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Pathways to digital literacy and engagement

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Distinct Skill Pathways to Digital Engagement

There is considerable variety in the type of activities that people undertake online (Dutton & Blank, 2011) and a number of inter-related individual and contextual explanations for why these differences exist. Two well documented factors are socio-demographic background and ICT related skills. Yet, despite the clear links between digital literacy and digital inclusion research, these two areas of research rarely come together. While digital literacy studies have been concerned with identifying different types of digital skills and Internet use; digital inclusion research mostly examines the links between individual characteristics and engagement with the Internet using a single skills measure. Thus, we know relatively little about how the range of different digital skills may vary due to the different socio economic and demographic backgrounds of internet users. Furthermore, even in digital literacy studies little work has been conducted to understand if certain types of digital skills are related to different kinds of digital engagement or the extent to which digital skills in one realm will transfer across to many kinds of online activities. We argue that this is caused by measurement issues and a lack of an integrated theory that combines different approaches to understanding the relationships between digital skills and engagement with ICTs. This paper uses data from the 2011 Oxford Internet Surveys (OxIS) to explore these issues in the UK context.

Background

Digital Skills and Literacy Debates

Research on digital skills forms part of a wider debate about defining and understanding the new literacies required to participate fully in the digital age. There is a great deal of research that explores the set of skills or competencies that are important and how they should be operationalised for research and practice (Ba, et al., 2002; Eshet-Alkalai

& Amichai-Hamburger's (2004); Gilster, 1997; Van Deursen, 2010). However, the area is complex to navigate due to competing (but overlapping) definitions of new literacies (Van Deursen & Van Dijk, 2008). For example, researchers may talk in terms of information, new media or digital literacy (Livingstone, 2004) and a number of authors use the plural term literacies to reflect the multiple and socio-cultural aspects of these concepts (Buckingham, 2007; Lankshear & Knobel, 2008). Given the significant controversies and issues of definition that are apparent in the area, we deliberately use the word skills to reflect the focus here.

Related to issues of definition is the question of measurement. As Van Deursen and Van Dijk (2008) note, it is important to separate skills' measurement from measurement of use. Typically measurement questions about skills follow the format: How good are you at 'X'?, while questions on engagement are 'How often do you do 'X'?' Yet doubts can be raised about whether someone can have or claim high skills on something they have never done or whether those who undertake an activity frequently would ever classify themselves as having low skills in that area. Indeed, correlations between these types of indicators are often, unsurprisingly, high.

To overcome some of these issues a pre-defined set of skills is necessary that is not linked to specific uses or applications but that group together a set of skills. Each group reflects a broader understanding of a particular kind of skill set that is required in the production and/ or management of different types of content online. Indeed, the majority of definitions of digital skills tend to encompass functional skills to operate and use technologies for a range of informational, social and creative purposes alongside a strategic understanding of how ICTs influence and are influenced by commercial and societal factors.

This study assumes four types of skills: critical, social, creative and technical skills because these four types of skills encompass the most common types of skills identified in new literacies debates (Livingstone, 2008). This categorisation identifies areas of literacy that are both operational (creative & technical) and based on a strategic understanding of risks and opportunities (social & critical) (see also Van Deursen, 2010).

This paper tests whether these skills are separate empirical constructs and whether they have differentiating explanatory values in relation to digital engagement. Thus, what we present here is an examination of the operationalization and links between skills and engagement based on existing data and an examination of the possible generalisation of these processes across different groups of people, rather than a redefinition and conceptualisation of digital or new media literacy.

