U.S. PIAAC
Program for the International Assessment of Adult Competencies

Commissioned Paper
February 2015

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Author:
Stephen Reder

Suggested Citation: Reder, S. (2015). *Digital Inclusion and Digital Literacy in the United States: A Portrait from PIAAC's Survey of Adult Skills*. Retrieved [insert date], from [insert website].

This project has been funded by the American Institutes for Research through a contract with the National Center for Education Statistics (NCES) of the U.S. Department of Education. This report is based on PIAAC data released in October 2013. The views expressed in this paper do not necessarily reflect the views or policies of the American Institutes for Research, National Center for Education Statistics, or the U.S. Department of Education, nor does mention of trade names, commercial products, or organizations imply endorsement of same by the U.S. Government.

AIR-PIAAC Contact:

Jaleh Soroui (AIR-PIAAC Director)
Saida Mamedova (Senior Research Analyst)
PIAACgateway.com
piaac@air.org

Author Contact:

Portland State University. Portland, OR.
Stephen Reder at reders@pdx.edu

Digital Inclusion and Digital Literacy in the United States:

A Portrait from PIAAC's Survey of Adult Skills

Stephen Reder
Literacy, Language and Technology Research Group
Department of Applied Linguistics
Portland State University
reders@pdx.edu

Acknowledgements

This paper has been commissioned by the American Institutes for Research, funded through a contract with the National Center for Education Statistics (NCES). The author would like to thank David Rosen and six anonymous reviewers for their helpful comments on draft versions of the paper. Errors that remain are the author's.

Abstract

This paper uses U.S. data from the Survey of Adult Skills (otherwise known as PIAAC) to explore a digital inclusion pathway leading from digital access to digital literacy. The pathway consists of four observable stages in the data: Digital Access, Digital Taste, Digital Readiness, and Digital Literacy. In looking at this inclusion, particular attention is paid to two sets of issues, digital equity and digital embedding. Digital equity is defined in terms of differences in groups' distribution in these pathway stages after accounting for differences due to other variables such as age, education and employment status. Digital equity is examined with regard to gender, race/ethnicity, and national origin. The analyses show systematic digital inequities tied to each of these characteristics.

The digital embedding of an economic or social outcome is defined as a specific pattern of association between that outcome and an index of ICT use at work or outside of work after statistically controlling for differences due to demographic characteristics, educational attainment and assessed proficiency. The digital embedding of six economic and social outcomes is examined: earnings, employment, social trust, volunteerism, political efficacy and general health. The paper finds digital embedding of earnings among workers but no digital embedding of current employment status among the general adult population. There is digital embedding of all four social outcomes examined among the general adult population. Implications of these findings for digital literacy policy and programs and future research are discussed.

Introduction

Amidst a constantly changing array of information and communication technologies (ICT) numerous concepts and statistics have emerged about the digital divide, digital literacy, digital inclusion, and digital equity. Research based on large national and international surveys of technology use and technology users can provide important information and perspective on these issues. International surveys conducted by the Organization for Economic Cooperation and Development (OECD) over the last two decades have provided valuable information to policymakers and rich data sets for researchers to investigate a range of economic, social and educational issues. OECD's surveys of adult populations, starting with the International Adult Literacy Survey (IALS) and continuing with the Adult Literacy and Lifeskills (ALL) survey and most recently with the Survey of Adult Skills (SAS) have profiled the distribution of cognitive and information processing skills within and between participating countries.[1]

The 2012 SAS survey, like its predecessors, included assessments of adults' literacy and numeracy proficiencies. The first international report of SAS results made a strong case that these proficiencies and everyday uses of reading, writing, and numeracy skills are of great economic importance to countries participating in the SAS (OECD, 2013a). The SAS results deepen and broaden previous research that showed that proficiencies and skill uses interact in adult learning and development over time (Reder, 2012, 2009) and combine to drive economic productivity (Desjardins & Rubenson, 2011).

The SAS introduced a number of important innovations in large-scale international adult surveys: the systematic measurement of skill uses in work and nonwork settings; conducting assessments by computer; and the assessment of a new proficiency, problem-solving in technology rich environments (PSTRE). This paper will utilize these innovations to look at two important issues in the United States related to digital inclusion and digital literacy. One issue is *digital equity* with respect to race/ethnicity, gender and national origin. The SAS data enable us to examine digital equity as part of a digital inclusion process measured in SAS. The paper will also look at *digital embedding*, defined as a particular form of statistical associations between uses of ICT at work (or uses of ICT outside of work) and specific economic and social outcome measures. Strong and persistent associations between the uses of ICT and these economic and social indicators motivates a policy focus on equity in the use of those digital technologies.

From the Digital Divide to Digital Inclusion

The PSTRE assessment in SAS follows research showing a changing mix of tasks and skills involved in specific occupations and industries over time, with increasing proportions of jobs requiring relatively non-routine cognitive skills (Autor, Levy & Murnane, 2003; Green, 2013; Levy & Murnane, 2013; Spitz-Oener, 2006). These trends imply that a growing proportion of the workforce will encounter work situations that pose unforeseen problems that they need to resolve. This increasing demand for problem-solving skills is accompanied by another trend, the growing adoption and use of ICT in workplaces and throughout societies (OECD, 2013a). For the United States, comprehensive data about the use of computers, smartphones and internet are provided by surveys such as those reported in the *National Broadband Plan* (Federal Communications Commission, 2010) and by the Current Population Survey in *Exploring the Digital Nation* (U.S. Department of Commerce, 2013), and in many publications of the Pew Research Center's *Internet & American Life Project* (http://www.pewinternet.org; Zickuhr & Smith, 2013, 2012). These surveys show increasing adoption and use of internet and computers, smartphones and other devices across American society but indicate that adoption and use of many ICTs lags well behind in traditionally vulnerable groups including Blacks, Hispanics, immigrants, residents of low-income households and rural communities, the elderly, and adults with disabilities.

As ICT adoption proceeds, what once was characterized as a monolithic *digital divide* is better understood in terms of *digital inclusion* of individuals with emerging technologies and applications (DiMaggio, Hargittai, Celeste & Shafer, 2004; Livingston & Helsper, 2007). This is a widespread problem in the U.S. where about 100 million Americans do not have a broadband connection to the internet (Institute for Museum and Library Services et al, 2011). Policymakers have emphasized the high individual and societal costs of such digital exclusion (FCC, 2010; U.S. Department of Commerce, 2013) and economic cases have been developed for expanding *digital inclusion* at the local and national levels, initiatives that analysts argue will lead to improved outcomes in education and employment, health and wellbeing, civic engagement, and consumer behavior (FCC, 2010; IMLS, 2011; U.S. Dept. of Commerce, 2013). Research has also linked increased digital inclusion with the broader goals of reducing social disadvantage and increasing economic equity (Helsper, 2008).

Digital inclusion has been defined in a variety of ways. One widely used definition appeared in the *Building Digitally Inclusive Communities* framework:

> "Digital inclusion is the ability of individuals and groups to access and use information and communication technologies. Digital inclusion encompasses not only access to Internet but also the availability of hardware and software; relevant content and services; and training for the digital literacy skills required for effective use of information and communication technologies." (IMLS et al, 2011: 1)

As communities across the country become more aware of the importance of digital inclusion, we may expect towns, cities and perhaps even states to address the policy issues involved. For example, an early innovator is Portland, Oregon, which is currently seeking to make digital inclusion part of the overall City Plan (Office of Community Technology, 2015). Part of Portland's strategic plan for digital inclusion involves the measurement and monitoring of digital equity, seen as equal access to digital technologies for groups based on race/ethnicity, gender, national origin and other characteristics.

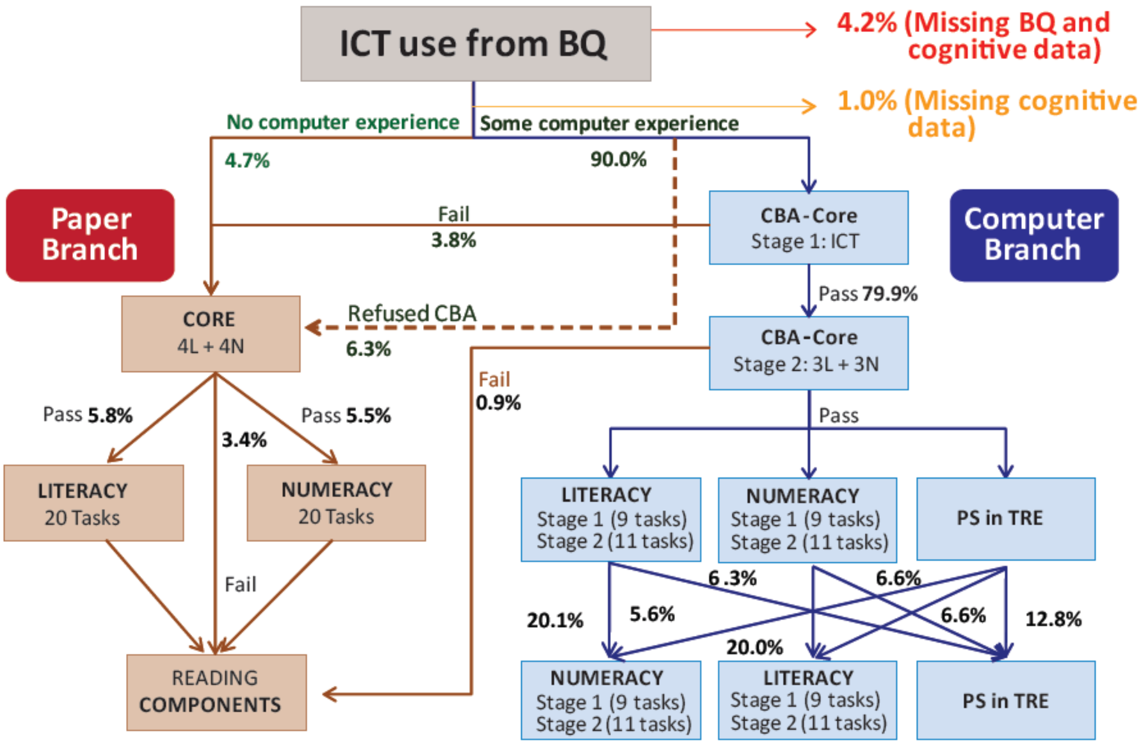
Previous research on digital inclusion has distinguished individuals' diverse ways and motivations for engaging with various ICT technologies. Livingston and Helsper (2007) conceived of digital inclusion as a graduated process of engagement with technologies and their uses. Helsper (2008) conceptualized digital engagement in three steps: basic, intermediate and advanced levels of engagement. She identified three major types of digital engagement according to the motivations involved: basic, social and economic engagement. The FCC's (2010) study of broadband technology users and nonusers identified three major barriers to adoption: lack of affordability, lack of perceived relevance, and lack of basic digital literacy skills. The Colorado State Library (2012), in a broad review of research, conceptualized digital literacy as three continua: interest and engagement; content and information literacy; and technical ability. Jacobs, Castek, Pizzolato, Withers and Pendell (2015) are investigating the learning pathways of new computer users in diverse adult populations and report a rich diversity of motivations for and stages of learning to use computer technologies. Horrigan (2013) has focused on "digital readiness", which he defined as the combination of trust in and skills needed to use powerful new applications in health care, education, commerce and government service delivery. Analyzing answers on a national survey of internet usage and attitudes, Horrigan estimates that 29% of American adults have low levels of digital readiness, including 18% of individuals who have advanced broadband access to the internet (Horrigan, 2013). He estimates that about as many adults are not "digitally ready" as are not connected to the internet.

There are clearly many approaches to conceptualizing and measuring digital inclusion and digital equity. They encompass considerations of hardware access, the perceived relevance of ICT to individual needs, as well as attitudes towards and abilities to use ICTs and advanced applications. Issues of digital equity, once relatively straightforward to define in relation to hardware and infrastructure access, have become more complex and are in need of further research (Helsper, 2008). Individuals need not only the basic skills to use ICTs but also the ability to solve everyday problems encountered in the technology-rich environments in workplaces and other settings. The PSTRE assessment and measurement of ICT uses in SAS offers new ways to understand these issues.

Equity in a Digital Inclusion Pathway

Although SAS was designed to assess the literacy and numeracy proficiencies of all respondents, it assessed the PSTRE proficiencies of only those respondents who were given the computer-based assessment (CBA) rather than the alternative paper-based assessment (PBA). A combination of factors determined whether respondents received the CBA or the PBA. Respondents were asked in the background questionnaire whether they had ever used a computer. After the background questionnaire was administered, those who indicated they had never used a computer were automatically routed to the PBA. Those who indicated they had previously used a computer were asked, at the conclusion of the background questionnaire, if they were willing to take the computer-based assessment. Those who declined were routed to the PBA. Those who agreed to take the CBA were given a core ICT screener on a computer to determine if they had the basic computer skills (e.g., mouse and keyboard) needed for the CBA. Those who failed the screener or a second literacy/numeracy screener were routed to the PBA, whereas those who passed both screeners received the CBA including the PSTRE. Figure 1 displays in flowchart format these various pathways that routed respondents to the PBA or to the CBA (that included the PSTRE) along with the estimated percentages of the population following these pathways.

