Internet skills can potentially predict VIU factors such as health, education, job search, and social media use. An Oxford Internet Institute report by Helsper et al. (2015) conceptualizes the usage outcomes, which we refer to as VIU, as "tangible outcomes of Internet use" that emerge from engagement with online resources.

VIU is related to the third-level digital divide that focuses on Internet usage outcomes or consequences. By understanding the factors that predict VIU, it becomes possible to extend our understanding of the digital outcome inequity. The extent of utilization of these services can potentially determine the citizens' participation in their communities.

Viewed from a social justice perspective, inequality in any form, access, skills, or beneficial outcomes, is undesirable. It is therefore argued that VIU in the form of health, education, job search, and social media will be limited for those with non-comprehensive-digital-access. The resources and appropriation theory (Van Dijk, 2005) reinforces this notion when stating that "unequal access to digital technologies brings about unequal participation in society" and therefore perpetuates social inequalities and resources distributions (Van Dijk, 2017, p. 3). The digital gap can further deepen the social divide especially because information is considered a source of social power that when missing can lead to exclusion (McLeod and Perse, 1994) for those already socially excluded.

We classify VIU factors into four major classifications according to the degree of their necessity to an individual: (i) wellbeing needs (such as health) (ii) knowledge/learning needs (such as formal and informal education) (iii) economic needs (such as job search and employment), and (iv) information and social connectivity needs (such as social media use). These vital uses of the Internet also inform us of the benefits attained through Internet use. The following sections discuss each VIU factor in further detail.

3.1. Health

The Internet is a popular place for health information seeking, health tracking, healthcare appointment and services, and doctor-patient interaction. In the U.S. a total of 12.5 million health-related searches were conducted daily online, and that the most common use of the Internet for health was a content search for medical information (Eysenbach, 2003). Citizen engagement with government healthcare services can be crucial in fulfilling people's need for vital health services (Van Dijk, 2017). While the benefits of health information online are evident, not everyone is able to utilize such information. Electronic health literacy is as important as access, especially among the already socially marginalized (Estacio et al., 2017).

Besides Internet access and skills, socioeconomic demographics can also predict Internet use for health information (Kontos et al., 2014). The Appalachian region is especially prone to the negative effects of diseases such as obesity, heart disease, smoking, cancer, and physical inactivity. A report by the Appalachian Regional Commission (a regional economic development agency representing federal, state, and local governments) indicated that the Appalachian region's mortality rate due to heart disease was 17% higher than the national rate, and deaths due to lung diseases were 27% higher than the national rate (ARC, 2017). These figures increase the need to conduct research that helps us understand the drivers for Internet use for health which is a vital information use online.

3.2. Education

The Internet provides access to a wealth of information and opportunities for formal and informal education. It can facilitate distance learning through richer mediums including video. The Internet also has the potential to improve the quality of learning (Cook et al., 2010), and help them collaborate with other students online (Khan et al., 2014). To unlock such opportunities, users need access and skills. According to PEW statistics, one in four lower-income teens do not have a computer at home, nearly one in five cannot finish their homework due to the digital divide, and 15% of US households who have school-age children do not have a broadband Internet connection at home (Anderson and Perrin, 2018). In the Appalachian region, education levels trail behind the U.S. national average. According to the Appalachian Regional Commission, "52.2 percent of adults ages 25 to 44 in Appalachian Ohio have some type of post-secondary education, compared to the 63.3 percent in the nation as a whole and the 65.3 percent in non-Appalachian Ohio" (ARC, 2017, p.5).

3.3. Job search

High-speed Internet or the mere availability of the Internet could possibly provide a level playing field to individuals in search of better employment opportunities. A person might get a job because the Internet provides ready access to information about job opportunities (Fountain, 2005; Jansen et al., 2005). Commonly known as the "coal-country", residents of the Appalachian region have historically lacked diverse employment opportunities, and thereby experienced higher levels of unemployment and lower levels of income compared to the national average (Ford, 2018).

Internet access has been found to be correlated with economic participation which included people finding jobs via Internet, and buying or selling products (van Deursen et al., 2014). Among other things, lack of internet facilities can create impediments in job growth by inhibiting businesses to relocate to that region, attract and retain talent (as qualified workers may tend to areas with better connectivity and offer their services), and provide potential learners access to online resources and training that can help them secure a high paying job. Even when training and education are available, the non-availability of Internet can inhibit search for online opportunities. In other instances, slow internet or lack of broadband facilities can lead to time-wasting thus inhibiting job search.

3.4. Social media

User interaction via the Internet is taking place at an unprecedented scale. A Pew report showed that a majority of Americans are using social media sites such as Facebook and YouTube (Smith and Anderson, 2018). Social media affords multi-faceted opportunities for its users in terms of healthcare (Moorhead et al., 2013); generation of social capital (Ellison et al., 2007); for business and marketing (Culnan et al., 2010; Khan, 2013), for entertainment via YouTube (Khan, 2017), and so much more.

Research has shown that if used rightly, social media can provide enormous benefits for disadvantaged individuals and communities. A study by Wohn et al. (2013) showed that social media proved especially beneficial for first-generation students, and that "finding information about college through social media was associated with higher levels of efficacy about college application procedures" (p.424).

Social media platforms are also a vital sources of news and information (Anderson and Jiang, 2018). In the age of rampant misinformation and fake news, users need media or information literacy to effectively utilize social media in an effective manner (Khan and Idris, 2019). In the modern social media environment, Internet users need to be have certain competencies that enable them to search for the needed information, share it, and critically evaluate it (Koltay, 2011). Social media use only becomes possible with Internet access and its efficient utilization through the needed literacies and skills.

Different levels of media literacy can augment or undermine use of social media. In a study involving 400 American high school students, those who participated in a media literacy program demonstrated higher levels of civic engagement and had substantially higher levels of media knowledge, news analysis, and advertising skills (Martens and Hobbs, 2015). Social media use is shown to a have positive relationship with civic engagement and other forms of participation (Skoric et al., 2016).

In this sense it becomes very important to be able to measure and explore which demographics, Internet access, and skills can predict Vital Internet Use (VIU) - health, education, job search, and social media- to understand who are not getting the most of Internet benefits, either taking those benefits for personal advance or making valuable contributions in the online community. Thus we pose the following research questions:

RQ1 Which demographic variables can predict Vital Uses of the Internet?
RQ2 How does Internet access location affect the way users benefit from VIU factors?
RQ3 How do digital skills impact VIU factors of health, education, job search, and social media?