Use and Engagement with ICTs

In parallel to the debates about digital literacy there has been a debate about the effective use of ICTs under the digital inclusion agenda. It is thought that improved uptake and engagement with ICTs leads to a range of positive outcomes for the individual and society. The majority of research in this area demonstrates that there are links between social exclusion and digital engagement. Those with fewer socio-economic resources are less likely to engage (Haddon, 2000). Furthermore, access to ICTs, individual motivation and digital skills are important in explaining the intensity and breadth of this engagement (Van Deursen & Van Dijk, 2009; Van Dijk, 2005). However, partly due to the focus on use of ICTs and the myriad of explanatory factors of which skills is only one aspect, the operationalisation of digital literacies is often underdeveloped in the digital exclusion literature (Van Deursen, 2010). More effort has been put into classifying different types of digital inclusion and ways of measuring use than into classifying different skills, thus not reflecting the research into digital literacy. Furthermore, it often falls into the trap of measuring skills through level of use. In addition, little work has been conducted to understand if certain types of digital skills are related to different kinds of digital engagement or the extent to which digital skills in one realm will transfer across to many kinds of online activities (Helsper, 2012). It seems logical that skills that correspond to the nature of specific digital activities are more likely to lead to an increase in engagement in that field than to subsequent engagement in another unrelated field.

We use the term digital engagement to reflect the development in the digital inclusion literature, which has shifted from a primary focus on use versus non-use of the Internet, towards breadth of use and gradations of inclusion (Jung, et al., 2001; Livingstone & Helsper, 2007), and is now moving towards understanding different ways of engaging with ICTs. Thus, here, we use the term digital engagement to refer to the ways in which people use and participate in different internet activities, contents and platforms. Drawing on Mehra and colleagues (2004) we suggest that quantitative measures of Internet use should reflect both intensity and breadth of use. We make the assumption that a broader, more frequent use of the technology shows that the technology is more integrated into everyday life, and thus identifies greater engagement with the Internet but that this, while related to it, is independent from skills (Helsper, 2012).

Research Questions and Methodology

Based on the literature a conceptual framework (Figure 1) was developed. Our focus here is on understanding digital engagement through the lens of digital inclusion research, but trying to develop this through a greater awareness of digital literacies research. Thus we see digital engagement as an outcome that is based in part on traditional inclusion and mediated through ICT related factors.

This paper uses data from the 2011 Oxford Internet Survey (OxIS). The survey is a face to face doorstep survey based on a stratified-random sample of the British population over 14 years old (N=2,057) with a response rate of 51% (Dutton & Blank, 2011).

The first research question is one of measurement: *Is it is possible to empirically distinguish four distinct types of digital skills – specifically creative, social, technical and critical skills*? *(block a in Figure 1)*

This paper aims to test the hypothesis that different types of digital skills relate to different kinds and depths of engagement with Internet. Thus, it positions itself against a hypothesis that all skills are equivalent so that ability in one area will translate seamlessly into engagement in other areas. Therefore, the second research question is directional: *Are specific digital skills related to specific digital engagement types? (path b in Figure 1)* For example, does an individual with a high level of digital creative literacy engage with the Internet in more creative ways but not with other online activities?

The relationship between digital exclusion and specific skills is not clear even though an overall link has been established to a measure of general skills. Consequently, the third exploratory question is: *how do different socio-demographic characteristics relate to different skill types (path c in Figure 1)?*

The final question concerns the digital engagement process: *in which way does the relationship between, socio-demographic factors and engagement depend on digital skills levels? (path d in Figure 1).* The hypothesis is that the four kinds of inclusion measures (economic, social, cultural and personal) influence engagement directly (independent of skill) as well as indirectly depending on specific engagement related skills (e.g. Eynon & Malmberg, 2011).

For simplicity, we leave the influence of access as a mediator out of the equation. There is a considerable body of digital inclusion research addressing the importance of access. Therefore we concentrate on the measurement and relationship between socio-demographic factors, skills and engagement amongst internet users.

Measures

Inclusion indicators. Based on the literature (Halford & Savage, 2010; Van Dijk, 2005) and the items available in OxIS, we identify four areas of inclusion: economic, cultural, social and personal.[1] The framework used was that proposed by Helsper (2012) which looks at resources as individual characteristics, differing from sociological resource theory as used by De Haan et al (2002).