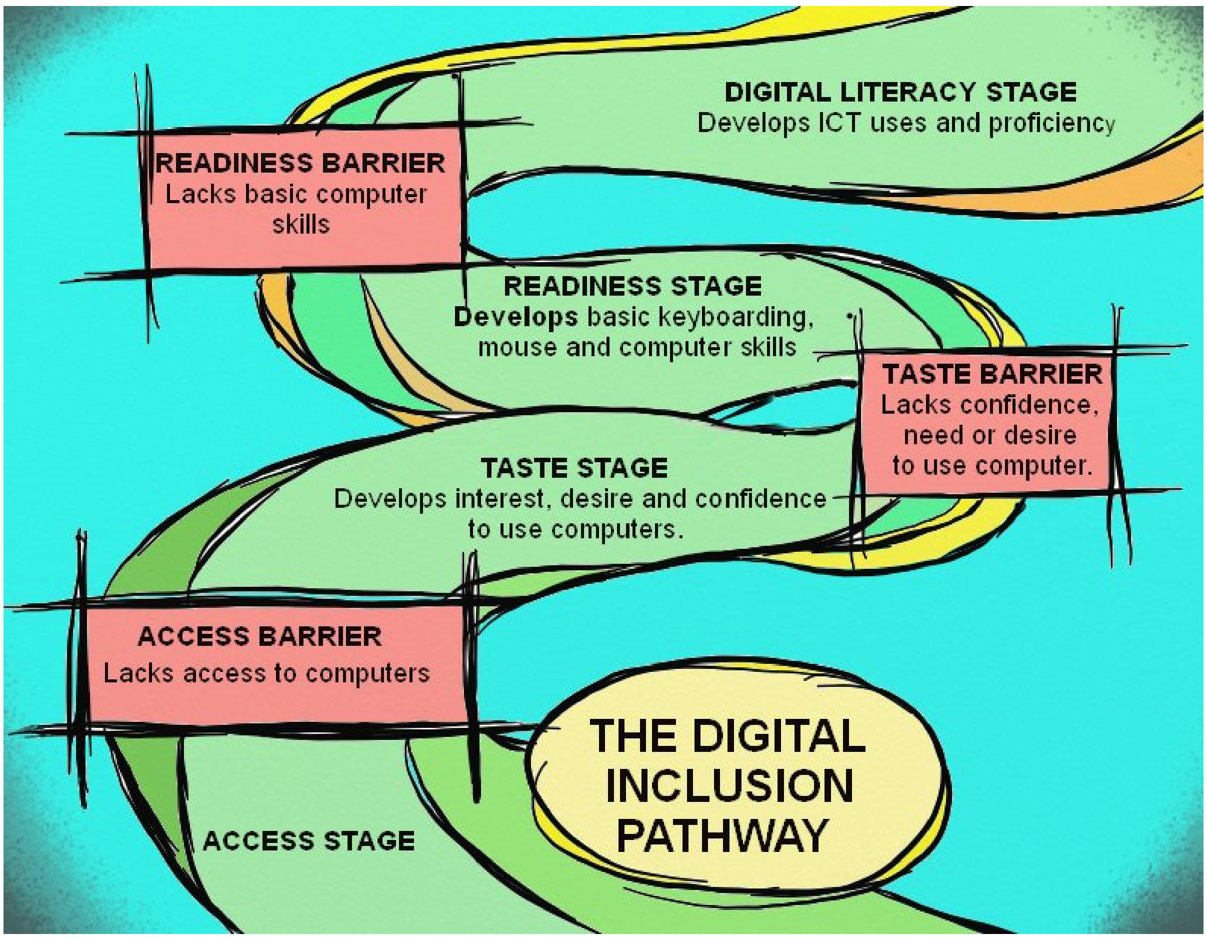
Figure 1. Assessment routing pathways in the Survey of Adult Skills. Numbers shown are U.S. population-weighted percentages following each pathway. Excerpted from p. 5 of: Goodman, M., Finnegan, R., Mohadjer, L., Krenzke, T., and Hogan, J. (2013). *Literacy, Numeracy, and Problem Solving in Technology-Rich Environments Among U.S. Adults: Results from the Program for the International Assessment of Adult Competencies 2012: First Look* (NCES 2014-008). Washington, DC: U.S. Department of Education, National Center for Education Statistics.



It is important to understand this routing process not only because it generated the observed pattern of missing PSTRE data but because its operation reflects substantively important aspects of a digital inclusion process. Seeing this administrative routing process as a model system of digital inclusion allows us to place PSTRE performance in a broader context of individual characteristics and behaviors that lead to (non)engagement in digital activities. There are four stages in this particular *digital inclusion pathway*. Individuals who have never used a computer are in the first stage, termed *Digital Access*. Individuals who have used computers are in the second stage called *Digital Taste*, in which they decide whether they want to use a computer for particular purposes. "Taste" is used here as the sociological concept of an individual's personal and cultural patterns of preference and choice in ways of doing things.

Individuals who have used computers and have taste for using them for certain tasks may lack the basic ICT skills needed to effectively use the technology for the particular task. Those lacking the basic technology skills are in the third or *Digital Readiness* stage, not yet "ready" to use the technology.[2] Individuals who have used computers and have taste and readiness for using them are in the final stage, called the *Digital Literacy* stage, in which they systematically develop their uses of ICT and proficiency in solving problems with it. Notice each stage has its own barrier that must be overcome to move forward in the pathway: In Digital Access, the barrier is initial use of a computer; in Digital Taste, the barrier is a lack of confidence, perceived relevance or desire to use computers and ICT; in Digital Readiness, the barrier is the basic skills for using computers and ICT, such as mouse and keyboarding skills. Individuals in the Digital Literacy stage are not necessarily digitally literate in terms of specific criteria often associated with that terminology, they are just involved in developing their ICTs and proficiencies in problem-solving with them.

Figure 2. The Digital Inclusion Pathway.



This digital inclusion pathway is diagrammed in Figure 2.[3] There are many nuances of digital inclusion processes in everyday settings that may not be well represented by the sequential pathway shown in the figure. For example, one's taste for using a technology could follow or partially depend upon having sufficient readiness to use it. Another counterexample: I have no "taste" for playing video games although I am "ready" (i.e., possess the basic computer skills) to do so; thus I am "ready" but lack "taste" for it. These and other examples indicate that the sequential digital inclusion pathway analyzed here is but one of several possible pathway structures, one that reflects the pathway generated by the SAS routing and is observable in the SAS data. We will accordingly analyze race/ethnicity, gender and national origin equity at each stage of the digital inclusion pathway leading from Digital Access to Digital Literacy.

In this paper, *digital equity* for groups is defined as the lack of statistically significant difference between groups' distribution in the digital inclusion pathway after differences due to educational attainment, age and other demographic variables are taken into account. In such analyses, the criterion stage of the digital inclusion pathway referenced (e.g., Digital Access, Digital Taste, Digital Readiness or Digital Literacy) may affect the determination of digital equity.

The Digital Embedding of Economic and Social Outcomes

The central importance of digital equity stems from the possible economic and social impacts of ICT use. Research based on previous surveys of adult skills has demonstrated the economic value of well developed literacy and numeracy skills for both individuals and societies (Hanushek & Wößmann, 2012a,b) With the PSTRE assessment and the systematic measurements of skill use in SAS, new analytical possibilities are emerging. The first SAS results reported by OECD (2013a) provided additional evidence of the central importance of both proficiencies and skill use for a range of economic and social outcomes. Hanushek, Schwerdt, Wiederhold & Woessmann (2013), in one of the first econometric analyses of the SAS data, found substantial wage returns to skills over and above the wage returns attributable to education for prime age workers in the U.S. and countries around the world.

The importance of these skills is not limited to economic outcomes. OECD (2013a,d) and Dinis da Costa et al (2014) analyzed the apparent contributions of skills to a number of social outcomes: social trust, volunteerism, political efficacy and general health. For each social outcome variable, an odds ratio for a negative social outcome was estimated, comparing low versus high levels of literacy skills; for example, U.S. adults with low levels of literacy proficiency are four times as likely to have a negative health outcome as their counterparts with the highest levels of literacy (OECD, 2013d: 25). Statistically significant odds ratios were found for each of the social outcomes when comparing very high versus very low levels of literacy proficiency, after taking into account the effects of other variables like demographics and education (Dinis da Costa et al, 2014; OECD, 2013a,d).

The mechanisms and processes linking information-processing skills with these social outcomes are likely complex and may well differ across outcome measures as well as between countries and social groups. Some possibilities have been discussed by OECD (2013a) and Desjardins (2008, 2003). There is widespread consensus among researchers that ICT use is linked to various forms of political participation (Mossberger, Tolbert & Anderson, 2014; Tolbert & MacNeal, 2003; Xenos & Moy 2007). There is also a substantial research base in health literacy that connects information-processing skills with health (e.g., Rains, 2008; Rudd, Kirsch & Yamamoto, 2004), although there is far more research about how skills are used for accessing health information than for communicating with health-care providers or managing one's own health and care.

The research conducted to date examining associations between information-processing skills and economic and social outcomes has been limited to literacy and numeracy proficiencies. This research can be extended by examining the associations between variables measuring digital literacy -- PSTRE proficiency and indexes of ICT use – and these economic and social outcomes. Since many of the practical applications of this research may be based in potential changes in policies and programs that have relatively small impact on proficiencies or skill use, we will examine the broad distribution of PSTRE proficiencies and ICT use in these analyses rather than estimating odds ratios for contrasts between the lowest and highest levels of proficiencies and skill use.

These statistical associations are *not* intended to identify specific causal or explanatory models of underlying mechanisms linking digital literacy measures to economic and social outcomes. To avoid such causal connotations, we will adopt the terminology of the *digital embedding* of a social or economic indicator to refer to the positive correlations of the index of ICT use (either ICT use at work or ICT use outside of work) with that indicator within a specific multivariate model. Thus we would say that earnings are "digitally embedded" if certain regression models of earnings have statistically significant, positive coefficients on PSTRE and ICT use. This terminology is trying to be parallel with such phrases as "literacy is embedded in poverty", referring to the myriad relationships between literacy and poverty that underlie their correlation. Such embedding does not imply a single, a simple or only a unidirectional influence between digital literacy and the social or economic outcome. The discovery of embedding can, however, be a starting point for other research to investigate possible underlying mechanisms and effective interventions.

Research Questions

RQ 1: For which demographic groups (race/ethnicity, gender, and national origin) is there evidence of *digital equity* in the adult population? Evidence of digital equity for a group will be the lack of a statistically significant difference in its digital inclusion pathway status with other demographic variables and educational attainment taken into account.

RQ 2: What is the extent of the *digital embedding* of economic (earnings, employment) and social outcomes for adults (social trust, volunteerism, political efficacy, health)? Evidence of the digital embedding of an outcome is the presence of a statistically significant association between the outcome and measures of ICT use after associations between the outcome and PSTRE proficiency, educational attainment and demographic variables are taken into account.

Methodology

Data

Data are from U.S. respondents in the first round of the OECD Survey of Adult Skills (SAS). The U.S. data was gathered from a sample of 5,010 respondents representative of adults age 16-65 living in households in 2012. Analyses were conducted with the U.S. country-specific Restricted Use File (RUF) data file.[4] Technical details about the file and the U.S. SAS procedures and data are available elsewhere (Hogan, Montalvan, Diaz-Hoffmann *et al*, 2014; OECD, 2013a). The RUF file was converted to Stata format and analyzed using Stata with publicly available, validated REPEST package that take the complex sampling and multiple imputation designs of SAS into account.

Variables

Problem Solving in Technology-Rich Environments (PSTRE). The framework for the assessment of the PSTRE domain was developed by an expert panel and is described in detail in OECD (2012). PSTRE represents the intersection of computer literacy (i.e., the basic capacity to use ICT tools and applications) and the cognitive skills to solve real-world problems encountered with those tools and applications. PSTRE is defined as "using digital communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks", emphasizing abilities "to solve problems for personal, work and civic purposes by setting up appropriate goals and plans, and accessing and making use of information through computers and computer networks." (2012: 47). This assessment is designed to evaluate adults' abilities to solve problems in which the information used is accessed through ICT and the solutions are facilitated by use of ICT tools. Some of the problems arise in part because of the nature of these ICT tools. The assessment presents problems adults encounter in everyday life -- as workers, citizens or consumers – in simulated environments with such ICT tools as browsers, email and spreadsheets. Problems varied in complexity – how explicitly they were stated, the number of steps in their solution paths, and the extent to which their solutions required self-monitoring, inferential reasoning, and evaluation of the relevance and credibility of information. PSTRE was assessed through performance of 14 tasks. Item response theory was used to estimate proficiencies on a 0-500 point scale, divided into four levels, which are described in detail with sample problems in Appendix C.

Indexes of ICT skill use. PIAAC developed a methodology for measuring individual use of skills based on the Job Requirements Analysis (JRA) framework (Felstead, Gallie, Green & Zhou, 2007; OECD, 2013abc). One module of the SAS background questionnaire asked respondents about their performance of specific tasks in their current or last job (if they were currently or recently employed) and another module asked about performance of those tasks outside of work:

- Email
- Better understand issues related to health or illnesses, financial matters, or environmental issues
- Conduct transactions, for example buying or selling products or services, or banking?
- Use spreadsheet software, for example Excel
- Use a word processor, for example Word
- Use a programming language to program or write computer code
- Participate in real-time discussions on the internet, for example, online conferences or chat groups

Respondents indicated, on a Likert scale, how often they did each task: Never; less than once a month; less than once a week but at least once a month; at least once a week but not every day; every day. In one module of the background questionnaire, respondents who were currently or recently employed were asked about how often they performed each of the tasks at work. In another module, all respondents were asked about how often they performed each task in outside of work.

Responses from all countries to items about how often each of the above tasks was performed were scaled into two indexes: ICT use at work (ICTWORK in the database) and ICT use outside of work (ICTHOME in the database).[5] These indexes were scaled using Item Response Theory (Partial Credit Model) and each was found to have acceptable psychometric properties (OECD, 2013b). Each scale was constructed to have a mean value of 2.0 and a standard deviation of 1.0. Slightly modified versions of these index variables, FICTWORK and FICTHOME, were used in the analyses of ICT skill use at work and ICT skill use outside of work, respectively.[6]

Digital inclusion pathway variables. A set of binary or flag variables – Access, Taste, Readiness – was constructed to mark the stage of the previously described digital inclusion pathway at which the individual was located. These flag variables were derived from the PBROUTE variable in the dataset, corresponding to the reason a respondent was routed to the paper-based assessment (PBA) or to the computer-based assessment (CBA) which included the PSTRE. Table 1 displays the how these three flag variables were coded for the various stages of the pathway:

Table 1. Digital Inclusion Pathway Variables

PBROUTE Value	Status	Pathway Stage	Access	Taste	Readiness	Ordinal Stage	Routing
1	No computer experience	Digital Access	0	0	0	1	PBA
2	Failed ICT screener	Digital Readiness	1	1	0	3	PBA
3	Opted out of CBA	Digital Taste	1	0	0	2	PBA
4	Took CBA	Digital Literacy	1	1	1	4	CBA
5	Uncategorized		(missing)	(missing)	(missing)	(missing)	(missing)

PBROUTE = 1 indicates that the respondent had never used a computer and is in the Digital Access stage (Ordinal Stage=1): Access=0, Taste=0, Readiness=0

PBROUTE = 2 indicates that the respondent had some computer experience, agreed to take the computer-based assessment, but failed the basic computer skills screener and is in the Digital Readiness stage (Ordinal Stage=3): Access=1, Taste=1, Readiness=0

PBROUTE = 3 indicates that the respondent had some computer experience but chose not to take the computer-based assessment and is in the Digital Taste stage (Ordinal Stage=2): Access=1, Taste=0, Readiness=0

PBROUTE = 4 indicates that the individual had previous computer experience, opted to take the computer-based assessment, and passed the basic computer skills screener and is in the Digital Literacy stage (Ordinal Stage=4): Access=1, Taste=1, Readiness=1

PBROUTE = 5 indicates that the respondent had an "uncategorized" reason for not taking the computer-based assessment; these individuals comprised 4.35% of the survey population. Most but not all of these individuals had language- or literacy-related reasons for not taking the computer-based assessment. Basic background information and literacy and numeracy assessment data were not available for these individuals, who were excluded from the analyses in this paper.