4. Methods

4.1. Sample frame, context and instruments

Our study is focused on documenting how community members in the Ohio Appalachian region vary in their patterns of Vital Uses of digital tools. Therefore, our sample frame targets users of public resources where we are less likely to over-sample members of the local universities, but have a good chance to reach community residents with a wide range of digital skills and use patterns. Random accidental sampling technique was employed in which participants were approached while coming in, leaving, or using the resource premises. Libraries were chosen as primary locations because previous digital divide studies that show how public libraries are proving instrumental in bridging the access gap by offering computers and Internet to their patrons. To increase the diversity of the sample, we included three other public resources: the farmer's market in Athens county, the Community Center in Athens county; and a supermarket in Perry County.

Participants in this study were recruited through sampling efforts at community resources in seven Appalachian counties in the Southeast Ohio region: Athens, Hocking, Meigs, Morgan, Washington, Perry, and Monroe county. Respondents indicated that they

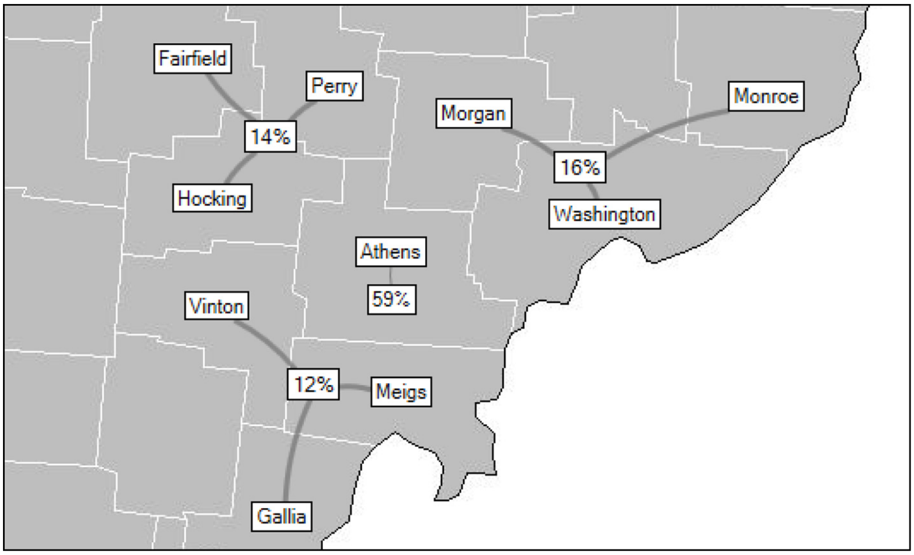

Fig. 2. Sampling frame of Southeast Ohio Appalachian Region. Note: Percentages indicate cases drawn from each sub region within the sampling frame. Map rendered with ggplot2 in R and NodeXL.

lived in one of ten counties in the SE Ohio area, which for the purpose of describing our sample we have grouped by regional attributes of the county. Fig. 2 depicts the sample percentage collected from each region with counties coded by per capita income rates ranging from darkest to lightest indicating the follow levels: \$21,795–\$32,610; \$32,611–\$37,602; \$37,603–\$44,352; \$44,353–\$62,006. Sampling is higher (59%) in Athens county which is central in the most economically disadvantaged counties, and it is distant from larger towns or cities. The Southwest region (12%) of Meigs, Gallia, and Vinton counties are sparsely populated, wooded and relatively isolated. The Northwest region (14%) includes Hocking, Fairfield, and Perry counties that straddle the northwest edge of Appalachia and are connected via a major highway to the Columbus metropolitan area. The Southeast region of Morgan, Washington, and Monroe counties lie to the east of Athens county, and while they are rural and wooded they can also include a substantial area that remains within commuting distance of Parkersburg West Virginia.

The small but steep hills of the sample region create complex patterns of isolation and connection as well as large areas of poverty interspersed with pockets of relative wealth. The 15 most impoverished counties in Ohio includes our sampled counties of Athens, Vinton, Meigs, Monroe, Morgan, Perry, and Hocking.

Measures: The survey was a 30-item paper questionnaire that was administered in the presence of the data collectors and immediately returned to them by the participants. A paper survey was chosen rather than an online survey so as to not bias the sample in favor of those who would have Internet access to fill out the survey online. The survey included questions about demographics, Internet access, digital literacy and skills, among others. The Internet items in the survey were adapted from a digital divide research survey by DeMaagd et al. (2013); the demographics items were taken from a study by Robins et al. (2001); and Internet information skills questions were adapted from Khan et al. (2014). The total number of participants was 200 but three were removed from the sample for being incomplete or due to inconsistencies indicating validity problems. Prior to data collection human subjects approval (17-E-268) was obtained from the Institutional Review Board of the university.

4.2. Methods of analysis

Data analysis was conducted using base R (R Core Team, 2013), MASS (Venables and Ripley, 2002), and the mice and BMA packages (Van Buuren and Groothuis-Oudshoorn, 2010; Raftery et al., 2018; Buuren and Groothuis-Oudshoorn, 2010). We examined how demographics, Internet access and skills related to the dependent variables to find out which may predict vital use of the Internet in a somewhat deprived region such as Southeast Appalachian Ohio. Our sample demographics are based on the full sample of completed cases per attribute.

Missing values: Approximately 3% of our 197 valid cases included missing values on key variables, like income and education. To maintain as many cases as possible while minimizing bias we employed a two-stage imputation strategy. First, we used the mice package in R (Van Buuren and Groothuis-Oudshoorn, 2010) to perform predictive mean matching and created a single dataset with imputed values. We then used this dataset for exploration, variable construction, and model development.

In the second stage of addressing missing values we performed multiple imputation with predictive mean matching and generated a group of 40 datasets. We then performed OLS multiple regression for full and reduced models of all four vital uses and reported the pooled weighted coefficients, significance levels and model fit statistics for all 40 datasets for each of the 8 models. We are especially interested in evaluating how much of the explained variance from the full model is maintained by the parsimonious and theoretically relevant reduced model.