Two *economic resources*, education and occupation, were measured. Education (M=*2.86*; SD=.84) was created by classifying those with up to high/secondary school education as 'Basic education' (42%), those with additional post-compulsory education as 'Further education' (29%), and those with University education as 'Higher education' (29%). For SES the standard acorn classification[2] unit based on income and occupation of the chief income earner was used: 28% Wealthy Achievers; 9% Urban Prosperity; 28% Comfortably Off; 15% Moderate Means; 19% Hard-Pressed.

Cultural resources includes socialization into certain types of behavior that differ between groups (Selwyn, 2004), two main socialization factors have been related to engagement with ICTs in previous research: gender and age. For other cultural factors, such as ethnicity and religion, links to digital engagement are less clear in the UK and therefore not incorporated in the analyses. Gender was noted by the interviewer (56% men / 44% women). To determine age the participant was asked in which year they were born (M=43.22; SD=17.04).

Social resources were measured in two ways: social isolation (Hughes et al. , 2004) and social capital (Wellman, et al., 2001). Isolation (M=55; SD=.72, α =.91) was calculated based on the average of how often respondent felt: 'lack of companionship'; 'left out'; 'isolated from others' (scale 0 to 4 from 'Never' to 'Always'). Social capital (M= 1.07; SD=1.28*)* was the sum of networks or organizations in which a person participates: in any social or sport club; a residents, neighborhood, school or other local group; an environmental or animal welfare organization; any other political or campaigning organization; a charity organization or social aid organization; and / or a religious or church organization. 50% did not participate in any.

Personal resources are indicative of individual health and well-being independent of their social or economic status, measured in this paper through locus of control and physical health. Internal Locus of Control (*M*=3.23; *SD*=1.02): was the average agreement with 'Becoming a success in life is a matter of hard work, luck has little or nothing to do with it'; 'What happens to me is my own doing'; 'Getting a good job depends mainly on being in the right place at the right time'; 'Sometimes I feel that I don't have enough control over the direction my life is taking (reversed)'. Poor physical health was calculated by asking participants: 'Do you have a health problem or disability which prevents you from doing everyday tasks at home, work or school or elsewhere?' 9% of internet users replied positively to this question.

These indicators of inclusion, even though they can be classified separately as economic, cultural, social and personal, are obviously not independent. Correlations between the variables were calculated and none of these correlations were high enough (range $-.26 < r < .41$) to cause concerns about multi-colinearity or to warrant creating a combined variable. All relevant and available OxIS variables were used, additional variables to enhance the construction of these indicators would be valuable in future research.

Digital skills and confidence indicators. Online skills were measured in two ways through items based on inquiring about eight specific activities and through an overall measure of digital self-efficacy. The former tends to give more reliable results (Livingstone & Helsper, 2007) but makes separating skills and use difficult and the latter is often used in studies of digital inclusion as a measure of overall confidence (Cheong, 2008; Hargittai & Hinnant, 2008; Broos & Roe, 2006).

Our hypothesized four measures of online skills were derived from the eight items. Participants were asked to judge how confident they felt about doing the following on a scale from 1 (not confident at all) to 5 (very confident). The items were ‘Judging the reliability of an on-line source?’ (M=3.78; SD=1.00), ‘Using the Internet to gather information?’ (M=4.34; SD=.77), ‘Removing a virus that infected your computer?’ (M=3.03; SD=1.46), ‘Learning how to use a new technology?’ (M=3.69; SD=1.22), ‘Participating in a discussion online?’ (M=3.25; SD=1.37), ‘Making new friends on the Internet?’ (M=3.16; SD=1.40), ‘Uploading photos to a website?’ (M=3.55; SD=1.22), and Downloading and saving music (MP3)?’ (M=3.49; SD=1.42). Digital self-efficacy (M=3.89; SD=.80): ‘How would you rate your ability to use the Internet?’ Answers were given on a scale from 1 (Bad) to 5 (Excellent).

