Does the "Do-it-yourself approach" reduce digital inequality? Evidence of self-learning of digital skills

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RUNNING HEAD: Trial and error learning and digital divide

Abstract

The development of individuals' digital skills has received much attention as a remedy for digital inequality. Whereas some researchers favor courses and guided learning for skills development, others propose learning by trial-and-error. However, studies examining the value of the so-called "do-it-yourself approach" for the development of digital skills remain lacking. One difficulty lies in the vicious circle of lack of skill leading to infrequent Internet usage and vice versa, which limits the value of cross-sectional data for assessing the impact of this approach. We present longitudinal data on a random sample of Internet users in a Dutch city, which shows that more frequent Internet use leads to more digital skills, but not the other way around. However, contrary to expectations about the potential of trial and error learning to reduce inequality results also suggests that this approach is not always more beneficial to the "have-little" as compared to the "have-more". The only inequality reducing effect of this approach is that that older users profit more from it than younger users do.

Key words: digital divide, digital inequality, digital skills, Internet use, learning

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Introduction

Both public opinion and public policy at the beginning of the new millennium were strongly concerned with reducing the digital divide between Internet users and non-users, with the general belief that the problem would be solved when everyone has access to the Internet (Mossberger, Tolbert, and Stansbury 2003; van Dijk and Hacker 2003). Here there was an assumption that simple access to computers with an Internet connection automatically leads to more equality of opportunity (DiMaggio et al. 2001). In spite of this, already in the 1990s, there was evidence indicating that access to the Internet does not necessarily lead to its use (National Telecommunications and Information Administration 2000).

With the widespread diffusion of Internet access in the population, the researchers' focus has shifted emphasis from the gap in access to the differences in use of the technology, which some researchers label as "digital inequality" (DiMaggio et al. 2004). These researchers argue that there are more dimensions of inequality that need to be taken into account (Hargittai 2002; van Dijk and Hacker 2003; van Dijk 2005; Haythornthwaite 2007). For instance, DiMaggio, Hargittai, Celeste, and Shafer (2004) argue that one should also study intensity of use.

At this point, there is widespread consensus among researchers that to use the Internet in meaningful ways, users must develop sufficient digital skills (Jenkins et al. 2007; van Dijk 2005; Mossberger, Tolbert, and Stansbury 2003). However, regarding how users could develop these skills, different answers are provided. Some suggest the use of public libraries or courses for guided training (Mossberger, Tolbert, and Stansbury

2003; Salovey et al. 2009; Kress et al. 1997). Others argue that learning by trial-and-error could be a very useful method for developing digital skills, especially when Internet usage takes place at home, which presumably leaves considerable room for exploration and experimentation (Kuhlemeier and Hemker 2007; Kerawalla and Crook 2002). Van Dijk (2005) calls this the "do-it-yourself" approach of developing digital skills.

A number of studies show that intensity of Internet use and digital skills are strongly associated (Hargittai 2003; Howard, Rainie, and Jones 2001; Kuhlemeier and Hemker 2007; Meneses and Momino 2010; Zillien and Hargittai 2009). Nevertheless, even in sophisticated multivariate analyses, strong associations between Internet use and digital skills do not tell very much about the underlying causation because of a vicious circle. Mossberger, Tolbert, and Stansbury (2003) suggest that disadvantaged users find themselves in such circles because "those without skills have little need to use computers and those without frequent availability have little chance to develop the skills" (p. 121). Causation can thus run in both directions. Researchers, at least implicitly, believe that there is an effect of digital skills on intensity of use (see, e.g., Hargittai and Hinnant 2008). Therefore it is still an open question whether and to what extent the do-it-yourself approach contributes to the development of digital skills. The studies cited above do not investigate the two hypotheses about causation separately due to the cross-sectional nature of the used data. With our longitudinal study, we aim to clarify this question. Moreover, we are interested in finding out whether learning by trial-and-error works the same for all groups of users or whether differential effects exist that may affect the degree of digital inequality in desirable or undesirable ways.

Depending on the answer, the results have important policy implications. For instance, exclusive evidence for the first proposition (namely, that more intensive Internet use leads to more digital skills) would support public policy that focuses on access to technology and on motivating users to explore the Internet. Exclusive evidence for the second proposition (namely, that more digital skills lead to more intensive Internet use) would support public policy that, apart from providing access to technology, encourages guided training of Internet users.