Economic outcome variables. Two labor market variables were used in the analyses, earnings and current employment status. Total monthly earnings (EARNMTHALL) was trimmed at the 1st and 99th percentile values to minimize the effects of outliers and coding errors, as previous economic research with SAS has done (Hanushek et al, 2013). Trimmed earnings were then converted to a logarithmic scale in the variables Log Earnings. The flag variable Working was derived from the employment status variable (C_D09). Working has value of 1 if the individual is currently employed (C_D09=1), otherwise Working has the value of 0.[7]

Social outcome variables. Four social outcome variables were used in the analyses, the same four social outcomes examined in previous research with SAS data (Dinis da Costa et al, 2014; OECD, 2013a,d): Social Trust, Volunteerism, Political Efficacy and General Health Status. Each variable reflects responses to one or two multiple choice questions asking respondents to rate their general health, extent of volunteering, feeling of political empowerment, or degree of trusting others, etc. Each variable has five ordered categories of response, arranged so that the most desirable outcome is highest.

Demographic and other background variables. Age was derived from AGE_R and Age^2 was derived as the square of Age. Three flag variables for the highest level of educational attainment were derived from EDCAT7: Low Educ (no secondary or postsecondary credential); Med Educ (secondary credential only); and High Educ (postsecondary credential). Flag variables for four race and ethnicity categories were derived from RACEETHN_4CAT. Hispanic, Black, White, Other. The flag variable Female was derived from GENDER_R. The flag variable US Born was derived from J_Q04A.

Occupation and work experience variables. Four flag variables were derived from ISCOSKIL4 to represent the category of the respondent's most recent occupation: Oc1 (Skilled Occupations), Oc2 (Semi-Skilled White Collar Occupations), Oc3 (Semi-Skilled Blue Collar Occupations), and Oc4 (Elementary Occupations). The underlying occupation codes are based on the ISCO 2008 classifications. Total years of potential work experience, Exper, was derived from a combination of age (AGE_R) and years of paid work experience (C_Q09). $Exper^2$ was derived as the square of Exper.

Analyses

Two major sets of multivariate regression analyses were conducted, one examining digital equity at the various stages of the pathway, and a second examining the embedding of ICT skill use in specific economic and social outcome variables.

Digital equity: Reaching specific pathway stages. Multivariate logistic regressions were conducted to predict whether individuals had reached a given stage of the digital inclusion pathway: Access, Taste, and Readiness. For each stage, three parallel regressions were carried out with different sets of predictors: (a) demographic variables including the key equity flag variables Hispanic, Black and Other (White being the reference category), Female, and US Born; (b) demographic and equity variables and educational attainment; and (c) demographic and equity variables, educational attainment and the flag variable for current employment. In each regression, the primary results of interest are whether the estimated coefficients on the equity flag variables are statistically significant predictors of the given pathway stage after taking account of the predictive effects of the other variables in the regression model. A statistically nonsignificant coefficient indicates digital equity for the group.

Digital equity in the overall inclusion pathway. In addition to the logistic regressions examining digital equity at each pathway stage, ordinal regressions were conducted to predict the Ordinal Stage (1, 2, 3 or 4) the individual reached from the same three sets of predictor variables described above. These ordinal regressions examined digital equity across the pathway as a whole rather than at one stage at a time. The ordinal regressions used maximum likelihood methods to estimate cutpoint constants for predicting the Ordinal Stage from the regression value generated by the predictor variables. As with the stage-specific logistic regressions described above, the primary results of interest here are whether the estimated coefficients on the equity flag variables are statistically significant predictors of the individual's stage within the inclusion pathway after taking account of the predictive effects of the other variables in the regression model. A statistically nonsignificant coefficient indicates digital equity for the group.

Digital Equity: ICT Skill Use and PSTRE Proficiency. For individuals reaching the Digital Literacy stage (i.e., those routed to the computer-based assessment), there are two major indicators of digital literacy available in SAS: the assessed PSTRE proficiency and the index of ICT skill use. Two sets of linear regressions were carried out, one set predicting PSTRE proficiency and another set predicting ICT skill use outside of work (since ICT use at work was measured only for those currently working).

The dependent variables PSTRE and FICTHOME were linearly regressed on two sets of predictors: (a) demographic variables including the equity flag variables and educational attainment variables; and (b) demographic variables, equity flag variables, educational attainment variables, and the other dependent variable. So the second regression model for PSTRE includes FICTHOME as a predictor, whereas the second regression model for FICTHOME includes PSTRE.

As before, the primary results of interest are whether the estimated coefficients on the equity flag variables are statistically significant predictors of the individual's stage within the inclusion pathway after taking account of the predictive effects of the other variables in the regression model. A statistically nonsignificant coefficient indicates digital equity for the group.

Although the same population – individuals age 16-65 who took *either* the paper-based or computer-based assessment -- is involved in testing for equity in reaching the Digital Access, Digital Taste and Digital Readiness stages, a subpopulation is involved in testing for equity within the Digital Literacy stage: individuals age 16-65 who were routed to the computer-based assessment. This distinction will be revisited below in comparing the two sets of digital equity findings.

Digital embedding. As defined in the introduction, the digital embedding of an outcome variable refers to a positive correlation between an index of ICT use and that variable in specific multivariate regression models. Because strong correlations are expected between proficiency and skill use measures (OECD, 2013a; Reder, 2009), we need to be careful interpreting positive coefficients observed for skill use measures in models that do not control for proficiency. Apparent effects of skill use could be proxies for effects of proficiency measures. The unique association of ICT skill use with the outcome variable could be better seen in predictive models that include the measure of ICT skill use with the proficiency measure and other variables included as controls.

The digital embedding of two economic outcomes (monthly earnings, current employment) and four social outcomes (social trust, volunteerism, political efficacy, and general health) will be examined. For each outcome, a pair of multivariate regression models is examined: a *baseline model* includes an ICT skill use measure and control variables, while an *enhanced model* adds PSTRE proficiency as an additional predictor. If the ICT skill use measure remains a statistically significant positive predictor of the outcome in *both* models – with and without PSTRE proficiency – then we identify the digital embedding of that outcome.

Digital embedding of earnings. Linear regression models of earnings were estimated for the population of prime age workers, age 25-54. One pair of models used the index of ICT skill use at work (FICTWORK) while a second pair of regression models used the index of ICT skill use outside of work (FICTHOME). The baseline model of each pair includes basic demographic variables, educational attainment, occupation identifiers and work experience variables, along with the index of ICT use. The enhanced model adds PSTRE as an additional control.

Digital embedding of employment. Digital embedding of current employment status was examined with logistic regression of employment on prime age adults, age 25-54. A pair of models was estimated. The baseline model included basic demographic variables, educational attainment and the index of ICT use outside of the workplace (FICTHOME). The enhanced model adds PSTRE as a control variable.

Digital embedding of social outcomes. Ordinal regressions were used to examine digital embedding of social trust, volunteerism, political efficacy, and health in the adult population, age 25-65. For each social outcome variable, measured on a 1 to 5 point scale, a pair of models was estimated. The baseline model of each pair included demographic variables, educational attainment, employment status and FICTHOME, the index of ICT use outside of work. The second or enhanced model added PSTRE proficiency as an additional control.

It is important to emphasize that the various linear, logistic and ordinal regression models are inherently correlational in nature. Our analysis of the presence or absence of digital equity and digital embedding is not intended to imply causality underlying relationships between the various outcome measures studied and measures of digital inclusion or digital literacy. These relationships, if present, may suggest broad areas for future research and policy development. We will return to this point after considering the results of these analyses.

Results

The results of the study are presented here in three sections. The first section briefly describes the population's distribution along the digital inclusion pathway, including indexes of ICT skill use along the pathway. The second section summarizes the findings about digital equity at the various stages of the pathway, with details of those findings presented in Appendix A. The final section summarizes the findings about the digital embedding of specific economic and social outcome variables, with details of those findings presented in Appendix B.

Describing the Digital Inclusion Pathway

Table 2 shows the estimated percentage of the U.S. adult population age 16-65 located in each stage of the pathway. Nearly 84% or 5 in 6 adults are in the Digital Literacy stage (many of whom have weak digital literacy skills), with the remaining 16% divided about equally among the preceding stages of the pathway: 5.5% in Digital Access (having never used a computer), 4.2% in Digital Taste (having used a computer but unwilling to use the computer to take the PIAAC assessment), and 6.6% in Digital Readiness (having used a computer before, willing to use a computer to take the PIAAC assessments but unable to pass a basic computer skills screener. Altogether, about 1 in 6 adults has not reached the Digital Literacy stage of the digital inclusion pathway.

Table 2. The proportion of the adult population and indexes of their ICT uses at various stages of the digital inclusion pathway. The indices of skill use were scaled by OECD to have means of 2.0 and standard deviations of 1.0.

Digital Inclusion Pathway Stage	% of Adults	ICT Use Outside of Work	ICT Use at Work
Digital Access	5.5 (0.43)	na	na
Digital Taste	4.2 (0.38)	1.66 (0.13)	1.28 (0.20)
Digital Readiness	6.6 (0.59)	1.51 (0.16)	1.31 (0.13)
Digital Literacy	83.7 (0.81)	2.20 (0.02)	2.01 (0.03)

(standard errors in parentheses)

The average values for the ICT skill use indexes shown in Table 2 suggest that little progress occurs in using ICT either at work or outside of work among those who have not reached the Digital Literacy stage. Each of these indexes, we recall, was scaled to have a mean value of 2.0 and a standard deviation of 1.0 pooled over all OECD nations participating in the SAS. Although U.S. adults in the Digital Literacy stage have average ICT skill usage above that of their international counterparts, there appears to be little difference among the US adults' ICT skill use between the Digital Taste and Digital Readiness stages. There is quite a large difference (more than half a standard deviation), however, between these US adults in the Digital Taste/Digital Readiness stages and those in the Digital Literacy stage.

Digital Equity

Table 3 summarizes the findings about digital equity from the models presented in detail in Appendix A. Each column of the table summarizes equity results about a particular stage or measure from the digital inclusion pathway. Readers wanting more details are referred to the table number in Appendix A shown in the bottom row of Table 3. The columns headed 'Digital Access', 'Digital Taste' and 'Digital Readiness' summarize the logistic regression results predicting which individuals have progressed through those stages according to the defined Access, Taste and Readiness criteria of the inclusion pathway. The column headed 'Digital Inclusion Pathway' summarizes results of the ordinal regression that predicts which of the four stages to which individuals have progressed.

For all models, tables in Appendix A contain the estimated regression coefficients and their standard errors and significance levels. In this summary Table 3, these coefficients are summarized by "+" if positive and statistically significant ($p < 0.05$), by "-" if negative and statistically significant ($p < 0.05$), and by "ns" if not statistically significant ($p > 0.05$).

The results shown for these three stages and for the overall pathway model are essentially the same. The pattern of statistically significant coefficients for the covariates in these models is consistent with previous research: younger age, greater educational attainment and current employment are positive predictors of completing the pathway stages. Even after the influence of these covariates is taken into account, there is a clear and consistent pattern of digital inequity in the pathway: Women, Whites and U.S. born adults are farther along the digital inclusion pathway than men, Blacks, Hispanics and foreign-born adults. There is thus a consistent lack of digital equity based on race, on gender and on national origin in the digital inclusion pathway.

Within the Digital Literacy stage, the equity pattern differs depending on whether PSTRE proficiency or ICT use outside of work is examined. Gender differences either disappear (for ICT use outside of work) or switch to favoring men (for PSTRE proficiency). The lower levels of digital inclusion in Black and Hispanic populations seem to correspond with those populations' lower PSTRE proficiency levels after taking other covariates into account. Their levels of ICT use outside of work settings, however, are *higher* after taking the other covariates into account. Other minority populations exhibit digital equity in the inclusion pathway but marked digital inequities in the Digital Literacy stage similar to those of Black and Hispanic groups: Their levels of PSTRE proficiency are lower and their levels of ICT use outside of work are higher with other covariates taken into account. A different pattern of digital inequity is seen among the foreign-born who, with other variables controlled, show statistically significant lower PSTRE levels than the U.S.-born population, as well as ICT use levels outside of work that are not statistically significant different from those of the U.S.-born population.

Table 3. Summary of Digital Equity Findings, full models. Detailed tables and explanations are given in Appendix A.

Outcome =>	Digital Access	Digital Taste	Digital Readiness	Digital Inclusion Pathway	Digital Literacy: PSTRE	Digital Literacy: ICT Use Outside of Work
Population	Adults 16-65	Adults 16-65	Adults 16-65	Adults 16-65	Adults 16-65 Who Took CBA	Adults 16-65 Who Took CBA
Regression Model	Logistic	Logistic	Logistic	Ordinal	Linear	Linear
Equity Group						
Female	+	+	+	+	-	ns
Black	-	ns	-	-	-	+
Hispanic	-	-	-	-	-	+
Other Race	ns	ns	ns	ns	-	+
U.S. Born	+	+	+	+	+	ns
Covariates						
Age	-	-	-	-	-	-
Education	+	+	+	+	+	+
Working	+	+	+	+	ns	ns
Table #	A1c	A2c	A3c	A4c	A5b	A6b

ns: not significant predictor ($p > 0.05$) + : significant positive predictor ($p < 0.05$) - : significant negative predictor ($p < 0.05$)

Note: Both Age and Age^2 were included in the models. Summary results shown are for the linear Age variable.

Females also display a different pattern in the Digital Literacy stage: they have *lower* PSTRE proficiencies (and do not have statistically significant differences in ICT usage levels) in contrast with their higher inclusion levels in the preceding pathway stages.