For this paper the construction of the measures is a partial answer to the first research question and is therefore summarized here and discussed in more detail as part of the findings section.

Digital engagement indicators. 25 items in OxIS were selected because they conceptually reflected creative, social, critical and technical types of engagement corresponding to the pre-established types of skills. The format of all the questions in OxIS was ‘How frequently do you use the Internet for the following purposes?’ Answer options ranged from ‘Never’ to ‘Several times per day’ (Dutton & Blank, 2011). Since OxIS was not designed apriori with the engagement types in mind, the most appropriate but not ideal indicators were used to construct the scales.

A factor analysis to determine engagement categories, fixing four factors in advance with as criteria eigenvalues greater than 1, showed classifications reflecting the skills scales. Items were included on a scale if their loading on that factor after Varimax rotation was greater than .40. The technical items were on a different scale so were analyzed separately.

All scales had high internal reliability: Technical engagement α = .82 (spam filtering, virus scanning, blocking unwanted messages); Critical engagement α = .85 (checking facts, looking up definitions, health information, news, local event information, travel information, school/work information, topics of personal interest, distance learning); Social engagement α = .87 (IM, chat, read blogs, write blogs, personal website, discussion boards, posting pictures/videos, social networking profile, posting stories); Creative engagement α = .90 (games, downloading music, listening to music, downloading videos, watching videos, uploading videos or music, social networking, posting stories). The items that loaded on more than one factor were included in the average across the items on that scale which means the engagement scales overlapped and thus correlated.

To create a scale including both intensity and breadth of use on all four types of engagement, a composite scale was created multiplying the average frequency with which the person engaged with the activities part of a scale with the number of activities that the person engaged with on that scale (breadth). The exception was the technical engagement scale where no frequency measure was available, therefore, that scale measured only breadth. This led to the following scales: Technical (*M* = 2.23; *SD* = 1.09), Critical (*M* = 12.67; *SD* = 9.05), Social (*M* = 6.07; *SD* = 8.30) and Creative (*M* = 8.78; *SD* = 10.20) engagement.

Results

a) Identifying Digital Skills

The skills items in the survey were examined using an exploratory factor analysis followed by a confirmatory factor analysis which fixed the rotated solution to the four factors identified. The exploratory factor analysis produced a single factor solution, an eigenvalue of greater than 1was used as the criterion for item inclusion. The single factor solution fit well, most items had factor loadings of over .50, α was .89 and total variance explained was 58%.

It is thus empirically justified to create one scale that measures digital literacy. However, the literature strongly suggests that a single skills measure does not reflect the complexity of digital literacy. A review of the theoretical literature suggested four types of skills: creative, social, critical and technical. A confirmatory factor analysis was conducted fixing the number of factors to four as hypothesized in the theoretical literature and only items with loadings higher than .40 were included on the scales. This lead to a grouping of skills scales that approximately followed the suggested classification: Technical skills $\alpha = .79$ (cleaning viruses, participating in discussions online, learning to use a new technology); Social skills $\alpha = .84$ (participating in discussions online, making new friends, uploading photos); Creative skills $\alpha = .87$ (uploading photos, downloading music, learning to use a new technology); Critical skills $r = .55$ (judging the reliability of a source, gathering information). As is clear, social and creative skills are more activity than skill related, a problem highlighted in the literature review and one that we return to in the discussion where we suggest that performance tests are needed to address this.