Model uncertainty: Using theory and prior research we developed a list of demographic, contextual, access, and skill variables which became the predictors in our full models. Neither theory nor prior research could tell us which of these predictors would best explain patterns of vital uses in the Appalachian context. Following Raftery (1995) and colleagues (Raftery et al., 1997; Hoeting et al., 1999) we employed Bayesian model averaging to identify the most parsimonious models while also choosing to include predictors like family SES for which there are strong empirical and theoretical justifications (Silver, 2014). This exploratory process resulted in different sets of predictors for the four vital uses. While the correlation matrix we report is based on the single exploratory instance of the imputed dataset, our regression tables report the findings from applying the full and reduced models to a group of 40 datasets. The reported coefficients, standard errors and other model attributes are averaged across the 40 datasets.

The independent variables are based on demographic attributes of the participants, their sources of Internet access, and their self-reported digital skills. The dependent variables are ordinal measures of the areas of use of the Internet that we had previously defined as VIU: health, education, job search, and social media. We employ multiple linear regressions to explore how differences in age, gender, education, employment, income, social class, Internet access locations, and Internet skills predict dependent variables of information seeking for health, education, job search, and social media. We compare R square and adjusted R square between the full model and the reduced models to look for evidence that the reduced models provide higher adjusted model fit, indicating that the more parsimonious models provide a better fit.

We recognize that the most appropriate regression models for ordinal dependent variables are proportional ordered logistic regression or ordered probit (Winship and Mare, 1984). However, we employ OLS regression because our research focus is on discovering patterns in the most important predictors of vital uses, and on comparison of adjusted explained variance between alternative models. OLS models applied to ordinal data will still result in unbiased coefficient estimates (see Winship and Mare 1984: 519). However, the estimates will be inefficient to the extent that the distribution of model errors deviate from normality. Applications with larger samples and larger numbers of evenly ordered levels that correspond to an underlying latent linear factor tend to reduce such deviations, and the fundamental features of the OLS results will then closely approximate those produced through proportional odds logistic regression. Although we report our OLS models in the text we replicated all eight models using proportional odds logistic regression to confirm that our substantive findings were not affected.

5. Results

5.1. Demographics

Table 1 presents the demographic profile based on our study's sample and compares key available attributes to two major counties in our sample region (Hocking and Athens Counties). Although we selected the sample by accidental sampling technique, the proportions of our study sample were quite similar with the proportions of the Appalachian population in the state of Ohio according to 2016 survey of Population Reference Bureau (Pollard and Jacobsen, 2018). The age distribution for out sample is roughly similar to Census values for both comparison counties, though the sample over-represents older respondents, notably in the 55 to 74 age range. The median range for household income corresponds to median household income for both counties, while education levels, when comparing those with a Bachelors Degree (29%) is more similar to Athens County (32%) than to Hocking (14%).

In this study, the respondents came from all counties in Southeast Ohio, except Noble County. Most of the respondents were residents of Athens County (58.9%), followed by Hocking (10.2%), Meigs (8.1%), Morgan (7.6%), and Washington (5.1%). Our respondents were predominantly White (89.3%), which is in line with figures from the Population Reference Bureau survey of 2016, according to which the proportion of Appalachian in Ohio was White (91.1%) and is between the percentages for our two comparison counties (see Table 1).

5.2. Internet access and quality

154 out of the 197 respondents indicated that they had Internet access at home while 43 respondents (21.8%) indicated that they did not have home Internet access. Of those, 36 respondents accessed the Internet from a public library. With respect to the location of Internet access, findings show that the most access to the Internet happens from home (77%) as well as by mobile (69%). However, there is a cause for concern in terms of access, since almost a third of the sampled population does have access to the Internet through these two means. Moreover, half of the respondents were not very happy with the quality of Internet service in the Appalachian region. Participants also revealed that more people find that the Federal government is not doing enough to provide them with the Internet than they did with the local government.

Table 2 provides a further overview of the Internet skills in terms of information seeking and information sharing, as well as the use of the Internet for health, education, etc. The values of the standard deviation of the Internet access and quality in this study were above 1, meaning that the respondents' answers were widely dispersed. In term of their Internet-related skills, Table 2 showed that the Appalachians in the state of Ohio were more confident in using the Internet to seek information rather than to share it. Moreover, results reveal that the Appalachians in the state of Ohio were using the Internet more for socializing and seeking knowledge rather than accessing public services.

Table 3 reports the four dependent variables and then all of the independent variables in our full models presented in the order they are entered into the regression. The majority of our indicators are ordered integers or binary indicators, ranges indicated in brackets. The final measure is an index of two ordinal indicators of skill at online discussion, with high internal consistency (Cronbach's Alpha = 0.88).

Table 1
Demographic Profile.

	Sample		Hocking	Athens
	N	%	%	%
What is your gender? (Gender)				
Male	84	42.6	49	50
How old are you? (Age) *				
18–24	35	17.8	14.4	26.4
25–34	30	15.2	13.8	22.1
35–44	29	14.7	15.6	12.9
45–54	26	13.2	18.1	12.3
55–64	36	18.3	17.5	12.3
65–74	31	15.7	13.1	9.2
75–84	9	4.6	7.5	4.9
Have you been employed within the last 3 months? [No]				
Unemployed, age 25–64	20	17	4.5	7.1
Select your household income? (Household Income)				
Under $15,000	40	20.3		
$15,001 to $30,000	51	25.9		
$30,001 to $50,000 **	40	20.3	48,073	44,247
$50,001 to $80,000	29	14.7		
$80,001 to $100,000	19	9.6		
$100,001 to $200,000	9	4.6		
Above $200,000	3	1.5		
Not Disclosed	6	3		
What is your highest level of education? (Education Level)				
Did not complete high school	3	1.5	11	10
High School/GED	34	17.3		
Some College	58	29.4		
Bachelor's Degree	57	28.9	14	32
Master's Degree	30	15.2		
Advanced Graduate Work or PhD	11	5.6		
Not Disclosed	4	2		
Please specify your race (Race)				
White	176	89.3	97	84
Black or African American	8	4.1		
Hispanic Latino	6	3		
American Indian or Alaska Native	4	2		
Asian American	1	0.5		
Native Hawaiian or Pacific Islander	2	1		

* Age range percentages are averaged from 2 adjacent census categories due to lack of range correspondance between survey item and census ranges.
** Median household income reported for reference counties, for median row value of sample.

Table 2
Summary of items measuring Internet-related Skills and Internet Use.