In general, digital equity appears to be shaped differently for the initial stages of digital inclusion than for the Digital Literacy stage's measures of PSTRE proficiency and ICT skill usage outside of work settings. These differences in digital equity are complicated to interpret since they are based on different populations. We will return to this point in the final section of the paper after we consider findings about digital embedding of economic and social outcomes.

Digital Embedding of Economic and Social Outcomes

Digital equity has been identified in terms of differences among groups' digital inclusion or digital literacy measures once differences due to educational attainment, work status and other demographic variables are controlled. The digital embedding of various economic and social outcomes will be identified with regression models of the outcome variables on ICT use and the control variables used in the digital equity models. In the digital embedding models, the primary focus is on the coefficients of ICT use (measured either at work or outside of work) rather than on the coefficients of the equity group flags.

Table 4 summarizes findings from the models presented in detail in Appendix B. Each column of the table summarizes the digital embedding results for a specific economic or social outcome variable. Readers wanting more details about the results for a particular outcome variable are referred to the table number in Appendix B that is shown in the bottom row of that column of Table 4.

Table 4. Summary of Digital Embedding Findings. Detailed tables and explanations are given in Appendix B.

Outcome =>	(1) Earnings	(2) Earnings	(3) Employment	(4) Social Trust	(5) Volun-teerism	(6) Political Efficacy	(7) Health
Population	Workers 25-54	Workers 25-54	Adults 25-54	Adults 25-65	Adults 25-65	Adults 25-65	Adults 25-65
Regression Model	Linear	Linear	Logistic	Ordinal	Ordinal	Ordinal	Ordinal
Context of ICT Use	Work	Outside of Work	Outside of Work	Outside of Work	Outside of Work	Outside of Work	Outside of Work
ICT Use Baseline Model	+	ns	ns	+	+	+	+
ICT Use Enhanced Model	+	ns	ns	+	+	+	+
PSTRE Enhanced Model	+	+	ns	+	ns	ns	ns
Digital Embedding?	Yes	No	No	Yes	Yes	Yes	Yes
						+	+
Age	ns	ns	ns	ns	ns	ns	ns
Female	-	-	-	+	+	+	ns
Black	ns	ns	ns	-	+	+	-
Hispanic	ns	ns	ns	ns	ns	+	-
Other Race	ns	ns	ns	-	-	-	-
U.S. Born	ns	ns	ns	ns	ns	ns	-
Education	+	+	+	+	+	+	+
Working				ns	+	ns	+
Table #	B1	B2	B3	B4	B5	B6	B7

ns: not significant predictor ($p > 0.05$) + : significant positive predictor ($p < 0.05$) - : significant negative predictor ($p < 0.05$)

Note: Both Age and Age^2 were included in the models. Summary results shown are the same for both Age and Age^2.
Note: The earnings models also include independent variables not shown in summary table: years of work experience and dummies for occupational categories. See Appendix B for details.

The upper group of rows in the table shows the population, the type of regression model, and the index of ICT use characterizing the embedding models for each given outcome. For the earnings model of column (1), the population was prime age workers (age 25-54), the type of regression was a linear regression, and the index of ICT use was ICT Use At Work.

As explained in the Methodology section, two regression models were used to determine whether there is digital embedding of an outcome variable: a baseline model that included ICT use and the control variables shown in the bottom group of rows of the table, and an enhanced model that added PSTRE proficiency as an additional control variable. For all models, tables in Appendix B contain the estimated regression coefficients and their standard errors and significance levels. In this summary Table 4, these coefficients are summarized by "+" if positive and statistically significant ($p < 0.05$), by "-" if negative and statistically significant ($p < 0.05$), and by "ns" if not statistically significant ($p > 0.05$).

Each column of Table 4 summarizes results for both the baseline and enhanced models of the outcome variable. The middle group of rows summarize the estimated coefficients of ICT Use for the baseline model and for the enhanced model and the coefficient of PSTRE proficiency in the enhanced model. The bottom group of rows in the table summarize the coefficients of the control variables that turn out to have the same "+" or "-" or "ns" in both models.

Earnings. Looking at the earnings model in column (1), we see that ICT Use (at Work) is a statistically significant, positive predictor of earnings in both the baseline and enhanced models. PSTRE proficiency is a statistically significant positive predictor of earnings in the enhanced model. By definition, since ICT Use at Work (FICTWORK) is a statistically significant positive predictor of earnings in both models, there is digital embedding of earnings.

The general structure of these earnings models resembles those used in other labor economic research (Mincer, 1974) and in particular those reported in previous cross-national analyses of PIAAC data (Hanushek et al, 2013; OECD, 2013d). We will not discuss this in detail, but note several important features relevant to the specific concerns of this paper. With respect to equity issues, it is noteworthy that there are *not* statistically significant effects of race/ethnicity or national origin on earnings evident here once digital literacy is taken into account either with FICTWORK (baseline model) or FICTWORK and PSTRE (enhanced model). There are, however, statistically significant and very substantial effects of gender on earnings even after adjustment by these and other important variables. In Table B1, the Female coefficient of -0.35 on log earnings indicates that women on average are earning 35% less than men after adjusting for general occupation, educational attainment, work experience, digital literacy and other covariates.

These results reflect substantial digital embedding of earnings for ICT use at work. The statistically significant positive coefficient of FICTWORK in both models reflects the importance of using ICT skills in the workplace for earnings and productivity. Even with PSTRE proficiency controlled, ICT use is a strong determinant of earnings. One indicator of the size of this effect is the partial correlation of FICTWORK and earnings after controlling for the other variables in the model. These partial correlations are estimated to be 0.25 and 0.23 for the baseline and enhanced models, respectively.

Desjardins and Rubenson (2011) conducted a related analysis using OECD's Adult Literacy and Lifeskills (ALL) survey data. They analyzed regression models of log earnings on measures of reading, writing and numeracy engagement in the workplace along with proficiency measures similar to those used in PIAAC.[8] Their models assumed proficiency was a supply side characteristic of the individual and skill use was a demand side characteristic of jobs. They found statistically significant effects of both types of predictors when simultaneously entered into earnings regressions, similar to results for the enhanced earnings model. It is an open question, however, whether ICT use in the workplace as measured in PIAAC is best considered to be a characteristic of the individual (as posited here) or a characteristic of the individual's job (as Desjardins and Rubenson assumed). In general, of course, both are possible; different individuals could perform the same job with different engagements of ICT. This is more than just an academic matter: If individuals engage more deeply with ICT in their work, will they become more productive, will their earnings increase, or must they change jobs for this to happen?

Some perspective on this is provided by the results in column (2) of Table 4 for another pair of earnings models that includes ICT use outside of work rather than ICT use at work. We see that ICT use outside of work is *not* a statistically significant predictor of earnings in either the baseline or enhanced model. With ICT use measured outside of work, there is not digital embedding of earnings, as there is with ICT use at work. Although these findings do not resolve the uncertainty of how to interpret the digital embedding earnings, they do provide a departure point for future research.

Employment. The only variables in Table 4 that are statistically significant predictors of current employment in either the baseline or enhanced models are gender (females are less likely to be employed) and education (the higher the educational attainment, the more likely is current employment). Gender negatively predicts employment (i.e., women are less likely to be employed after adjusting for other variables in the specification). Neither ICT Use outside of work nor PSTRE proficiency has a statistically significant relationship with employment in these multivariate models. There is no evidence for the digital embedding of employment.

In comparing the digital embedding of earnings with the lack of digital embedding of employment, it is important to keep in mind that the two outcomes are necessarily modeled with different populations. Earnings are modeled with prime age adults who are currently employed, whereas current employment is modeled with all prime age adults. Among prime age workers, ICT use at work is digitally embedded in their earnings, but their ICT use outside of work is not. Among prime age adults, ICT use outside of work is not digitally embedded in their current employment status.

Social outcomes. Columns (3) through (7) of Table 4 summarize the digital embedding results for Social Trust, Volunteerism, Political Efficacy and Health, respectively. The results are highly similar across these four social outcomes. Each outcome was modeled with ordinal regressions for the population age 25 to 65, and included ICT use outside of work. There is consistent digital embedding of these social outcomes. PSTRE proficiency is associated with only one of these social outcomes, namely social trust, once ICT use outside of work and other controls are in the model.

The pattern of covariate relationships in these models is also noteworthy. Educational attainment has positive associations with all of the economic and social outcomes examined after adjusting for other covariates, particularly the highest level of attainment (college degree). Gender has a statistically significant association with all outcomes examined, with females having lower economic outcomes and higher social outcomes (other than health) when other variables are statistically controlled. Age does not have a statistically significant association with any of the outcomes in these models, although for the earnings outcome, the effects of age are captured by the independent variable of years of work experience that is positively associated with earnings.[9] Neither minority group status (Black, Hispanic, Other) nor national origin are significantly associated with economic outcomes when education and digital literacy measures (PSTRE, ICT use) are controlled. Minority group status and national origin are associated in various ways with some social outcomes, with membership in each group being positively associated with at least one outcome, negatively associated with some other outcome, and not significantly associated with some third outcome after taking remaining covariates into account.

Conclusions

By framing equity in a digital inclusion pathway with multiple stages -- Digital Access, Digital Readiness, Digital Taste and Digital Literacy – a more nuanced and useful conception of digital equity has emerged. Digital equity is defined as the lack of statistically significant differences in inclusion pathway status among subpopulations based on race/ethnicity, gender, and national origin at given levels of educational attainment. In terms of gender, there is a consistent lack of digital equity across the inclusion pathway, with females having higher levels of access, readiness and taste yet lower assessed PSTRE proficiencies than men. There are no gender differences in ICT use outside of work after taking other variables into account.

Different patterns of digital equity appear in groups based on race/ethnicity and national origin. Foreign-born adults, compared with adults born in the U.S., have lower levels of digital access, readiness and taste and lower PSTRE proficiencies when other variables in the model are controlled. Black and Hispanic adults have lower levels of digital access, readiness and taste and lower PSTRE proficiencies compared with White adults when other variables in the model are controlled. Black and Hispanic adults have *higher* levels of ICT use outside of work settings than White adults, whereas foreign-born and U.S.-born adults do not have statistically significant differences in ICT use outside of work when other variables are controlled. Women and men do not differ in their ICT use outside of work when other variables are controlled.

Digital embedding of a social or economic outcome is defined as a statistically significant, positive association of ICT use with the outcome variable after taking demographic characteristics, educational attainment, and PSTRE proficiency into account. There is digital embedding of the earnings of prime age workers but no digital embedding of the employment status of prime age adults. The digital embedding of earnings occurs only if ICT use is measured for the workplace context; there is no embedding of earnings if ICT use is measured outside of the work context. With ICT use outside of work, however, there is consistent digital embedding of social outcomes -- social trust, volunteerism, political efficacy and general health. With ICT use outside of work and other covariate controls in place, PSTRE proficiency has a statistically significant association with only social trust. Minority group status (Black, Hispanic, Other) and national origin are not significantly associated with economic outcomes after controlling for effects of education and digital literacy (as measured by ICT use or PSTRE proficiency).

Before turning to implications of these findings, there are some important limitations to the study that should be mentioned. Although PIAAC's framework for PSTRE is broadly conceived to deal with a range of technologies and networked environments, the PSTRE assessment in SAS was concerned only with computers. Furthermore, the SAS questionnaire and assessment routing process – the basis of the digital inclusion pathway studied here -- dealt only with computers, not with other platforms and devices. Thus the analysis of progression through a digital inclusion pathway, based on individuals' behavior in a computerized assessment setting, needs further attention. Care must be taken with the inferences drawn from such a model system or microcosm of digital inclusion. Finally, it should be emphasized one more time that the findings in this study about digital embedding should not be construed causally. Digital embedding is a weaker and more general relationship than a causal relationship between ICT use and an outcome but is a more specific relationship than is just a correlation. Although the results showing digital embedding of a range of economic and social outcomes may suggest that policies and programs designed to increase digital literacy do have considerable promise, the results are not strong enough to imply that such changes would necessarily lead to improved social and economic outcomes. Certainly these findings warrant further research, some possibilities for which are suggested below.

Implications

There are a couple implications of the digital equity and digital inclusion findings that future researchers and policymakers should consider carefully. One implication is that different strategies may be needed to facilitate digital inclusion among specific populations at different points in the digital inclusion pathway. The overall pattern of digital equities is similar when comparing men to women, or Black and Hispanic groups to Whites, or foreign-born to U.S.-born adults. Men, Blacks and Hispanics, and the foreign-born are less likely than their comparison groups (Women, Whites and U.S.-born, respectively) to have passed each barrier in the pathway prior to the Digital Literacy stage: they are less likely to have ever used a computer; they are less likely to agree to use a computer even if they have used one before; and they are less likely to have the basic computer skills needed for doing certain tasks even if they agree to try. These inequities are apparent even after differences in age, education, employment status and other covariates are taken into account.

Yet once these groups *do* reach the Digital Literacy stage, their digital equity experiences diverge. Groups that showed less digital inclusion at all stages of the pathway leading up to Digital Literacy have different relative profiles within the Digital Literacy stage. Blacks and Hispanics display *lower* PSTRE proficiencies and *more* ICT use outside of work than comparable Whites. Men show *higher* PSTRE proficiencies than comparable women within the Digital Literacy stage (women and men do not have statistically significant differences in ICT use within the Digital Literacy stage). U.S.-born adults have statistically significant, higher PS-TRE proficiencies than comparable foreign-born adults within the Digital Literacy stage (U.S-born and foreign-born adults do not have statistically significantly differences in ICT use within the Digital Literacy stage).

Because different populations are examined in the pre-Digital Literacy and Digital Literacy stages, care must be taken interpreting changing equity patterns between the stages. Nevertheless, these digital equity findings do suggest that consideration should be given to having a variety of approaches to inclusion at different pathway stages, perhaps tailored to the different barriers involved for the various groups.

A second implication comes from the myriad of equity-related findings in which group differences in proficiency and those in ICT use do not necessarily go together. Although we know from previous research that proficiency and skill use are positively correlated (OECD, 2013a), the distinct equity patterns shown by the two measures suggests that proficiencies and skill uses are acquired differently. This may indicate that PSTRE proficiency, framed as a blend of ICT and problem-solving skills, develops differently and requires additional instructional support than does ICT use. Further research and development should look more closely at how these and other dimensions of digital literacy develop across the adult lifespan and what types of instructional approaches are likely to be most effective with different groups of adult learners.