It is interesting to note that Web 2.0 activities (i.e. uploading photos) load highly on both the creative and the social dimensions, that participating in discussions is part of both the social and technical dimensions and that learning about new technologies was close to both technical and creative skills. This indicates the difficulties in identifying separate skills in an interactive communication environment. Uploading photos may be done to strengthen connections with others or as a creative practice where feedback from others may be valued. Learning about new technologies is related to learning about technical, operational skills but also to creative, production skills. It seems that in such an environment, skills do not fall into neat, clearly defined categories. Because the aim was to test a conceptual model of pathways of correspondence between skills and engagement types we decided to only select the conceptually relevant indicators to create each scale: Technical skills $r= .55$, $M = 3.87$, $SD =$

1.19 (cleaning viruses, learning to use a new technology); Social skills *r* = .69, *M* = 3.21, *SD* = 1.28 (participating in discussions online, making new friends); Creative skills *r* = .71, *M* = 3.53, *SD* = 1.30 (uploading photos, downloading music) and critical skills *r* =.55, *M* = 4.06, *SD* = .79 (judging the reliability of a source, gathering information).

The exploratory factor analysis showed that some items loaded on both factors, it is therefore not surprising that the technical and creative (r=.69) and creative and social factors were highly correlated (r = .68) even when items were not included on both scales. They were, however, below the threshold of concern of .80 for multi-colinearity (Variance Inflation Factors were all lower than 4). The correlation between the digital self-efficacy measure and technical skills was also relatively high (*r* = .56). Critical skills had the lowest correlations with the other skills (*r* = .51 with technical skills, *r* = .46 with social skills, *r* = .51 with creative skills) indicating that this construct distinguishes itself most and might have the clearest independent effect on engagement. The global measure of digital self-efficacy (often used as a proxy for perceived Internet skills) measures something independent from the four digital skills identified. The correlations with non-technical skills were lower (*r* = .41 with social skills, *r* = .48 with creative skills, *r* = .37 with critical skills).

b) Relationship between Skills and Engagement

To answer question two, whether the four types of digital skills (technical, social, critical and creative) relate to specific kinds of digital engagement, path modeling was used. Path modeling assesses the relative strength of direct and indirect relationships of variables with the dependent variables. Thus, it can determine whether a model such as the one shown in Figure 1 can explain the pattern of correlations in the data, since it allows the researcher to fix certain relationships to zero and others to vary. The direction of the paths proposed in the model is determined by theoretical assumptions; significance of the coefficients and model fit do not indicate causality. AMOS18 was used to test the hypothesized paths from skills to engagement.

The construction of the path diagram was theoretical and empirical. The first theoretical step was to relate specific skills to specific types of engagement (figure 2a). In a second, observation based step, correlations between skills were used as a starting point to construct paths (figure 2b). Based on this procedure, paths between technical skills and social, critical and creative engagement, between social skills and technical and creative engagement, between critical skills and technical engagement, and between creative skills and technical and social engagement were added to the first model with paths between only corresponding skills and engagement types.

The overall model fit for the initial model is good[3] (figure 2a). For social and creative skills, the relationship with the corresponding types of engagement is strong. Technical skills and critical skills are not significantly related to the corresponding types of engagement. It should be noted that the strongest predictor of critical, social and creative engagement is digital self-efficacy. After adding the paths based on the correlations and fixing the non-significant paths to zero the fit of the model improves significantly (figure 2b). The analysis give a mixed message; for interactive digital engagement types (i.e. social and creative) that could be considered more complex, skills were most closely related to corresponding types of engagement even when links between skills and non-corresponding types of engagement were included. However, for the more individual, relatively traditional engagement types (i.e. critical and technical) this was not the case. Instead skills were stronger predictors of cross-conceptual types of engagement than of the corresponding type of engagement. This can be a sign of true relationships or indicate measurement issues related to the difficulty of conceptualizing and defining separate skills areas as discussed earlier.

c) Relationship between Exclusion and Skills

To examine if there is a relationship between specific structural inclusion factors and specific types of skill (RQ3, c in Figure 1) we applied General Linear Multivariate (GLM) modeling.