	Mean	S.D.
How confident would you be if you were asked to do the following on a computer or smartphone? [1:5] Not at all, Very confident		
Information Seeking:		
Use the Internet to gather information?	4.47	1.12
Learn advanced skills by viewing YouTube tutorial videos?	4.16	1.36
Information Sharing:		
Turning to an online discussion in a forum or writing comments?	3.73	1.44
Make valuable contributions to the online community?	3.50	1.47
How much do you use the internet for these things? [1:5] Never, Very often		
Use of the Internet for:		
News	3.33	1.39
Education	3.23	1.44
Social Networks (Facebook, Twitter or others)	3.38	1.61
Job searching/Employment opportunities	2.22	1.41
Government services	2.12	1.18
Health services	2.21	1.26

Table 4 reports bivariate correlations, range, the mean and standard deviation for all model variables. The first four columns provide preliminary insight into how our model variables predict variation in our four vital use measures: health seeking,

Table 3
Measurement of variables for regression models.

Variable	Measurement
Health seeking	How often do you use the Internet for health services? Never, rarely, sometimes, often, very often; [1:5]
Educational	How often do you use the Internet for education? [1:5]
Job search	How often do you use the Internet for job searching / Employment opportunities? [1:5]
Social media	How often do you use the Internet for social networks? [1:5]
Retirement age (65+)	Selected ago option of 65 and older [0,1]
Age	Age grouped into ranges, 18 to 24 through 75 to 84 [1:8]
Gender identity	What is your Gender? Female, male [0,1]
Employed	Have you been employed within the last three months? [0,1]
Unemployed work age	Unemployed and of work age 25 to 64 [0,1]
Income	Annual household income: Under $15,000; $15,001 to $30,000; $50,001 to $80,000; $80,001 to $100,000; $100,001 to $200,000; Above $200,000 [1:7]
Education level	What is your highest level of education? Did not complete high school; High School/GED; Some College; Bachelor's Degree, Master's Degree, Advanced Graduate work or PhD [1:6]
Family SES	Class categories from Working class to Upper middle [1:4]
Home (internet)	How do you access the internet? From home: Never, Rarely, Sometimes, Often, Very Often [1:5]
Mobile	How do you access the internet? By mobile phone [1:5]
School	How do you access the internet? At school or university campus [1:5]
Community center	How do you access the internet? At community center [1:5]
Work	How do you access the internet? At work [1:5]
Work (work age)	Access at work and of prime work age, (25 to 54 years) [1:5]
Skill find info	How confident if asked to use internet to gather information? [1:5]
Skill learn Youtube	How confident if asked to learn advanced skills by viewing YouTube tutorial videos [1:5]
Skill Com/Discuss	Index of two confidence items: writing comments and making valuable contributions to online community [2:10], Cronbachs alpha = 0.88

Note: brackets indicate range of coded answers.

educational, job search and social media. The use of conditional highlighting draws attention to the central region where demographic attributes demonstrate lower levels of correlation with other model variables. An important insight drawn from this, and reinforced in our analysis is that these attributes intersect in ways that are not linear, and reflect social structural positions of respondents in our sample.

Three clear and important patterns are revealed in the correlation matrix linking demographic attributes and digital involvement. First we see strongly negative relationships between age and most measures of digital involvement, ranging from VIUs, forms of internet access, and digital skills. Second, age is positively related to both SES and income. Third, is a surprising lack of a clear positive relationship between measures of economic advantage (SES and income) and some of the same measures of digital involvement. While SES and income are positively related to both mobile and home access (consistent with much previous literature), the relationship between economic access is positive but less strong with mobile access. This is consistent with the strong negative correlation between frequency of mobile access and age. In combination, these patterns indicate that age and economic advantage are two demographic factors have contradictory influence on digital involvement.

To better explore these dynamics we produced two summary measures; an economic advantage index of [SES + income level] and an index of digital involvement that combines [mobile internet access + skills YouTube + skills communicating/collaborating]. Dividing the sample into older cohorts (55 and over) and younger cohorts (under 35) provides insight into the anomalous failure of economic advantage to drive greater digital involvement. The highly constrained variance in the younger cohorts on both dimensions provides evidence of a demographic transition in the relationship between economic advantage and socially encouraged dimensions of digital involvement (Fig. 3).

Among older cohorts, the standard wisdom that economic advantage leads to greater digital involvement is supported. However, the younger cohorts greatly undermine this link because, based on our measures, their digital involvement is almost universally high, and their economic status is low to moderate.

We model vital uses as resulting from the intersection of demographic attributes and social structure, Internet access, and digital skills. The demographic attributes are operationalized to represent different combinations of needs for particular vital uses, and capacities to use the internet for vital needs. For instance, age can be operationalized as an ordinal variable that represents a potentially increasing demand or need for health information. Age can also be operationalized as an age-based status group (over 65) for whom social media use and job searching are less relevant.

We report both a full and a reduced regression model for each of four dependent variables. For each vital use, the reduced model highlights the factors that proved to be most strongly predictive as well as those that are most relevant for theoretical and empirical reasons. To discover the reduced models we first developed a list of theoretically and empirically relevant predictors (the full models) and then introduced the full list of those potential predictors for each of the four dependent variables in the BMA (Bayesian Model Averaging) package in R (Fragoso et al., 2018). In practice, applying BMA methods results in the discovery of combinations of variables that are common in the best models as well as those that are absent, these patterns can both confirm expectations and generate surprise. Bayesian model averaging (Raftery 1995; Raftery et al., 1997) provides a disciplined solution to the problem of model uncertainty where numerous plausible combinations of variables need to be considered. Our interest is in discovering how