The findings about digital embedding of economic and social outcomes also have some important implications. The lack of digital embedding of current employment status is striking given the strong digital embedding of earnings among those who are working. Although the interpretation of this will need to be clarified by additional research, it suggests that very different rationale and policies may be needed for digital literacy training in an employment search or job development context than in an incumbent worker context. Further implications about incumbent worker training and technology support may follow from better understanding of the finding that ICT use in the workplace is embedded in workers' earnings but their ICT use outside of work is not. The digital embedding of all of the social outcomes examined – social trust, volunteerism, political efficacy and health – may indicate promising policy and program directions for blending support of technology use with other social aims and initiatives. The digital embedding of general health is of particular interest in this regard because of the large economic returns associated with improved health status; such cost-savings could go a long way to fueling new education and training programs for adults.

Future Research

There are many lines of research that could strengthen the present findings and identify some of the underlying mechanism and promising interventions and policies to promote greater digital inclusion and digital literacy in the United States and around the world. Some of the needed research can be based on further analysis of the PIAAC SAS data. Other types of research will be helpful where SAS does not contain the needed type of information and data. A few examples of each type will suffice.

Further research with SAS data. This study was conducted with the SAS data from the United States. There are numerous extensions of the models developed that could usefully be examined with the U.S. data These include (1) using more fine-grained levels of educational attainment in the predictive models; (2) trying to disentangle the observed effects of national origin from effects of English language proficiency, perhaps using variables such as the length of time in country (for the foreign-born) and language chosen for the background questionnaire (English vs. Spanish); (3) examining the effects of earnings as a predictor of digital equity; and (4) adding the interaction between race and gender to the earnings and employment models.

Systematic application of the digital equity and digital embedding models to other countries' SAS data will be very useful not only for replication but for comparative purposes. There is considerable reason to expect cross-national differences in the structure of both digital equity and digital embedding. Related embedding models could be constructed and compared based on literacy proficiency with use of reading at work, writing at work, reading outside of work and writing outside of work (Pellizari & Fichen, 2013). Another embedding model would consider numeracy proficiency and use of math at work and math outside of work. These studies could even try to use multiple proficiencies at once, though collinearity problems resulting from high intercorrelations among proficiency scales might be formidable (Braun, 2013). An important study would try to use more nuanced models, perhaps including additional variables about workplaces and jobs available in certain countries' unique data sets, to disambiguate the interpretation of the strong embedding of skill use at work in earnings.

It would be useful for future research with SAS data to more fully develop the IRT-scaled indexes of reading, writing and math skill uses at work and outside of work. Respondents' background characteristics could be used to estimate plausible values for each index, much as done with the proficiency measures. This would allow measurement error to be represented more accurately in analyses involving the skill use measures, especially for cases where all individuals have missing or "never" responses on items about the frequency of using particular skills.

Further research with other data sets or new PIAAC-based data. The anticipated release of the web-based PIAAC assessment system called Education and Skills Online (ESO) opens up some important opportunities for the collection of new data sets for researchers. These studies could combine SAS-comparable assessment data with other types of data collected from the same individuals. For example, Jill Castek is directing a grant project being conducted jointly by Portland State University and Multnomah County Library. With funding from the Institute for Museum and Library Services, the project will use ESO to assess the PSTRE skills of library patrons (both walk-in and online) and analyze their skills in relation to the task demands of using 21st century libraries.[10] This type of study will create research data that will be invaluable not only to the original project but to future researchers who will be able to analyze it. Other projects relevant to the issues of this paper that could be conducted with ESO would be longitudinal studies that involve repeated assessments of

PSTRE and ICT skills use as individuals experience known changes in technology-rich environments and instructional programs of various types designed to facilitate acquisition of specific skills and knowledge.

References

Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent". *Science, 344*, 843-851.

Autor, D. H., F. Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*, 1278-1333.

Braun, H. (2013). *The relationship of problem-solving in technology-rich environments to literacy and numeracy: Insights from PIAAC.* Paper presented at the ETS-OECD PIAAC Research Conference, Washington DC, November 14-15, 2013.

Colorado State Library (2012). *Digital literacy continuum*. Denver: Colorado Department of Education. Retrieved 8 September 2014 from http://www.cde.state.co.us/sites/default/files/documents/cdelib/librarydevelopment/publiclibraries/download/pdf/digital-literacy-continuum.pdf

Desjardins, R. (2008). Researching the links between education and well-being. *European Journal of Education, 43*(1), 23-35.

Desjardins, R. (2003). Determinants of economic and social outcomes from a life-wide learning perspective in Canada. *Education Economics, 11*(1), 11-38.

Desjardins, R., & Rubenson, K. (2011). An analysis of skill mismatch using direct measures of skills", *OECD Education Working Papers*, No. 63, OECD Publishing. http://dx.doi.org/10.1787/5kg3nh9h52g5-en

DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). From unequal access to differentiated use: A literature review and agenda for research on digital inequality. In K. Neckermann (Ed.), *Social Inequality* (355–400). New York: Russell Sage Foundation.

Dinis da Costa, P., Rodrigues, M., Vera-Toscano, E., & Weber, A. (2014). *Education, adult skills and social outcomes: Empirical evidence from the Survey on Adult Skills*. Ispra, Italy: European Commission Joint Research Centre.

Federal Communications Commission. (2010). *Connecting America: The National Broadplan Plan.* Washington, DC: Author.

Green, F. (2013). *Skills and skilled work: An economic and social analysis***.** Oxford: Oxford University Press.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2013). *Returns to skills around the world: Evidence from PIAAC.* Paris: OECD Education Working Paper No. 101.

Hanushek, E., & Wößmann, L. (2012a). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. *The Journal of Economic Growth*, *17*(4), 267-321.

Hanushek, E., & Wößmann, L. (2012b). The role of cognitive skills in economic development. *Journal of Economic Literature, 46*(3), 607-668.

Helsper, E. J. (2008). *Digital inclusion: An analysis of social disadvantage and the information society*. London: Department for Communities and Local Government.

Hogan, J., Montalvan, P., Diaz-Hoffmann, L., Dohrmann, S., Krenzke, T., Lemay, M., Mohadjer, L., & Thornton, N. (2013). *Program for the International Assessment of Adult Competencies 2012: U.S. Main Study Technical Report* (NCES 2014-047). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Available from http://nces.ed.gov/pubsearch.

Horrigan, J. B. (2014). *Digital readiness: Nearly one-third of Americans lack the skills to use next-generation 'Internet of things' applications.*

Institute of Museum and Library Services, University of Washington, & International City/ County Management Association. (2012). *Building Digital Communities: A framework for action.* Washington, DC: Institute of Museum and Library Services.

Jacobs, G., Castek, J., Pizzolato, A., Withers, E., & Pendell, K. (2015). *Adult new computer users: A glimpse into the learner path.* http://blog.imls.gov/?p=5541#sthash.LwV0XzGZ.dpuf

Levy, F., & Murnane, R. J. (2013). *Dancing with robots: Human skills for computerized work.* Washington, DC:, Third Way. Accessed 15 September 2014 from http://content.thirdway.org/publications/714/Dancing-With-Robots.pdf.

Livingston, S., & Helsper, E. (2007). Gradations in digital inclusion: Children, young people and the digital divide. *New Media Society*, *9*(4), 671–696.

Mossberger, K., Tolbert, C. J., & Anderson, C. (2014, July). *Digital citizenship: Broadband, mobile use, and activities online*. Paper presented at the International Political Science Association Conference, Montreal.

Mincer, J. A. (1974). *Schooling, experience, and earnings*. Washington DC: National Bureau of Economic Research (NBER) Books.

OECD (2013a). *OECD skills outlook 2013: First results from the Survey of Adult Skills*. Paris: OECD Publishing.

OECD (2013b). *Technical Report of the Survey of Adult Skills (PIAAC)*. Paris: OECD Publishing.

OECD (2013c). The Survey of Adult Skills: Reader's Companion. Paris: OECD Publishing. http://dx.doi.org/10.1787/9789264204027-en

OECD (2013d). *Time for the U.S. to reskill?: What the Survey of Adult Skills says*. Paris: OECD Publishing.

OECD (2012). *Literacy, numeracy, and problem solving in technology-rich environments: Framework for the OECD Survey of Adult Skills*. Paris: OECD Publishing.

Office for Community Technology, City of Portland (2015, February). *RFP for a Digital Inclusion Strategic Plan*. Portland, OR: Author.

Pellizari, M., & Fichen, A. (2013). *A new measure of skills mismatch: Theory and evidence from the Survey of Adult Skills (PIAAC)*. OECD Social, Employment and Migration Working Papers No.153. Paris: OECD.

Rains, S. A. (2008). Health at high speed: Broadband Internet access, health communication, and the digital divide. *Communication Research*, 35(3), 283-297.

Reder, S. (2012). *The Longitudinal Study of Adult Learning: Challenging assumptions.* Montreal: The Centre for Literacy.

Reder, S. (2009). The development of literacy and numeracy in adult life. In S. Reder & J. Bynner, (Eds.), *Tracking adult literacy and numeracy: Findings from longitudinal research* (pp. 59-84). New York and London: Routledge.

Rudd, R., Kirsch, I., & Yamamoto, K. (2004), *Literacy and health in America: A Policy Information Center report.* Princeton, NJ: Educational Testing Service.

Spitz-Oener, A. (2006), Technical change, job Tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics, 24*, 235-270.

Tolbert, C. J., & McNeal, R. S. (2003). Unraveling the effects of the Internet on political participation? *Political Research Quarterly*, 56(2), 175-185.

U. S. Department of Commerce (2013). *Exploring the digital nation: America's emerging online experience.* Washington, DC: Author.

Xenos, M. & Moy, P. (2007). Direct and differential effects of the Internet on political and civic engagement. *Journal of Communication, 57*(4), 704-718.

Zickuhr, K., & Smith, A. (2013). *Home Broadband 2013.* Pew Internet and American Life Project. Available at http://www.pewinternet.org/2013/08/26/home-broadband-2013/

Zickuhr, K., & Smith, A. (2012). *Digital differences*. Pew Internet and American Life Project. Available at http://pewinternet.org/Reports/2012/Digital-differences.aspx.

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[1] Some readers may have initially heard the Survey of Adult Skills called the "PIAAC" survey. PIAAC, how is a program division of OECD that has developed assessment frameworks and tools to be used in numerous surveys, including the Survey of Adult Skills, the to-be-released Education and Skills Online assessment system and in future surveys conducted by OECD and/or its partner countries. All of these data will be "PIAAC" data and OECD designates the 2012 survey as the Survey of Adult Skills in its publications.

[2] Digital "readiness" differs from Horrigan's (2013) use of the term; Horrigan's construct includes elements of both the "taste" and "readiness" attributes used here.

[3] Thanks to Kathryn Reder for the illustration in Figure 2.

[4] Thanks to Saida Mamedova and Katherine Landeros of the American Institutes of Research for running the author's analyses with the RUF data.

[5] The item about using programming languages was not used in scaling ICTHOME.

[6] A limitation of the way these data were scaled is that individuals who responded "Never" to all items comprising a particular scale were not assigned a scale score, they were given a missing value for that particular scale. For example, an individual who did not use ICT at work (i.e., answered "Never" to each question about how often they performed the tasks at work) was assigned a missing value rather than a low scale score for ICTWORK. In contrast, an individual who answered "Never" to each item except for one item answered "Less than once a month" received a very low scale score. A relatively small number (0.8%) of the population responded with all 'Never's to questions about how often they usually performed the ICT tasks outside of work, whereas a larger number (6.5%) of those recently employed responded all 'Nevers's to questions about how often they typically performed those tasks at work. This excludes the 5.2% of the U.S. SAS population that reported having no computer experience at all – these individuals were not asked any further questions about ICT use and are excluded from analyses of ICT skill use and PSTRE proficiency. Since the all-Never responders had some prior computer experience, it seemed appropriate to assign them a very low index score rather than a missing value for ICT use in order to include them in analyses of ICT use. Alternative versions of the ICTWORK and ICTHOME index variables, FICTWORK and FICTHOME, replaced the missing values originally assigned to the all-Never cases with the lowest internationally observed scale score on each index, -1.79982 on ICTHOME and -0.4538059 on ICTWORK. (These 'all-Nevers' are included in the digital equity analyses prior to the Digital Literacy stage.)

[7] Individuals were considered in the survey to be currently employed if they were currently working, paid or unpaid.

[8] Note that the ALL did not include measures of PSTRE or scaled indexes of ICT use at work.

[9] Although they are not shown in Table 4, variables for years of experience and occupational categories were included in the earnings models, as detailed in Appendix A.

[10] For more information about this project, please refer to http://www.pdx.edu/linguistics/pstre

Appendix A

This appendix presents technical details about the digital equity analyses discussed in the report. Digital equity was examined using regression-based analyses at each stage of the report's Digital Inclusion Pathway: Digital Access, Digital Taste, Digital Readiness, and Digital Literacy. For the first three stages, in which individuals were not given computer-based assessments, equity was measured with at each stage with a binary (0/1) variable:

<u>Digital Access</u>: If individual ever used a computer, Access = 1; otherwise, Access = 0
<u>Digital Taste</u>: If Access = 1 and individual willing to take the computer-based assessment, Taste = 1; otherwise, Taste = 0
<u>Digital Readiness</u>: If Taste = 1 and individual passed the basic computer skills and literacy and numeracy screeners, Readiness = 1; otherwise, Readiness = 0

Because the Access, Taste and Readiness variables are binary, logistic regression models were used for the digital equity analyses. Three models were examined that predict each variable. Model "a" was the baseline model that used the independent variables of *Age* and Age^2 along with dummy variables indicating membership in the equity groups based on gender, race/ethnicity and national origin. The dummy variable *Female* was the gender indicator. Indicators of race/ethnicity were the dummy variables *Black*, *Hispanic* and *Other* (with White being the reference group). The indicator of national origin was the dummy variable *US Born*. Model "b" added the highest educational credential as a predictor to Model "a": none, secondary or postsecondary. Two dummy variables represented the highest credential: *Med Educ* (coded 1 for secondary) and *High Educ* (coded 1 for postsecondary); no credential was the reference group. Model "c" added current employment status, measured by the dummy variable *Working*, as a predictor to Model "b".

A group is defined here as having digital equity with respect to an outcome if its corresponding dummy variable is *not* a statistically significant predictor of that outcome in these multivariate modeling contexts. Conversely, that group does *not* have digital equity if its dummy variable is a statistically significant predictor.