Table 1 shows that most indicators of inclusion significantly predicted at least one type of skill in a multivariate analysis, SES (i.e. ACORN), locus of control and social capital did not. The *economic* indicator education was related to all indicators of digital skills and self-efficacy; those with university education perceived themselves to be more skilled than those without for all types of skill. Amongst the *cultural* indicators, age related to all skills, the older individuals were less confident and felt less skilled. Gender was similarly related to all skills; men perceived themselves to be more skilled and had higher levels of digital self-efficacy. The other *social* indicator, social isolation was (negatively) related to all skills except for social skills and digital self-efficacy. Socially isolated people were less likely to indicate that they, for example, knew how to judge whether information online is reliable. Health, a *personal* indicator, was not significantly related to most skills but related marginally to creative skills. Internet users without a disability indicated having a higher level of creative skills than those with a disability. Thus, in general when an exclusion indicator was related to one skill it was related to other skills in the same manner. All skills, with the exception of social skills (R^2=.07), were explained, to a significant and large extent, by socio-demographic variables (R^2 between .18 and .28).

d) Relationships between Digital Inclusion, Digital Skills and Engagement

To determine whether including specific skills in the explanation of the relationship between social and digital exclusion adds significantly to explaining engagement, a GLM model was hierarchically tested. In Step 1, only social exclusion factors were included to explain engagement (Table 2). In Step 2, the skills indicators were entered and the R^2 change was tested (Table 3).

As can be seen in Table 2, the economic indicator, *education*, was important in understanding all critical and social engagement. Those with basic education were less likely to engage in technical and critical uses of the Internet than those in university education but more likely to engage socially. Those with university education were more likely to participate in critical types of engagement with the Internet compared to individuals who had basic or further education, and more likely to participate in social activities online than those with basic education. For the second economic indicator, higher socio-economic status was related to more technical and less creative and critical engagement with the Internet.

Cultural indicators, *age* and *gender* were significantly related to creative, critical and social engagement. Men and those who were younger were more likely to engage with these activities. Social capital was positively related to technical and critical types of engagement. While this relationship is not surprising, it is interesting – as social capital was not related to social engagement. Social isolation was positively related to critical engagement. That is those who were socially isolated were more likely to seek information and educate themselves online, but not more likely to engage socially or creatively with the internet. Health was positively related to critical engagement. The second personal indicator, locus of control was not related to any type of engagement.

At Step 2, skills were added to the model (Table 3). Technical skills were related to critical engagement. Critical skills related positively to technical and negatively to creative and social engagement in a model which controlled for structural inclusion factors. Social skills were related to social and creative engagement and creative skills to creative engagement. Finally, self-efficacy was related to critical, social and creative engagement but not to technical engagement. The strongest relationships were between social and creative skills and the corresponding types of engagement.

Once skills were added to the model, several relationships between inclusion and engagement identified above changed. The relationship between education and social engagement lost its significance. The relationship between SES and engagement types remained unchanged. Similarly, nothing changed for the relationships between age and engagement. However, the relationship between gender and critical and social engagement became insignificant. Locus of control gained a significant relationship with creative engagement, the relationship between health and critical engagement lost strength but remained significant. Social isolation remained significantly related to critical engagement and social capital to technical and critical engagement.

For all types of engagement, adding skills to traditional indicators of digital exclusion added significantly to the explanatory power of the model, although this was the least clear for technical types of engagement for which the R^2 and the R^2 change were very small. Thus, when skills indicators were added to a regression with socio-demographic resource explanatory variables, the small proportion of technical engagement that the model explained increased significantly but not substantially and other explanations for technical forms of engagement should be explored.

Discussion

In this paper, we have brought together two important areas of work that should help to inform our understanding of how and why people engage with the Internet. The digital exclusion debate would benefit from including a more nuanced understanding of skill - going beyond general skill, to look at how kinds of online engagement vary in relation to different kinds of skill. Digital literacy research could benefit from a more detailed understanding of how offline inequalities influence different types of skill and how this mediates links with different types of engagement.