Table 4
Correlations and descriptive statistics for model variables.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Health seeking																					
2	Educational	0.43																				
3	Job search	0.36	0.5																			
4	Social media	0.42	0.49	0.55																		
5	Retirement age (65 +)	−0.1	−0.19	−0.41	−0.33																	
6	Age	0	−0.29	−0.44	−0.38	0.7																
7	Gender identity	−0.1	0.04	0.02	−0.1	0.05	0.03															
8	Employed	0.17	0.15	0.32	0.26	−0.48	−0.36	−0.1														
9	Unemployed work age	−0.2	−0.1	−0.1	−0.1	−0.21	−0.1	0.06	−0.64													
10	Income	0.23	0.14	−0.1	0.07	0.1	0.22	−0	0	−0.12												
11	Education level	0.1	0.13	−0.1	−0.1	0.28	0.38	−0.1	−0.09	−0.13	0.5											
12	Family SES	0.21	−0	−0.1	−0	0.17	0.18	−0	−0.09	−0.01	0.46	0.26										
13	Home (internet)	0.38	0.59	0.31	0.54	−0.06	−0.18	−0.1	0.05	−0.03	0.23	0.2	0.09									
14	Mobile	0.27	0.41	0.46	0.55	−0.4	−0.5	−0.1	0.28	−0.01	0.15	−0.05	0.09	0.43								
15	School	0.1	0.41	0.4	0.26	−0.28	−0.43	0.05	0.14	0.04	0.02	0.02	−0.04	0.2	0.33							
16	Community center	0.24	0.27	0.25	0.2	−0.16	−0.19	0.1	0.14	−0.05	0.08	0.01	0.06	0.18	0.21	0.43						
17	Work	0.31	0.22	0.32	0.34	−0.41	−0.3	−0.1	0.53	−0.27	0.18	0.08	0.07	0.25	0.41	0.2	0.26					
18	Work (prime work age)	0.15	0.17	0.3	0.24	−0.38	−0.29	−0	0.37	−0.16	0.15	0.15	0.02	0.17	0.29	0.1	0.19	0.68				
19	Skill find info	0.2	0.21	0.19	0.31	−0.3	−0.35	−0.1	0.23	0	0.07	−0.07	0.09	0.26	0.41	0.12	0	0.21	0.18			
20	Skill learn Youtube	0.25	0.32	0.29	0.34	−0.36	−0.42	−0.1	0.32	−0.09	0.07	−0.01	0.07	0.3	0.45	0.15	0.09	0.3	0.27	0.73		
21	Skill Com/Discuss	0.3	0.31	0.37	0.47	−0.47	−0.5	−0.1	0.31	−0.03	0.11	−0.05	0.12	0.34	0.56	0.15	0.18	0.4	0.32	0.6	0.74	
	Min	1	1	1	1	0	1	1	0	0	1	1	1	1	1	1	1	1	0	1	1	2
	Mean	2.21	3.23	2.29	3.38	0.2	4.63	1.43	0.71	0.14	2.89	3.58	2.24	3.83	3.57	1.96	1.32	2.69	1.53	4.47	4.16	7.23
	SD	1.27	1.44	1.33	1.61	0.4	1.88	0.5	0.45	0.35	1.55	1.17	0.98	1.55	1.7	1.4	0.91	1.73	2.05	1.12	1.36	2.75
	Max	5	5	5	5	1	8	2	1	1	7	6	4	5	5	5	5	5	5	5	5	10

Note: N = 198 all correlations > 0.14 are significant at the 0.05 level or better for non directional tests.

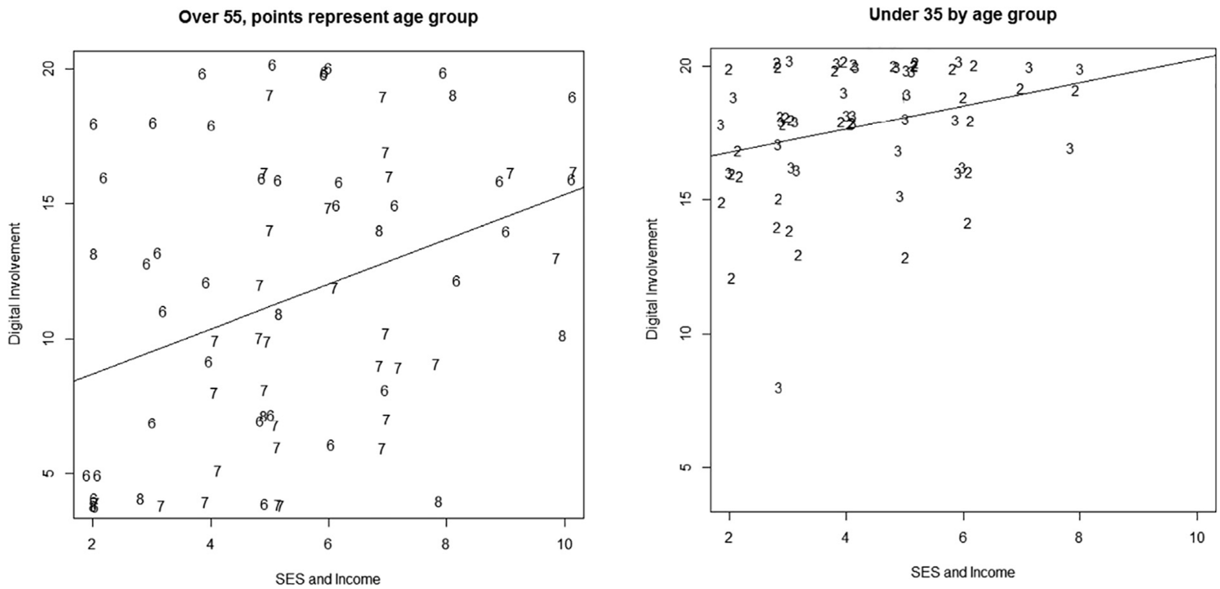

Fig. 3. (a and b): Compared to older cohorts younger adults in our sample report high mobile internet involvement but low income and low SES.

different dimensions of context and access better explain alternative vital uses. The full models provide grounds for comparing more directly across the four vital uses, and for assessing how much the more parsimonious models can (or cannot) maintain the predictive power of the full model.

Because our sample drew primarily from Athens county we employed weighted least squares to help offset deviations between our sample and that of the wider South East Ohio region. Athens county exemplifies some of the key attributes of the SE Ohio Appalachian area: high poverty rates, geographic isolation, rurality and the absence of a large metropolitan area. However, it differs demographically in important ways from the less populous counties like Vinton, Meigs, and Hocking due to the presence of Ohio University. We have used the attributes of Hocking county as a source of target values for demographic attributes of age, education, and income while also reducing influence of cases sampled from Athens County (see Appendix 1 for details). The resulting combined weight term reduces the influence of cases whose attribute levels are typical of Athens County residents and increases the influence of cases similar to those of Hocking county residents. The weight (range: 0.4 to 2.5) is balanced between the goals of increasing representativeness while avoiding extreme design effects and over-inflation of standard errors that are especially problematic with moderate samples sizes.

Table 5 presents models predicting the use of the Internet for health and educational reasons. Analysis of health uses reveals an interesting contrast to the moderate bivariate correlation (0.21) of Table 3. Here family socio-economic status is not significant in both the full and reduced models. This suggests that, although people with higher SES may be using the internet to search for health information, this advantage in the digital divide can be explained through differences of age and improved internet access at home and at work. Community center internet access is a positive (0.21, < 0.05) predictor for health and this could indicate a couple of different interpretations. First, the people who access the Internet at the community center might have additional need/awareness of health uses of the internet; or, access at the community center might be an important entry point to the Internet for those with the need of this vital use.