<u>Equity in Digital Access</u>

Table A1 shows results of equity tests within the three logistic regression models for the Digital Access outcome. Tables A1a, A1b and A1c display results for the three models a, b and c, respectively. As described above, Model a has demographic predictors, Model b has demographic and educational attainment predictors, and Model c has demographic, educational attainment and current employment status predictors. These three models have pseudo R^2 values of 0.22, 0.35 and 0.36, respectively, indicating that they predict approximately 22%, 35% and 36% of the variance in who has Access. Each of these model shows essentially the same results for digital equity: with demographic variables, educational attainment and employment status statistically controlled, there is statistically significant evidence of inequities of access to computers based on race/ethnicity, gender and national origin. Blacks, Hispanics, foreign-born individuals and men have significantly lower rates of access.

Table A1. Logistic Regressions of Digital Access

Table A1a

	Coef.	Std. Err.	z	P>z
Age	-0.1251	0.0413	-3.03	0.002
Age^2	0.0005	0.0004	1.17	0.244
Female	0.3531	0.1530	2.31	0.021
Black	-1.0228	0.2575	-3.97	0.000
Hispanic	-2.0631	0.2134	-9.67	0.000
Other	-0.0007	0.4428	0.00	0.999
US Born	1.0142	0.2073	4.89	0.000
Constant	6.7893	1.0495	6.47	0.000

pseudo R^2=0.222 N= 4881

$p < 0.05$

Table A1b

	Coef.	Std. Err.	z	P>z
Age	-0.1796	0.0382	-4.71	0.000
Age^2	0.0011	0.0004	2.43	0.015
Female	0.3831	0.1623	2.36	0.018
Black	-0.6382	0.2698	-2.37	0.018
Hispanic	-1.3945	0.2471	-5.64	0.000
Other	-0.4361	0.3952	-1.10	0.270
US Born	0.7278	0.2571	2.83	0.005
Med Educ	2.0286	0.1675	12.11	0.000
High Educ	3.7120	0.2570	14.44	0.000
Constant	6.2721	0.9608	6.53	0.000

pseudo R^2=0.353 N= 4878

$p < 0.05$

Table A1c

	Coef.	Std. Err.	z	P>z
Age	-0.2182	0.0375	-5.81	0.000
Age^2	0.0015	0.0004	3.62	0.000
Female	0.5693	0.1776	3.20	0.001
Black	-0.5472	0.2733	-2.00	0.045
Hispanic	-1.4111	0.2396	-5.89	0.000
Other	-0.3559	0.3922	-0.91	0.364
US Born	0.8966	0.2411	3.72	0.000
Med Educ	1.9473	0.1663	11.71	0.000
High Educ	3.5649	0.2474	14.41	0.000
Working	0.8925	0.1438	6.21	0.000
Constant	6.0962	0.9445	6.45	0.000

pseudo R^2=0.367 N= 4877

$p < 0.05$

To quantify the extent of these digital inequities, odds ratios for Access can be calculated for gender, race/ethnicity and national origin while taking other variables into account. Odds ratios reflect the relative likelihood that individuals from one group (e.g., females) will have Access vis-à-vis the reference group (males). Adjusting for all variables in the full model (Model c), the odds ratio for females is calculated to be 1.77, meaning women are 77% more likely than men to have previously used a computer after taking into account effects of the other variables – age, race/ethnicity, national origin, educational attainment and employment status. Blacks and Hispanics have adjusted odds ratios of 0.59 and 0.25, respectively, indicating that White non-Hispanics (the reference group) are, more likely than Blacks and Hispanics to have previously used a computer (adjusting for other variables). U.S. born adults have an adjusted OR of 2.48, indicating they are much more likely than foreign-born adults to have previously used a computer (adjusting for other variables).

Equity in Digital Taste

Table A2 displays the results of evaluating digital equity within the three models for Digital Taste. Results for the three models are shown in Tables A2a, A2b and A2c corresponding to three models shown above in Table A1 for Access. The results for Taste are very similar to those for Access. Although the pseudo R^2 values of 0.16, 0.25 and 0.26 are somewhat lower than their counterparts in Table A1, the overall pattern of statistically significant coefficients is the same. There is again clear evidence of digital inequities based on race/ethnicity, gender and national origin in who opted to take the paper-based as opposed to the computer-based assessments. Blacks, Hispanics, the foreign born and men were more likely, with statistically significant adjusted odds ratios of 2.31, 3.22, 2.91 and 1.66, to opt for taking paper-based rather than computer-based assessments (and thus not taking the PS-TRE).

Table A2. Logistic Regressions of Digital Taste

Table A2a

	Coef.	Std. Err.	z	P>z
Age	-0.0144	0.0222	-0.65	0.518
Age^2	-0.0005	0.0002	-2.21	0.027
Female	0.1838	0.0933	1.97	0.049
Black	-0.6934	0.1956	-3.54	0.000
Hispanic	-1.3635	0.1603	-8.51	0.000
Other	0.2385	0.3023	0.79	0.430
US Born	0.8138	0.1561	5.21	0.000
Constant	3.1536	0.5776	5.46	0.000

pseudo R^2=0.137 N= 4881

$p < 0.05$

Table A2b

	Coef.	Std. Err.	z	P>z
Age	-0.0876	0.0207	-4.23	0.000
Age^2	0.0002	0.0002	0.83	0.405
Female	0.1655	0.0994	1.66	0.096
Black	-0.3774	0.2094	-1.80	0.071
Hispanic	-0.7811	0.1981	-3.94	0.000
Other	-0.0560	0.2699	-0.21	0.836
US Born	0.6860	0.1921	3.57	0.000
Med Educ	1.6310	0.1591	10.25	0.000
High Educ	3.2335	0.1986	16.28	0.000
Constant	3.1956	0.5191	6.16	0.000

pseudo R^2=0.250 N= 4878

$p < 0.05$

Table A2c

	Coef.	Std. Err.	z	P>z
Age	-0.1177	0.0208	-5.67	0.000
Age^2	0.0006	0.0002	2.48	0.013
Female	0.2775	0.1015	2.73	0.006
Black	-0.3099	0.2161	-1.43	0.151
Hispanic	-0.7807	0.1881	-4.15	0.000
Other	0.0107	0.2764	0.04	0.969
US Born	0.7689	0.1856	4.14	0.000
Med Educ	1.5494	0.1532	10.11	0.000
High Educ	3.0950	0.1879	16.47	0.000
Working	0.6783	0.1061	6.39	0.000
Constant	3.1264	0.5091	6.14	0.000

pseudo R^2=0.260 N= 4877

$p < 0.05$

Equity in Digital Readiness

Table A3 shows the results of evaluating equity within the three models of Digital Readiness. As in the preceding analyses of Access and Taste, this Table summaries results for three logistic regression models, shown in Tables A3a, A3b and A3c. The three models have pseudo R^2 values of 0.13, 0.24 and 0.25, respectively, slightly less than their counterparts for Digital Taste. Nevertheless the pattern of results is basically the same as those for Access and Taste. There is again clear evidence of digital inequities based on race/ethnicity, gender and national origin. Blacks, Hispanics, the foreign born and men are more likely lack the basic computer skills required to take the computer-based assessment, with statistically significant adjusted odds ratios of 1.82, 2.38, 2.91 and 1.43, respectively.

Table A3. Logistic Regressions of Digital Readiness

Table A3a

	Coef.	Std. Err.	z	P>z
Age	0.0098	0.0190	0.52	0.605
Age^2	-0.0007	0.0002	-3.35	0.001
Female	0.2580	0.0827	3.12	0.002
Black	-0.9301	0.1679	-5.54	0.000
Hispanic	-1.3817	0.1344	-10.28	0.000
Other	0.1486	0.2449	0.61	0.544
US Born	0.9762	0.1152	8.48	0.000
Constant	1.8906	0.4213	4.49	0.000

pseudo R^2=0.136 N= 4881

$p < 0.05$

Table A3b

	Coef.	Std. Err.	z	P>z
Age	-0.0731	0.0176	-4.15	0.000
Age^2	0.0001	0.0002	0.60	0.548
Female	0.2437	0.0892	2.73	0.006
Black	-0.6766	0.1820	-3.72	0.000
Hispanic	-0.8810	0.1737	-5.07	0.000
Other	-0.1501	0.2146	-0.70	0.484
US Born	0.9435	0.1388	6.80	0.000
Med Educ	1.5103	0.1510	10.00	0.000
High Educ	3.0600	0.1789	17.11	0.000
Constant	2.0957	0.3754	5.58	0.000

pseudo R^2=0.242 N= 4878

$p < 0.05$

Table A3c

	Coef.	Std. Err.	z	P>z
Age	-0.1031	0.0181	-5.70	0.000
Age^2	0.0005	0.0002	2.39	0.017
Female	0.3529	0.0898	3.93	0.000
Black	-0.6151	0.1852	-3.32	0.001
Hispanic	-0.8782	0.1683	-5.22	0.000
Other	-0.0848	0.2167	-0.39	0.696
US Born	1.0122	0.1355	7.47	0.000
Med Educ	1.4230	0.1451	9.81	0.000
High Educ	2.9168	0.1748	16.69	0.000
Working	0.6780	0.1006	6.74	0.000
Constant	2.0343	0.3855	5.28	0.000

pseudo R^2=0.252 N= 4877

$p < 0.05$

Equity of Stage within the Digital Inclusion Pathway

Ordinal logistic regressions were used to predict an individual's stage within the defined Digital Inclusion Pathway: Digital Access, Digital Taste, Digital Readiness, or Digital Literacy. The ordinal regression models compute a continuous variable that is compared with three cutpoint constants to predict the ordinal stage: values below *Cut1_Constant* predict Digital Access; values between *Cut1_Constant* and *Cut2_Constant* predict Digital Taste; values between *Cut2_Constant* and *Cut3_Constant* predict Digital Readiness; and values above *Cut3_Constant* predict Digital Literacy. Maximum likelihood estimation is used to estimate the three cutpoint constants along with the logistic regression coefficients for each model.

Table A4. Ordinal Regressions of Digital Inclusion Pathway

Table A4a

	Coef.	Std. Err.	z	P>z
Age	0.0036	0.0179	0.20	0.841
Age^2	-0.0007	0.0002	-3.34	0.001
Female	0.2437	0.0833	2.92	0.003
Black	-0.9012	0.1650	-5.46	0.000
Hispanic	-1.4553	0.1383	-10.52	0.000
Other	0.1488	0.2577	0.58	0.564
US Born	0.9790	0.1199	8.16	0.000
Cut1_Constant	-3.4489	0.3938	-8.76	0.000
Cut2_Constant	-2.4815	0.3949	-6.28	0.000
Cut3_Constant	-2.0822	0.3969	-5.25	0.000

pseudo R^2=0.106 N= 4881

$p < 0.05$

Table A4b

	Coef.	Std. Err.	z	P>z
Age	-0.0860	0.0166	-5.18	0.000
Age^2	0.0002	0.0002	1.20	0.231
Female	0.2511	0.0873	2.88	0.004
Black	-0.6141	0.1755	-3.50	0.000
Hispanic	-0.9123	0.1750	-5.21	0.000
Other	-0.1939	0.2286	-0.85	0.397
US Born	0.8967	0.1434	6.25	0.000
Med Educ	1.6761	0.1402	11.96	0.000
High Educ	3.2252	0.1768	18.25	0.000
Cut1_Constant	-3.8776	0.3524	-11.00	0.000
Cut2_Constant	-2.7636	0.3462	-7.98	0.000
Cut3_Constant	-2.3084	0.3449	-6.69	0.000

pseudo R^2=0.193 N= 4878

$p < 0.05$

Table A4c

	Coef.	Std. Err.	z	P>z
Age	-0.1168	0.0164	-7.11	0.000
Age^2	0.0006	0.0002	3.24	0.001
Female	0.3694	0.0904	4.09	0.000
Black	-0.5436	0.1769	-3.07	0.002
Hispanic	-0.9186	0.1699	-5.41	0.000
Other	-0.1328	0.2361	-0.56	0.574
US Born	0.9747	0.1390	7.01	0.000
Med Educ	1.5931	0.1345	11.85	0.000
High Educ	3.0881	0.1732	17.83	0.000
Working	0.6929	0.0978	7.08	0.000
Cut1_Constant	-3.8257	0.3574	-10.71	0.000
Cut2_Constant	-2.7002	0.3506	-7.70	0.000
Cut3_Constant	-2.2400	0.3506	-6.39	0.000

pseudo R^2=0.202 N= 4877

$p < 0.05$

Table A4 shows results for three ordinal logistic regression models that predict stage from the same sets of independent variables considered previously in models a, b and c. The results are summarized in Tables A4a, A4b and A4c. These three ordinal regression models have pseudo R^2 values of 0.11, 0.19 and 0.20, respectively, indicating that the three models predict about 11%, 19% and 20% of the variance in the categorization. The patterns of inequity by gender, race/ethnicity and national origin seen in previous models for individual stages appear again here. The dependent variable for inclusion, used to categorize individuals into the four stages using Location on the digital inclusion continuum, is significantly related to gender (men are less included), race/ethnicity (Blacks and Hispanics are less included) and national origin (foreign-born are less included) when variables of age, educational attainment and current employment status are taken into account.

Equity in Digital Literacy

Individuals who took the computer-based assessment (which included the PS-TRE) are defined here as being in the Digital Literacy stage. This terminology is not meant to suggest that they are fully digitally literate, only that they are confortable and skilled enough using computers to have their PS-TRE and other skills assessed by computer. Two measures are used to assess the extent of their digital literacy: individuals' proficiency in problem-solving in technology-rich environments (PSTRE) and index of ICT use in nonwork settings (FICTHOME).

Table A5 displays two linear regression models of the PSTRE measure. Each model includes the same demographic, educational attainment and current employment variables as baseline predictors. The first model, summarized in Table A5a, uses only these baseline predictors. A second model, summarized in Table A5b, adds another predictor, the index of ICT use in nonwork settings (FICTHOME). These two regression models explain 25% and 32% of the variance in PSTRE, respectively.