Is it possible to empirically identify four distinct types of digital skills?

It is possible to empirically identify the four distinct types of skills (creative, social, technical and critical) recognized in the literature. These four skills are highly correlated. Creative skills were the most highly correlated with all of the three other skills. This is not surprising, taking a broadly constructivist view of learning, the development of one type of skill may well be informed by or impact upon the development of skills in related areas (Greeno et al., 1996). A global measure of digital self-efficacy (which is often used as a measure for perceived Internet skills) does seem to measure something different from the four digital skills as the correlations with that scale were relatively lower. This supports other work in this area which criticizes using a global measure of self-efficacy as a proxy for online skills (Hargittai, 2005; Livingstone & Helsper, 2007) and argues that self-efficacy measures confidence learned through socialisation, not always reflecting actual skills (Bandura, et al., 1982). The strong relationship between self-efficacy and web2.0 engagement types suggests that general confidence in Internet skills can be as or more important than actual skills in steering more complex forms of engagement.

Are specific types of digital skills related to specific kinds of digital engagement?

The value of trying to measure different types of skills instead of using a global measure becomes more pertinent when exploring the relationship between specific skills and specific types of engagement.

While the relationships between the four types of skills identified and the corresponding types of engagement were not clear cut, for the potentially more advanced interactive types of engagement the relationship with the corresponding types of skill were strongest. For example, social skills were most strongly related to social engagement (β = 0.25) and creative skills were most strongly related to creative engagement (β = 0.22). Once the requirements of the model were relaxed from only corresponding skill engagement paths, the cross-conceptual relationships between technical and critical skills and engagement became stronger. It is important to note that where the links were strongest the operationalisations of skills reflected confidence in being able to carry out specific (social and creative) activities rather than more general (technical and critical) digital skill types. Thus, the data suggests that different skills relate to a greater or lesser extent with different kinds of engagement and a model which allows more than one skill to map onto each type of digital engagement improves the model fit. It also highlights the need for better empirical measures of digital skills that are not worded in terms of specific online activities.

This multifaceted relationship between skills and engagement suggests that some forms of engagement online require a range of skills, particularly those kinds of online activities that are potentially more complex and interactive. These findings could be explained if social and creative practices required a broader range of skills to enable users to engage with more complex platforms. Indeed, this argument is supported by other work that has shown that web 2.0 (interactive and production) practices tend to develop later as experience with the Internet grows (Dutton & Blank, 2011; Livingstone & Helsper, 2007). However, taking into consideration structural inclusion factors changes the relationship between skills and engagement (see section below). Problematic in all of these calculations is whether these conflicting findings are attributable to the operationalisation of the different skill types or to genuine, stable and consistent empirical relationships. Analysis on previous databases, not presented in this paper, suggest that it is a combination of both. What is clear is that further work is needed to examine this issue in more detail, with an aim of developing skills measures that are disconnected from specific activities or platforms and that are more transferable across situations, supported by the extensive literature on this topic in the field of education. It is also vital that performance measures are developed and the work of Van Deursen (2010) is promising in this regard. Yet, more work is needed particularly in relation to creative and social digital skills.

Do different types of social exclusion relate differently to different types of skills?

The analysis showed that to some extent different types of social exclusion are related to different types of skills. Education, gender, age and social isolation related to all types of skill and digital self-efficacy, reinforcing theories of the relationship between social and digital exclusion (Helsper, 2012; Van Dijk 2005). Nevertheless, other indicators such as SES, social capital and health only related to certain types of skill or to digital self-efficacy or to none of the skills. Some of the findings contradicted theories about, for example, social resources and their effect on engagement because no effect was found of social indicators and social types of engagement (Peter et al., 2006; Wellman et al., 2001).