None of the digital skills are significant in the full model for health. However, because the digital skill indicators are strongly correlated with each other we explored numerous alternative models, including and excluding these measures in different combinations. Of these, the strongest evidence for the possible impact of digital skills on health-related vital uses stems from the more collaborative skills of commenting and discussing which are significant at the 0.05 level in the reduced model.

Assessing fit for our models predicting health-related vital uses we find that the only significant predictors are age, family SES, discussion skills, and accessing from home, community center, and work. These are all positive, and the overall model fit is modest (0.23 adjusted R-square) which suggests that measured variables are missing some important impediments to involvement in this vital use. We note that SES is positive and significant for the prediction of health related vital uses. This makes sense especially because in our sample, our health VIU and SES are positively related to age. Older adults are likely to have more need for health information and thus are likely to search more often for that information. Finally, the superiority of the adjusted R-square for the reduced model (0.26 vs 0.24) suggests that several full model variables are extraneous and the variables in the reduced model provides a better grounds for understanding differences in this vital use.

Our model variables offer a substantially better basis for understanding differences in education vital uses, explaining almost half of the variation in our sample. Respondents of retirement age were not surprisingly found to be less involved in educational uses, either for themselves or as caregivers. Women were more involved, as are those who are unemployed but not of prime work ages. Internet and school provided the most important access mean for this vital use, and among our skill areas, the most closely associated

Table 5
Pooled Weighted Least Squares regression coefficients predicting health and education uses.

Model	Health		Education	
	Full	Reduced	Full	Reduced
Variable				
Intercept	−0.78	−0.85	0.87	0.63
Background				
Retirement age (65 +)	−0.39		−0.59	−0.7
Age	0.13	0.12*	−0.03	
Gender identity	0.01		0.34	0.38*
Employed	−0.26		−0.43	−0.59
Unemployed (work age)	−0.47		−0.78	−0.93
Income	0.08		0.06	
Education level	−0.02		0.1	
Family SES	0.14	0.18*	−0.15	
Internet access				
Home	0.19**	0.23***	0.46***	0.51***
Mobile	0.06		0.11	
School	0.01		0.22**	0.27***
Community center	0.26*	0.26**	0.08	
Work	0.13	0.11*	−0.07	
Work (work age)	−0.06		0	
Skills				
Finding information	0.07		−0.15	
Learn from Youtube	0		0.14	0.07
Comment/Discuss	0.05	0.08*	−0.01	
Adjusted R^2	0.24	0.26	0.46	0.46
R^2	0.31	0.29	0.51	0.48

Note: N = 198; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; $p < 0.10$.

Table 6
Pooled Weighted Least Squares regression coefficients predicting job searching and social media use.

Model	Job Searching		Social Media	
	Full	Reduced	Full	Reduced
Variable				
Intercept	0.76	1.18**	1.79*	1.16**
Background				
Retirement age (65+)	−0.7	−0.65*	−0.58	
Age	0.03		0.03	
Gender identity	0.14		−0.13	
Employed	0.13		−0.05	
Unemployed (work age)	−0.37	−0.38	−0.51	−0.4
Income	−0.06	−0.06	0.05	
Education level	−0.02		−0.18	−0.16
Family SES	0.01		−0.12	−0.11
Internet access				
Home	0.15*	0.14*	0.37***	0.37***
Mobile	0.18**	0.16*	0.31***	0.33***
School	0.24***	0.24***	0.03	
Community center	0.04		0.04	
Work	−0.09		0.02	
Work (work age)	0.07	0.03	−0.01	
Skills				
Finding information	−0.11	−0.12	−0.04	
Learn from Youtube	−0.01		−0.15	
Comment/Discuss	0.06	0.06	0.1	0.07
Adjusted R^2	0.3	0.32	0.44	0.45
R^2	0.36	0.35	0.49	0.47

Note: N = 198; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; $p < 0.10$.

is using YouTube for learning, though this result only nears marginal significance. Dropping the least significant predictors between the full and reduced models increases the significance levels on most of the key predictors while maintaining the same high level of adjusted model fit (0.46).

Table 6 reports pooled weighted OLS regression models for job searching and social media vital uses. The reduced model for job searching controls for retirement age since these respondents are less likely to be in need of jobs. Interestingly we find that those who are unemployed and of work age are less likely to use internet access to aid their job searching. A couple of possible explanations warrant discussion. First, it may be the case that potential workers who are unemployed but are under-utilizing the internet in job searching are not job-seeking (students for instance). Alternatively, this finding may suggest that residents in Appalachia may need better training in how to use the internet in their job search, or it could also indicate that Internet job search systems are not relevant to the types of work available to these unemployed citizens in Appalachia. A qualitative investigation may be needed to discern between these.

The finding that school access is the clearest predictor of job searching using internet tools reinforces the explanation that some of the respondents have the cultural capital to use the internet resources for their job search (via their school access) but others may either lack the digital skills or the opportunity structure to access the types of jobs available through those means.

Frequency of social media use is well predicted (adjusted R-square 0.46), though with only four predictors showing significance in the reduced model. Education level is negative and modestly significant at the 0.05 level. Frequency of social media use is unrelated to unemployment and family SES, which suggests that controlling for SES and employment reveals a slight tendency for the less educated to use social media more. The major explanations for higher use rates of social media are driven by the home and mobile access. To the extent that dimensions of the digital divide contribute barriers to social media use these are explained by how those resources enable these types of individually expensive access. Commenting and discussing online are clearly and positively related to social media uses, which is unsurprising since these activities are central to the use of social media platforms.

Social media use in itself might not be considered a vital use and is often maligned as a distraction or trivial use (Carr, 2011). However, the development of communication and self-presentation skills as well as developing social capital are important dimensions that can result from social media use. Exercising the strength of weak ties through informal interaction can bring unexpected benefits, and can incentivize digital skills that lead to pragmatic digital literacies.

6. Discussion

Our study describes important dimensions of digital inequality in Appalachian Ohio. In terms of Internet access, it is important to note that 23% of the respondents do not have Internet at home and that is still a high percentage of people without proper Internet access. This may be the reason why individuals are using public libraries to access their Internet and computer services, as this study has confirmed by showing that 52% of the participants were using these public facilities to bridge their home Internet gap. Moreover, the fact that the overall quality of Internet was rated as average and below by half of the respondents demonstrates that there is room for improvement in terms of quality, as well as in terms of accessibility. Both the local and the federal government need to help bridge the digital gap by making good quality Internet affordable and accessible.