Table A5. Regressions of PSTRE Proficiency

	Table A5a					Table A5b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
Age	-1.6472	0.4267	-3.86	0.000		-1.0611	0.4162	-2.55	0.011
Age^2	0.0099	0.0053	1.85	0.064		0.0047	0.0052	0.90	0.367
Female	-5.6452	1.4860	-3.80	0.000		-5.3711	1.4441	-3.72	0.000
Black	-31.0600	3.0820	-10.08	0.000		-31.9471	3.0121	-10.61	0.000
Hispanic	-21.4820	4.0527	-5.30	0.000		-22.8119	3.9714	-5.74	0.000
Other	-8.3629	3.3632	-2.49	0.013		-11.9025	3.5188	-3.38	0.001
US Born	18.2620	2.9080	6.28	0.000		17.6723	3.0853	5.73	0.000
Med Educ	17.5953	3.1379	5.61	0.000		13.1712	3.2323	4.07	0.000
High Educ	43.2283	3.4334	12.59	0.000		32.2981	3.6157	8.93	0.000
Working	1.3685	1.8938	0.72	0.470		1.8221	1.8782	0.97	0.332
ICT Use						11.1648	0.8406	13.28	0.000
Constant	298.8648	8.6663	34.49	0.000		267.5810	8.8370	30.28	0.000

N = 3685 $R^2 = 0.255$ N = 3685 $R^2 = 0.318$

(ICT Use is outside of work)

$p < 0.05$

As in previous models, digital equity in PSTRE is defined in terms of the statistical significance of regression coefficients of variables indicating membership in gender, race/ethnicity and national origin groups in the multivariate models that take effects of age, educational attainment and current employment status into account. Black, Hispanic and Other (non-white) groups, the foreign-born and females all exhibit significantly lower PSTRE proficiencies with age, education and employment status controlled. There are thus significant race, gender and national origin disparities in PSTRE proficiency.

Appendix Table A6 displays the corresponding results for the other measure of digital literacy, the index of ICT use in nonwork settings (FICTHOME). Regression results are shown for two models analogous to the ones shown in the previous Table. Both models use the same demographic, educational and employment status predictors. The model shown in Table A6b adds the additional predictor of PSTRE. These two regression models explain 12% and 20% of the variance in FICTHOME, respectively.

There are not significant differences between gender groups or between national origin groups in these models of ICT use; the coefficients on *Female* and *US Born* are not significantly different from zero. Hispanic and Black populations show significantly *higher* levels of ICT usage in these models. There is thus evidence of digital equity in ICT use (outside of work) by gender and national origin, and evidence of a lack of digital equity in ICT use (with Blacks and Hispanics having *higher* levels).

Table A6. Regressions of Index of ICT Use Outside of Work

	Table A6a					Table A6b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
Age	-0.0525	0.0084	-6.22	0.000		-0.0401	0.0084	-4.77	0.000
Age^2	0.0005	0.0001	4.51	0.000		0.0004	0.0001	3.86	0.000
Female	-0.0245	0.0307	-0.80	0.425		0.0181	0.0309	0.59	0.557
Black	0.0795	0.0666	1.19	0.233		0.3141	0.0665	4.72	0.000
Hispanic	0.1191	0.0474	2.51	0.012		0.2814	0.0524	5.37	0.000
Other	0.3170	0.0832	3.81	0.000		0.3801	0.0877	4.34	0.000
US Born	0.0528	0.0694	0.76	0.447		-0.0853	0.0748	-1.14	0.254
Med Educ	0.3963	0.0835	4.75	0.000		0.2634	0.0848	3.11	0.002
High Educ	0.9790	0.0760	12.89	0.000		0.6525	0.0786	8.30	0.000
Working	-0.0406	0.0469	-0.87	0.386		-0.0509	0.0467	-1.09	0.276
PSTRE						0.0076	0.0005	13.90	0.000
Constant	2.8020	0.1591	17.61	0.000		0.5432	0.2503	2.17	0.030
	N = 3685		$R^2 = 0.122$			N = 3685		$R^2 = 0.196$	

$p < 0.05$

Appendix B

This appendix presents technical details about the digital embedding analyses discussed in the report. Digital embedding of an outcome is said to occur when a measure of ICT use (either the index of ICT Use at Work, FICTWORK, or the index of ICT Use Outside of Work, FICTHOME) is significantly and positively associated with the outcome measure after effects of demographic variables and educational attainment and PSTRE proficiency are statistically controlled. We test for digital embedding with a pair of regression analyses of the outcome variable on the index of ICT use and these additional variables:

(a) demographic variables and educational attainment (and work-related variables as appropriate)

(b) demographic variables, educational attainment (and work-related variables as appropriate) and PSTRE proficiency

If the coefficient for the index of ICT use is statistically significant and positive in both of these regressions, we will say there is digital embedding of the outcome. This signifies that ICT use is positively associated with the outcome measure after taking demographics, education and PSTRE proficiency into account. This is a specific type of correlational relationship between the outcome and ICT use measures, one that does *not* imply causality.

Digital Embedding of Economic Outcomes

Digital embedding was examined for two outcomes, a continuous measure of earnings and a binary measure of employment status.

Earnings. Table B1 shows results for the two regression models used to examine the embedding of ICT use in the workplace in earnings, estimated for prime age workers, age 25-54. The dependent variable in each regression is the logarithm of monthly earnings, trimmed at the 1st and 99th percentiles of the earnings distribution to minimize the influence of extreme values likely associated with data coding errors (Hanushek et al, 2013).

Both regressions include the independent variables of basic demographics, dummies for levels of educational attainment (with no credential as the reference group, *Med Educ* flags a secondary credential as the highest received, *High Educ* flags a postsecondary credential), years of work experience (linear and quadratic terms), dummies for broad occupational categories, and the FICTWORK index of ICT use in the workplace. The regression shown in Table B1b adds PSTRE proficiency as an independent variable to the base model shown in Table B1a. Each of the regressions accounts for about 39% of the variance in log earnings.

Table B1. Regressions of Log Earnings on ICT Use in the Workplace, PSTRE and Control Variables, Prime Age Workers

	Table B1a					Table B1b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	0.1513	0.0144	10.50	0.000		0.1503	0.0158	9.49	0.000
PSTRE						0.0012	0.0006	1.99	0.047
Age	0.0419	0.0240	1.75	0.081		0.0447	0.0237	1.88	0.060
Age^2	-0.0005	0.0003	-1.80	0.071		-0.0005	0.0003	-1.84	0.066
Female	-0.3669	0.0288	-12.76	0.000		-0.3550	0.0308	-11.51	0.000
Black	-0.0820	0.0566	-1.45	0.148		-0.0337	0.0596	-0.57	0.572
Hispanic	-0.0641	0.0945	-0.68	0.498		-0.0154	0.0961	-0.16	0.873
Other	-0.0170	0.0746	-0.23	0.819		-0.0097	0.0770	-0.13	0.900
US Born	-0.0841	0.0695	-1.21	0.226		-0.0657	0.0793	-0.83	0.407
Med Educ	0.0424	0.0714	0.59	0.553		0.0663	0.0729	0.91	0.363
High Educ	0.2994	0.0639	4.69	0.000		0.3021	0.0705	4.28	0.000
Oc2	-0.4144	0.0509	-8.14	0.000		-0.3990	0.0488	-8.18	0.000
Oc3	-0.2324	0.0528	-4.40	0.000		-0.2025	0.0609	-3.33	0.001
Oc4	-0.7765	0.1602	-4.85	0.000		-0.7781	0.1581	-4.92	0.000
Exper	0.0353	0.0119	2.95	0.003		0.0328	0.0126	2.60	0.009
$Exper^2$	-0.0005	0.0002	-1.84	0.066		-0.0004	0.0003	-1.68	0.094
Constant	7.2374	0.4162	17.39	0.000		6.7319	0.4591	14.66	0.000

$R^2 = 0.386$ N=1674 $R^2 = 0.390$ N=1586

Earnings trimmed at 1st and 99th percentiles

$p < 0.05$

There are *not* significant effects of race/ethnicity or national origin on earnings evident here once digital literacy is taken into account either with FICTWORK (Table B1a) or FICTWORK and PSTRE (Table B1b). There are, however, significant and very substantial effects of gender on earnings even after adjustment by these and other important variables. In both equations, the gender coefficient of -0.35 on log earnings indicates that women on average are earning 35% less than men after adjusting for general occupation, educational attainment, work experience, digital literacy and other covariates.

Table B1 shows substantial digital embedding of earnings. The significant positive coefficient of FICTWORK in both regressions reflects the importance of using ICT skills in the workplace for earnings and productivity. Even with PSTRE proficiency controlled, ICT use is a strong determinant of earnings. One indicator of the size of this effect is the partial correlation of FICTWORK and earnings after controlling for the other variables. These partial correlations are estimated to be 0.25 and 0.23 for the models in Tables B1a and B1b, respectively.

Table B2. Regressions of Log Earnings on ICT Use Outside of the Workplace, PSTRE and Control Variables, Prime Age Workers

	Table B2a					Table B2b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	0.0192	0.0164	1.17	0.242		-0.0123	0.0159	-0.78	0.436
PSTRE						0.0027	0.0006	4.37	0.000
Age	0.0322	0.0231	1.39	0.164		0.0299	0.0224	1.34	0.182
Age^2	-0.0005	0.0003	-1.76	0.079		-0.0004	0.0003	-1.59	0.112
Female	-0.4112	0.0339	-12.14	0.000		-0.3893	0.0353	-11.02	0.000
Black	-0.0602	0.0616	-0.98	0.329		0.0348	0.0670	0.52	0.603
Hispanic	-0.0420	0.0863	-0.49	0.626		0.0699	0.0883	0.79	0.428
Other	0.0410	0.0734	0.56	0.577		0.0654	0.0751	0.87	0.384
US Born	-0.0784	0.0558	-1.40	0.160		-0.1226	0.0659	-1.86	0.063
Med Educ	0.1777	0.0989	1.80	0.072		0.0927	0.1056	0.88	0.380
High Educ	0.4676	0.0968	4.83	0.000		0.3312	0.1019	3.25	0.001
Oc2	-0.5663	0.0525	-10.79	0.000		-0.5460	0.0504	-10.84	0.000
Oc3	-0.4023	0.0557	-7.22	0.000		-0.3672	0.0594	-6.18	0.000
Oc4	-1.1463	0.1299	-8.82	0.000		-1.1231	0.1500	-7.49	0.000
Exper	0.0536	0.0115	4.66	0.000		0.0538	0.0122	4.42	0.000
$Exper^2$	-0.0007	0.0002	-3.01	0.003		-0.0008	0.0003	-2.97	0.003
Constant	7.5788	0.3995	18.97	0.000		6.9476	0.4415	15.74	0.000

$R^2 = 0.367$ N=1783 $R^2 = 0.374$ N=1689

Earnings trimmed at 1^{st} and 99^{th} percentiles

$p < 0.05$

Table B2 shows results for the same two regression models, substituting ICT use *outside of work* (FICTHOME) for ICT use at work (FICTWORK). Although the results in Table B2 are generally quite similar to those of Table B1, FICTHOME is not a significant predictor of earnings in Table B2 as FICTWORK is in Table B1.

Thus, ICT use at work is embedded in workers' earnings while their ICT use outside of work is not embedded in their earnings.

Employment. Table B3 displays the results for the two logistic regressions of individuals' binary employment status (i.e., whether they were employed at the time of their interview). The two models used to test for the embedding of ICT use (outside of work) in employment status are shown in Tables B3a and B3b. These regressions are estimated for prime age adults age 25-54.

Table B3. Logistic Regressions of Employment Status on ICT Use Outside of the Workplace, PSTRE and Control Variables , Prime Age Adults

	Table B3a					Table B3b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	-0.0416	0.0689	-0.600	0.546		-0.0477	0.0800	-0.600	0.551
PSTRE						0.0029	0.0020	1.460	0.144
Age	0.0177	0.0680	0.260	0.794		0.0460	0.0704	0.650	0.513
Age^2	-0.0001	0.0009	-0.140	0.889		-0.0004	0.0009	-0.490	0.624
Female	-0.9591	0.1182	-8.110	0.000		-0.8983	0.1223	-7.340	0.000
Black	0.0309	0.1660	0.190	0.852		0.2553	0.2049	1.250	0.213
Hispanic	-0.0431	0.2078	-0.210	0.836		-0.0094	0.2383	-0.040	0.969
Other	-0.3662	0.1765	-2.080	0.038		-0.4054	0.1736	-2.330	0.020
US Born	-0.0615	0.1860	-0.330	0.741		-0.0841	0.2206	-0.380	0.703
Med Educ	0.6365	0.2454	2.590	0.009		0.5059	0.2593	1.950	0.051
High Educ	1.3042	0.2564	5.090	0.000		1.0885	0.2843	3.830	0.000
Constant	1.8695	1.3319	1.400	0.160		0.5501	1.4377	0.380	0.702

Pseudo R^2 = 0.053 N=2471 Pseudo R^2 = 0.051 N=2316

$p < 0.05$

Relatively few independent variables are statistically significant predictors of employment status in either model. Women and members of an “Other” race/ethnicity group are less likely to be employed after taking other variables into account. Adults with college degrees are more likely to be employed. Neither of the digital literacy measures, PSTRE proficiency and FICTHOME, is significantly related to employment. There is thus no evidence for the digital embedding of employment status.

Digital Embedding of Social Outcomes

Digital embedding was analyzed for a set of social outcomes: social trust, volunteerism, political efficacy and health status. As described in Appendix C, each of these outcomes is measured with an ordinal variable on a 1 to 5 scale. Digital embedding of each of these social outcomes is examined with a pair ordinal logistic regression models. As before, the first model of each pair contains a baseline set of independent variables: demographic variables, dummies for levels of educational attainment, and the binary variable Working for current employment status, and the FICTHOME index of ICT use outside of work. The second model in each pair adds PSTRE proficiency to the baseline set of predictors. For each social outcome, the two ordinal regressions are estimated for adults 25-65 years of age.

Each ordinal regression model computes a continuous variable that is compared with four cutpoint constants to predict one of the five ordinal values of the dependent variable: below *Cut1_Constant* predicts the lowest ordinal value; between *Cut1_Constant* and *Cut2_Constant* predicts the second value; between *Cut2_Constant* and *Cut3_Constant* predicts the third value; between *Cut3_Constant* and *Cut4_Constant* predicts the fourth value; and above *Cut4_Constant* predicts the highest value on the five-point scale.

Maximum likelihood estimation is used to estimate the four cutpoint constants along with the logistic regression coefficients for each model.