The relationship between social inclusion factors and engagement was not clear cut, as was the relationship between skill and engagement. There are, thus, important conceptual distinctions to be made when it comes to constructing and testing skill levels and effects. It is important to know which types of skills training to target to which groups, as blanket skills training is unlikely to be effective. To be able to constructively pursue this, more sophisticated research is needed that allows researchers to construct directional hypotheses about the links between social exclusion and specific skills types from which specific types of engagement follow. A key issue in this respect is the reliance on self-reported measures and problems in operationalizing clearly separate skills. A well-constructed theoretical framework that incorporates conceptualizations of literacies and exclusions and how they are related is fundamental to future design of empirical survey research. Finding measures that are not dependent on self-report bias but can still be used in generalizable studies is urgent (Hargittai, 2005; Van Deursen & Van Dijk , 2009, 2010).

Does the relationship between structural, inclusion factors and engagement depend on digital skill levels?

The answer to our final question about the mediating role of specific skills in the relationship between inclusion and digital engagement is consequently not straightforward. A few of the relationships between structural, social inclusion factors and engagement became insignificant when skills were taken into account. This effect was spread over different types of engagement for different types of inclusion factors but occurred mostly for social engagement. This suggests that digital, as opposed to social, skills are perhaps more important than previously thought in relation to online communication and social interaction. Including skills diminished the importance of gender in relation to engagement, indicating that differences between men and women in digital engagement are explained by different levels of skill and not by socialization factors. Similarly, education no longer related significantly to social engagement after incorporating skills. These relationships indicate the value of operationalising different kinds of skills when exploring the relationship between digital engagement and inclusion. It also suggests that some traditional paths to engagement are explained by differences in skill levels between socio-demographic groups and that, thus, some social inequalities in digital engagement can be circumvented through specific digital skills training. To further substantiate these conclusions better performance measures are needed as well as longitudinal research that shows whether skills lead to use and/or use leads to skills.

However, other relationships gained marginal significance, specifically, the relationship between locus of control and creative engagement which provides a counterargument to the independent strength of skills training. Equalizing skills might bring out personal differences in use that were not observable before. To make model testing more manageable future research could focus on testing specific paths comparing groups on socio-demographic characteristic or specific types of engagement and the mediating effect of specific types of different skills within these group comparisons or for these specific types of engagement.

More important for earlier conclusions is that when structural inclusion factors were taken into consideration, critical skills gained significance in predicting a broad set of engagement types. A different picture emerged when the key skills to motivate engagement were social and creative and not critical, further contesting the idea that blanket skills training will increase engagement across all socially disadvantaged groups. While our analysis demonstrates a complex picture, it highlights that future work with improved measures and constructs is necessary to understand relationships between social exclusion, digital skills and engagement.

Conclusions

Research on digital literacy can benefit from a stronger connection with digital exclusion studies that focus the different ways in which people engage. In terms of how people engage, which skills they have matters. Similar to other studies, we suggest that skills training is important (Buckingham, 2007). Yet, while skills are important, skills training is only part of the story and other economic, cultural, social and personal inequalities must also be taken into account. While there are challenges in separately measuring different kinds of skills and engagement, the added value of working with separate skills is high because it allows for a more nuanced understanding and practice in breaking the vicious cycle between social and digital exclusion.

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Notes:

[1] All descriptive statistics in this section are for internet users and not the total population.

[2] The SES measures social class according to the standard market research categories: A—Upper middle class (Higher managerial administrative or professional occupations, top-level civil servants); B—Middle class (Intermediate managerial administrative or professional people, senior officers in local government and civil service); C1—Lower middle class (Supervisory or clerical and junior managerial administrative or professional occupations); C2—Skilled working class (Skilled manual workers); D—Working class (Semi and unskilled manual workers); E—Those at lowest levels of subsistence (All those entirely dependent on the State long term, casual workers, those without regular income). ABC1 is here labelled ‘‘middle class’’ and C2DE is labelled ‘‘working class.’’

[3] For goodness of fit on CFI and RMSEA indicators see (Hu & Bentler, 1999).