Rahman and Monahan (2014) highlighted how poverty affects the Appalachian regions, looking at lower wages, higher employment rates, and low educational attainment as compared to the rest of the country. These findings show how there is an important gap in accessing educational or informational content on their private premises that drives individuals without the Internet into public libraries and facilities.

Our first question inquired about the demographic factors that predict VIU. Although most of the background factors were not predictive of VIU factors, our regression analyses did reveal that health outcomes are significantly predicted by age. This is understandable since older age individuals are more likely to look for health-related information via the Internet. In addition, gender identity, was significant in predicting education as a VIU.

Substantial research on digital inequality (Robinson et al., 2015) anticipates that economic advantage should be clearly and positively related to digital access and even digital skills, but not necessary frequency of VIUs. We did find that SES was positively related to frequency of health related VIUs and we attribute this the fact that age would reinforce both of these: older adults would have more need for health information, and older adults tended to be of higher SES, which in turn reduces barriers to frequent health VIUs.

It is important to recognize that not all uses of the digital systems are equally important to all users. Younger adults may use social media constantly, while older adults may use it far less frequently while not being restricted by imposed barriers to that use. It is also important to recognize that different uses may have different underlying base rates of use. People who are happy in their job do not need to frequently search for jobs, and people in good health may seldom search for health information. People in school or with kids that they help with their school will need to interact digitally and in person with educational systems far more frequently than others.

Even with these observations we recognize that the literature and our own expectations led us to expect lingering effects of economic advantage to shape not just home and mobile access, but all of the uses as well. With the exception of health VIU's our regression models did not support this expectation. Reflecting on this negative finding caused us to explore cohort effects on the relationship between economic advantage and digital involvement in general. We found that economic advantage did correlate with greater digital involvement among older cohorts. However, younger cohorts revealed not only a weaker relationship but strongly constrained variation in both dimensions. We suspect that this may be indicative of two historical transitions that are highlighted by the Appalachian social context. Compared to earlier generations, younger adult cohorts today face relatively depressed economic prospects (Matsudaira, 2016). The reality of reduced economic well-being and opportunity is even worse in rural Appalachia (Ziliak, 2019). Not many jobs in rural SE Ohio pay well, and those that do are not as accessible to younger cohorts. SE Ohio is part of the North Central Region of Appalachia where poverty rates among younger cohorts are higher than they are among older cohorts. Second, for younger cohorts there are strong and growing social/cultural pressures to be digitally involved, and the primary pathway for digital involvement is now the cell phone. Because their peers are more involved, younger cohorts experience strong network externalities (Katz and Shapiro, 1986) that make involvement valuable. These same network effects are absent or even negative for some of the members of older generations whose peers may not be online at all. We suggest that these historical trends represent a demographic transition that should enrich our understanding of how digital involvement is shaped by both economic and social values.

The second research question explored how variation in types of internet access may be related to VIU factors. Internet access especially from home was strongly predictive of health, education, job searching, and social media VIU factors. This finding highlights the importance of home internet access as an important factors that enables effective internet use. While accessing internet from places outside the home could prove beneficial, having home internet access provides a higher level of convenience and comfort where a user is not constrained by time (Khan et al., 2014). Our regression analyses also revealed that besides home internet access, internet access from community center and work was predictive of health VIU. Community centers, workplaces, and libraries provide additional opportunities to explore health-related information. For education VIU, in addition to home, internet access from school was a strong predictor of internet use.

Mobile internet use has considerably gained prominence. According to PEW research, by 2016, 88% of Americans used the internet, 77% owned a smartphone, and about 69% of them used social media (Smith, 2017). Our analysis reveals that job searching and social media use as a VIU is predicted by mobile Internet access. Looking at these numbers together, it can be argued that internet access matters. Most importantly, quality internet from home and via mobile options are even more important for the Appalachian region as distance from libraries and community centers leaves fewer options to tap into health, education, employment and social media use.

Our third research question investigated how digital skills may impact VIU. Bivariate correlations showed moderate to strong positive relationships between digital skills and VIU. However, our regression analysis suggested that the potential impacts of skills were usually better explained by variation in access, primarily though home, school and mobile. The more social of the digital skills retained some explanatory power in the reduced models for two of our important uses. In terms of skills, individuals who commented and engaged in an online discussion were more likely to search for health-related information, and use social media (which in turn could make possible a range of other social affordances including commerce, interaction, connection with the local community, leisure etc.). This finding is supported by past research by Khan et al. (2014), according to which, information seeking and sharing (in the form of comments) is predictive of online education and academic collaboration. We anticipate that evidence for the importance of skills would be stronger and more extensive if skills were measured directly as Hargittai and Shafer (2006) suggest, rather than through subjective self-report.

Estacio et al. (2017) pointed out that the importance of digital inclusion by noting, "it is important that widening Internet access is coupled with the provision of digital skills development to enable individuals to utilize digital technology more effectively" (p.7). Looking at the fact that there are efforts done to reach marginalized and hard-to-reach communities, there need to be health literacy checks that enable individuals to access the Internet for health-related purposes. Van Deursen and Helsper (2017) emphasized the importance of interventions aimed at skills training to overcome the digital divide. Their findings suggested that "what people do online and the skills they have are more important than who they are when it comes to inequalities in outcomes of Internet use" (Van Deursen and Helsper, 2017, p.12).

All these findings have a common theme: the need for having home Internet access and possessing information skills that help individuals to be active Internet users who participate in online discussions. A study by Khan (2017) highlighted the importance of active engagement in the form of liking, commenting, and sharing on social media.

It is also important to notice that even though entertainment was the least of uses, it is still a high 52%, which means the participants find in the public libraries and facilities a space for leisure they could otherwise have at home. Alternatively, it may also be possible that libraries may limit use of their facilities for leisure-related activities on the internet. Therefore, leisure activities via smartphones and home internet gain more importance. Leisure is an important component of human life since it leads to reflection and creation, enriches and promotes sociality in today's online environment. This item should not be overlooked. A study done by Hassani (2006) points out that people who have Internet service at home, work, or other places are more likely to access health information, employment opportunities, banking information, and online shopping than people who have it at one place only. This implies that the amount of Internet access points affects people's connection to such important services as health, banking, employment, and shopping. The results of the current study may indirectly support this assertion.