Social trust. Table B4 displays the two ordinal regressions for social trust. There is statistically significant digital embedding of social trust: FICTHOME is positively associated with social trust in Tables 12a and 12b. Females and adults with college degrees have higher adjusted levels of social trust, while adults in the Black and "Other" (Race/ethnicity) groups have significantly lower levels of social trust after other variables are taken into account.

Table B4. Ordinal Regressions of Social Trust on ICT Use Outside of the Workplace, PSTRE and Control Variables, Adults Age 25-65

	Table B4a					Table B4b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	0.1880	0.0454	4.14	0.000		0.1101	0.0505	2.18	0.029
PSTRE						0.0065	0.0013	4.94	0.000
Age	0.0020	0.0225	0.09	0.930		0.0069	0.0234	0.29	0.769
Age^2	0.0001	0.0003	0.51	0.607		0.0001	0.0003	0.47	0.636
Female	0.2191	0.0866	2.53	0.011		0.2609	0.0897	2.91	0.004
Black	-0.5146	0.1438	-3.58	0.000		-0.3010	0.1473	-2.04	0.041
Hispanic	-0.2101	0.1817	-1.16	0.248		-0.0674	0.1818	-0.37	0.711
Other	-0.5506	0.1420	-3.88	0.000		-0.4678	0.1443	-3.24	0.001
US Born	0.0194	0.1228	0.16	0.874		-0.0875	0.1173	-0.75	0.456
Med Educ	0.3459	0.2231	1.55	0.121		0.2159	0.2189	0.99	0.324
High Educ	0.9655	0.2163	4.46	0.000		0.7238	0.2111	3.43	0.001
Working	0.0953	0.1061	0.90	0.369		0.0674	0.1047	0.64	0.520
Cut1_Constant	0.8322	0.5059	1.64	0.100		2.4938	0.6004	4.15	0.000
Cut2_Constant	2.0396	0.4964	4.11	0.000		3.7175	0.5940	6.26	0.000
Cut3_Constant	3.3974	0.4879	6.96	0.000		5.0907	0.5937	8.57	0.000
Cut4_Constant	5.3545	0.4785	11.19	0.000		7.0551	0.5932	11.89	0.000

Pseudo R^2 = 0.028 N=2990 Pseudo R^2 = 0.033 N=2990

$p < 0.05$

Volunteerism. Table B5 displays the two ordinal regressions for volunteerism. There is statistically significant digital embedding of volunteerism: FICTHOME is positively associated with volunteerism in Tables B5a and B5b. PSTRE is not significantly associated with volunteerism in Table B5b. Females, Blacks and currently employed adults all have significantly higher levels of volunteerism, whereas "Other" (Race/ethnicity) adults have significantly lower levels of volunteerism after other variables are taken into account.

Table B5. Ordinal Regressions of Volunteerism on ICT Use Outside of the Workplace, PSTRE and Control Variables, Adults Age 25-65

	Table B5a					Table B5b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	0.4617	0.0483	9.57	0.000		0.4432	0.0488	9.08	0.000
PSTRE						0.0016	0.0011	1.44	0.151
Age	0.0408	0.0217	1.88	0.060		0.0415	0.0219	1.90	0.058
Age^2	-0.0003	0.0003	-1.10	0.269		-0.0003	0.0003	-1.09	0.275
Female	0.2712	0.0794	3.42	0.001		0.2797	0.0795	3.52	0.000
Black	0.2560	0.1042	2.46	0.014		0.3086	0.1045	2.95	0.003
Hispanic	-0.0551	0.1298	-0.42	0.671		-0.0187	0.1376	-0.14	0.892
Other	-0.4926	0.1482	-3.32	0.001		-0.4660	0.1510	-3.09	0.002
US Born	0.1653	0.1214	1.36	0.173		0.1418	0.1215	1.17	0.243
Med Educ	0.3335	0.2322	1.44	0.151		0.2984	0.2340	1.28	0.202
High Educ	0.7519	0.2328	3.23	0.001		0.6877	0.2388	2.88	0.004
Working	0.2231	0.0995	2.24	0.025		0.2152	0.1005	2.14	0.032
Cut1_Constant	2.9840	0.5129	5.82	0.000		3.3756	0.5903	5.72	0.000
Cut2_Constant	4.2628	0.5028	8.48	0.000		4.6563	0.5810	8.01	0.000
Cut3_Constant	5.2503	0.5069	10.36	0.000		5.6435	0.5881	9.60	0.000
Cut4_Constant	7.2351	0.5024	14.40	0.000		7.6272	0.5982	12.75	0.000

Pseudo R^2 = 0.039 N=2990 Pseudo R^2 = 0.039 N=2990

$p < 0.05$

Political efficacy. Table B6 displays the two ordinal regressions for political efficacy. There is statistically significant digital embedding of political efficacy: FICTHOME is positively associated with political efficacy in Tables B6a and B6b. PSTRE is not significantly associated with political efficacy in Table B6b. Blacks, Hispanics and those with higher education degrees have significantly higher levels of political efficacy after other variables are taken into account. The coefficient for the “Other” race/ethnicity is statistically significant and negative in Table B6a but is nonsignificant in Table B6b.

Table B6. Ordinal Regressions of Political Efficacy on ICT Use Outside of the Workplace, PSTRE and Control Variables, Adults Age 25-65

	Table B6a					Table B6b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	0.2816	0.0459	6.13	0.000		0.2091	0.0471	4.44	0.000
PSTRE						0.0062	0.0011	5.53	0.000
Age	0.0287	0.0245	1.17	0.242		0.0322	0.0247	1.31	0.192
Age^2	-0.0002	0.0003	-0.74	0.458		-0.0002	0.0003	-0.72	0.470
Female	0.2586	0.0809	3.20	0.001		0.2949	0.0823	3.58	0.000
Black	0.6322	0.1614	3.92	0.000		0.8345	0.1510	5.53	0.000
Hispanic	0.4077	0.1639	2.49	0.013		0.5523	0.1625	3.40	0.001
Other	-0.3326	0.1612	-2.06	0.039		-0.2530	0.1605	-1.58	0.115
US Born	0.1102	0.1051	1.05	0.294		0.0010	0.1038	0.01	0.993
Med Educ	0.3299	0.1786	1.85	0.065		0.2009	0.1790	1.12	0.262
High Educ	0.7046	0.1815	3.88	0.000		0.4591	0.1851	2.48	0.013
Working	0.0941	0.0926	1.02	0.310		0.0692	0.0943	0.73	0.463
Cut1_Constant	0.5968	0.5890	1.01	0.311		2.1126	0.6009	3.52	0.000
Cut2_Constant	1.7913	0.5993	2.99	0.003		3.3206	0.6105	5.44	0.000
Cut3_Constant	2.6154	0.5990	4.37	0.000		4.1581	0.6083	6.84	0.000
Cut4_Constant	4.5888	0.5988	7.66	0.000		6.1469	0.6073	10.12	0.000

Pseudo R^2 = 0.022 N=2998 Pseudo R^2 = 0.027 N=2990

$p < 0.05$

__Health__. Table B7 displays the two ordinal regressions for self-reported general health status. There is statistically significant digital embedding of health: FICTHOME is positively associated with health in Tables B7a and B7b. PSTRE is not significantly associated with health in Table B7b. Adults with higher education degrees and adults with current employment have significantly higher levels of health, whereas members of minority groups (Blacks, Hispanics, “Other” race/ethnic groups) and the foreign-born have significantly lower levels of health after other variables are taken into account.

Table B7. Ordinal Regressions of General Health Status on ICT Use Outside of the Workplace, PSTRE and Control Variables, Adults Age 25-65

	Table B7a					Table B7b			
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
ICT Use	0.1445	0.0408	3.54	0.000		0.1260	0.0421	2.99	0.003
PSTRE						0.0015	0.0012	1.28	0.200
Age	-0.0524	0.0294	-1.78	0.074		-0.0515	0.0295	-1.74	0.081
Age^2	0.0004	0.0003	1.28	0.202		0.0004	0.0003	1.28	0.202
Female	0.0782	0.0747	1.05	0.295		0.0850	0.0749	1.14	0.256
Black	-0.5148	0.1179	-4.37	0.000		-0.4671	0.1277	-3.66	0.000
Hispanic	-0.3631	0.1589	-2.29	0.022		-0.3265	0.1640	-1.99	0.047
Other	-0.5823	0.1864	-3.12	0.002		-0.5597	0.1869	-2.99	0.003
US Born	-0.3739	0.1514	-2.47	0.014		-0.3989	0.1545	-2.58	0.010
Med Educ	0.1063	0.2246	0.47	0.636		0.0748	0.2325	0.32	0.748
High Educ	0.7990	0.2085	3.83	0.000		0.7398	0.2216	3.34	0.001
Working	0.7147	0.1268	5.63	0.000		0.7078	0.1283	5.52	0.000
Cut1_Constant	-4.2230	0.6361	-6.64	0.000		-3.8494	0.7307	-5.27	0.000
Cut2_Constant	-2.6422	0.6577	-4.02	0.000		-2.2679	0.7435	-3.05	0.002
Cut3_Constant	-0.9321	0.6597	-1.41	0.158		-0.5569	0.7469	-0.75	0.456
Cut4_Constant	0.7360	0.6621	1.11	0.266		1.1122	0.7497	1.48	0.138

Pseudo R^2 = 0.037 N=2989 Pseudo R^2 = 0.038 N=2989

$p < 0.05$

Appendix C

This appendix describes the assessment of Problem Solving in Technology-Rich Environments (PSTRE). The PSTRE framework is described in detail in OECD (2012). PSTRE was assessed through performance of 14 tasks. Item response theory was used to estimate proficiencies on a 0-500 point scale, divided into four levels, as shown below

Here are OECD's descriptions (2013a: 88) of the tasks that individuals are able to do at each level.

Below Level 1 (scale scores of 240 and below)

> *"Tasks are based on well-defined problems involving the use of only one function within a generic interface to meet one explicit criterion without any categorical or inferential reasoning, or transforming of information. Few steps are required and no sub-goal has to be generated."*

Level 1 (241-290)

> *"At this level, tasks typically require the use of widely available and familiar technology applications, such as e-mail software or a web browser. There is little or no navigation required to access the information or commands required to solve the problem. The problem may be solved regardless of the respondent's awareness and use of specific tools and functions (e.g. a sort function). The tasks involve few steps and a minimal number of operators. At the cognitive level, the respondent can readily infer the goal from the task statement; problem resolution requires the respondent to apply explicit criteria; and there are few monitoring demands (e.g. the respondent does not have to check whether he or she has used the appropriate procedure or made progress towards the solution). Identifying content and operators can be done through simple match. Only simple forms of reasoning, such as assigning items to categories, are required; there is no need to contrast or integrate information."*

Level 2 (291-340)

> *"At this level, tasks typically require the use of both generic and more specific technology applications. For instance, the respondent may have to make use of a novel online form. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g. a sort function) can facilitate the resolution of the problem. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, though the criteria to be met are explicit. There are higher monitoring demands. Some unexpected outcomes or impasses may appear. The task may require evaluating the relevance of a set of items to discard distractors. Some integration and inferential reasoning may be needed."*

Level 3 (341 and higher)

> *"At this level, tasks typically require the use of both generic and more specific technology applications. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g. a sort function) is required to make progress towards the solution. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, and the criteria to be met may or may not be explicit. There are typically high monitoring demands. Unexpected outcomes and impasses are likely to occur. The task may require evaluating the relevance and reliability of information in order to discard distractors. Integration and inferential reasoning may be needed to a large extent."*

Sample problems at each level were provided in the OECD report (2013a: 89):

“Level 1: Party invitations (Item ID: U01A)
Cognitive strategies: Plan and use information
Technology: E-mail
Context: Personal
Difficulty score: 286

This task involves sorting e-mails into pre-existing folders. An e-mail interface is presented with five e-mails in an Inbox. These e-mails are responses to a party invitation. The test-taker is asked to place the response e-mails into a pre-existing folder to keep track of who can and cannot attend a party. The item requires the test-taker to “Categorise a small number of messages in an e-mail application in existing folders according to a single criterion.”

The task is performed in a single and familiar environment and the goal is explicitly stated in operational terms. Solving the problem requires a relatively small number of steps and the use of a restricted range of operators and does not demand a significant amount of monitoring across a large number of actions.”

“Level 2: Club membership (Item ID: U19b)
Cognitive strategies: Set goals and monitor progress, plan, acquire and evaluate information and use information
Technology: Spreadsheet, E-mail
Context: Society and community
Difficulty score: 296

This task involves responding to a request for information by locating information in a spreadsheet and e-mailing the requested information to the person who asked for it. The test-taker is presented with a word-processor page containing a request to identify members of a bike club who meet two conditions, and a spreadsheet containing 200 entries in which the relevant information can be found. The required information has to be extracted by using a sort function. The item requires the test-taker to ‘Organise large amounts of information in a multiple-column spreadsheet using multiple explicit criteria and locate and mark relevant entries.’ The task requires switching between two different applications and involves multiple steps and operators. It also requires some amount of monitoring. Making use of the available tools greatly facilitates identifying the relevant entries.”

“Level 3: Meeting rooms (Item ID: U02)
Cognitive strategies: Set goals and monitor progress, plan, acquire and evaluate information and use information
Technology: E-mail, Internet
Context: Work-related
Difficulty score: 346

This task involves managing requests to reserve a meeting room on a particular date using a reservation system. Upon discovering that one of the reservation requests cannot be accommodated, the test-taker has to send an e-mail message declining the request. Successfully completing the task involves taking into account multiple constraints (e.g. the number of rooms available and existing reservations). Impasses exist, as the initial constraints generate a conflict (one of the demands for a room reservation cannot be satisfied). The impasse has to be resolved by initiating a new sub-goal, i.e. issuing a standard message to decline one of the requests. Two applications are present in the environment: an e-mail interface with a number of e-mails stored in an inbox containing the room reservation requests, and a web-based reservation tool that allows the user to assign rooms to meetings at certain times. The item requires the test-taker to “Use information from a novel web application and several e-mail messages, establish and apply criteria to solve a scheduling problem where an impasse must be resolved, and communicate the outcome.” The task involves multiple applications, a large number of steps, a built-in impasse, and the discovery and use of ad hoc commands in a novel environment. The test-taker has to establish a plan and monitor its implementation in order to minimise the number of conflicts. In addition, the test-taker has to transfer information from one application (e-mail) to another (the room-reservation tool).”