7. Conclusion

This research revealed that there is a digital divide in Appalachian Ohio (Southeast Ohio region). Even though there is a high percentage of individuals who have Internet at home (77%), the percentage of individuals without Internet is still high (23%) for a developed country like the U.S. The study also shows that half of the participants have either an average or below average Internet quality and reliability. This is an indication that there is still much to do in this region in terms of quality of the Internet especially at home. The main reasons stated by participants who do not have Internet for not adopting the service were that they found it "too expensive", that they do not need it much, and that the service is "not available in their area". This shows an economic gap, and infrastructure gap and a development gap for people in this area.

Regarding public libraries, a strong relationship was found between not having access to the Internet at home and approaching libraries to access the Internet. The findings confirm that these public facilities are bridging the Internet access and quality gap. More than half of the participants revealed using them for their Internet activities. Although half of them felt confident about their digital skills, the other half rated themselves as not at all skilled, not very skilled, and fairly skilled. Pointing into an important digital competence gap to be still be addressed by the local and federal government to increase the computer and Internet skills of citizens in Appalachian Ohio.

Data gathered through this research contributes to helping better understand the implications of 21st century digital divide in the U.S., and can be used by public and private institutions to better supply their services to the still unconnected of America. While this paper aimed to provide an in-depth study on the digital access divide in Southeast Ohio, several limitations were encountered. Due to logistical capabilities, the study focused on several Appalachian counties in Southeast Ohio and could not cover all Appalachian areas in the US that are also experiencing the Internet divide. Furthermore, this paper focused on patrons of libraries, farmer‘s markets, and the Community Center leaving out people who do not visit those places. Also, future studies can be conducted including a qualitative component to further analyze and understand Internet access in the Appalachian region.

7.1. Limitations and future research

Through an analysis of demographics, internet access, and skills, this study has provided a useful and innovate way to understand the contributing factors to the Vital Information Use (VIU) framework. We contend that four vital uses can determine citizens' political and civic participation, societal contribution, and overall benefit to their communities. These VIU factors comprise health, education, job search, and social media use.

Despite these important contributions, there are certain limitations of this study that are worth mentioning. Like all survey-based research, our data is based on self-reported information. Self-reported survey responses can present validity issues. Future studies can employ more novel research measures including internet use data from smartphones and computer terminals at the libraries. Nevertheless, self-reported survey measures provide a vital basis to study VIU to determine citizens' political and civic participation, societal contribution, and overall benefit to their communities. Without any notable empirical research in the selected region, our study provides a much needed foundation to further rexplore these issues.

Another limitation is that our sample size could have been larger. The small sample size makes it harder to distinguish real effects and diminishes statistical power and real effects cannot be clearly observed. Although, we are able to clearly see the types of access but some other important demographic attributes are not strong enough to be observed clearly. A large sample size is always preferable and future studies can be based on a large pool of participants. However, we were encouraged by the fact that there were clear evidence of effects as we found significant results from several of our predictors in the model. We remain cautiously optimistic that future studies can also incorporate more comprehensive measures of Internet skills. That said, this research does open further avenues for future digital divide studies in the in terms of access, skills, and effective internet use especially from a VIU perspective.

Future work can also build upon this research to expand the focus to more Appalachian regions that are economically deprived. Moreover, additional determinants of VIU can be explored to expand the model in light of other theoretical constructs. Additionally, researchers can measure both impediments and incentives for connectivity. In other words, they can measure both sources of barriers (including quality of Internet) and reasons for demanding or needing to do more with digital systems for fulfilling VIUs.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Weighting process for age, education, income, and county

1. Age

Age groups	Sample %	Weight	Weighted percent	Target Percent
18–24	17.8	0.805	14.329	14.375
25–34	15.2	0.905	13.756	13.75
35–44	14.7	1.064	15.6408	15.625
45–54	13.2	1.375	18.15	18.125
55–64	18.3	0.95	17.385	17.5
65–74	15.7	0.8378	13.15346	13.125
75–84	4.6	1.64	7.544	7.5

2. Education: Compared to other counties in our region our sample under represented low levels of education and over represented high levels.

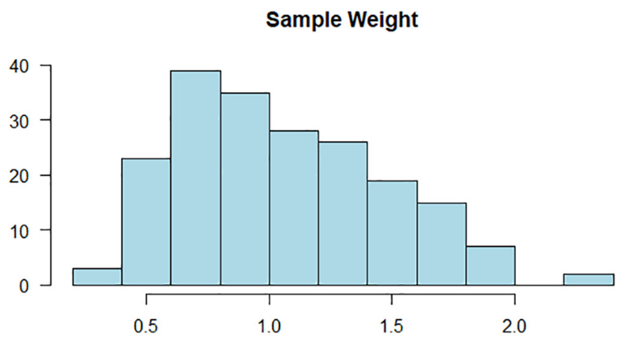
	Sample %	Weight	Sample × Weight	Standardized Weighted percent
Did not complete high school	1.5	2	3	2.40%
High School/GED	17.3	2	34.6	27.72%
Some College	29.4	1.5	44.1	35.34%
Bachelor's Degree	28.9	1	28.9	23.16%
Master's Degree	15.2	0.75	11.4	9.13%
Advanced Graduate Work or PhD	5.6	0.5	2.8	2.24%

3. Income: we were not able to obtain income data for the same categories as our data was collected in. However, it is clear that even compared to more general measures from Hocking County and from the SE Ohio region our sample slightly over represented low income levels and underrepresented higher income levels.

	Sample %	Weight	Sample × Weight	Standardized Weighted percent
Under $15,000	20.3	0.82	16.65	17.23%
$15,001 to $30,000	25.9	0.9	23.31	24.12%
$30,001 to $50,000**	20.3	1	20.30	21.01%
$50,001 to $80,000	14.7	1.1	16.17	16.73%
$80,001 to $100,000	9.6	1.2	11.52	11.92%
$100,001 to $200,000	4.6	1.4	6.44	6.66%
Above $200,000	1.5	1.5	2.25	2.33%

As discussed above, we further reduced the influence of the Athens cases by applying a weight of 0.8 to the Athens subsample. This combined with the weights above results in a weight factor that increases the weight of cases with attributes that were under-represented in our sample, but also does not result in a total weight that greatly deviates to far from the range between 0.5 and 2, as suggested by [find the author who made this suggestion].

4. County: Athens 0.8 All other counties 1



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