To investigate the causality of the relationship between digital skills and intensity of Internet usage, we use panel data consisting of two measurements of the same respondents. In the next section, the theoretical background about the discussion of the relationship between digital skills and Internet usage is introduced, resulting in a set of hypotheses to be tested. Afterward, the research design, the panel data set from a random selection of Internet users in a large Dutch city, the measurements, and the method of data analysis are presented. We conduct so-called lagged regression analyses to examine changes in digital skills and intensity of Internet use within seven months of use, controlling for a number of other potential factors of influence. This design overcomes a number of restrictions that earlier research could not solve. The results of the analysis support the hypothesis that a higher intensity of Internet use does result in higher digital skills, and not the other way around. However, contrary to expectations in the literature, there is only limited evidence for an inequality-reducing effect. Users with fewer skills do not always profit more from the do-it-yourself approach, suggesting that at least some inequalities in skills between the "have-little" and "have-more" remain. With respect to inequality-reducing effects, we only found that older users profit more from this approach than younger ones, providing some indirect evidence of an inequality-reducing effect. Finally, we discuss the policy implications of our findings and perspectives for further research on the digital divide and digital inequality.

Theoretical framework and earlier research

In this section, we discuss the relationship between digital skills and intensity of Internet use. We first briefly characterize the concept of "digital skills" in more detail. Thereafter we present earlier research examining the relationship between digital skills and Internet usage leading to three complementary hypotheses.

Digital skills

A mastery of Internet use is regarded as an important determinant of quality of life (Jenkins et al. 2007). Some empirical studies suggest that users can reap benefits from digital skills, such as higher earnings (DiMaggio and Bonikowski 2008) or better language skills (Judson 2010). Defining digital skills, however, is not a trivial matter. Bawden (2001) demonstrates that a multitude of different, but related concepts exist, such as information literacy and digital literacy. Some authors, as Bawden (2001) summarizes, understand the concept of digital skills in a broader sense including not only technical skills of Internet users but also issues of understanding the retrieved information and being able to deal with information overload. Van Dijk (2005) also summarizes different concepts of digital and media literacy leading to a more sophisticated understanding of digital divide and the focus of digital skills. He understands digital skills as the "set of skills that users need to operate computers and their networks, to search and select information, and the ability to use them for the fulfillment of one's goals" (ibid, 73). This broader concept of digital skills is divided into operational, informational, and strategic skills. Operational skills are the abilities needed to operate computer and network hard- and software components. Information skills are required for searching, selection, and processing information in digital environments. Strategic skills are defined in a much broader sense. They include an individual's capabilities to use these sources as a means for the fulfillment of his/her goals. Van Dijk (2005) relates these goals particularly to improvements in an individual's position in society, such as the individual's position on the labor market, educational position, position in the household and position in social relationships. Later, he and his colleague van Deursen disaggregate the concept of information skills even further into two distinct categories, namely, a) “formal” (informational) skills for hyperlink navigation and orientation and b) “information” (informational) skills for searching, selecting, and evaluating information in digital media (van Deursen and van Dijk 2009).

However, empirical field studies examining the digital skills of Internet users mostly take the first two aspects of digital skills into account and include operational and formal informational skills in their analyses (see e.g., Hargittai 2005; 2009; Howard, Rainie, and Jones 2001; Torkzadeh and van Dyke 2001). Van Deursen and van Dijk (2009; 2010) propose some measurements of all four dimensions, but these are geared toward small-scale laboratory studies. Measurements of all dimensions that are applicable to population surveys have yet to be developed (van Deursen and van Dijk 2010). As we elaborate in the section on design and measurements, we therefore also focus on the first two aspects (i.e., operational skills and “formal” informational skills) in our own empirical study.

Relationships between digital skills and Internet use

A number of studies have examined digital skills and their relationship with Internet use. For instance, Hargittai (2003) found that intensity of use is a strong predictor of the success and rapidity with which respondents completed online tasks, which is an indicator of their digital skills. Howard, Rainie, and Jones (2001) found that frequency of Internet use is a good predictor of the breadth of activities people undertake online, which in turn is likely to be related to digital literacy. Other studies also report an association between digital literacy and specific forms of Internet use (e.g., Zillien and Hargittai 2009; Hargittai and Hinnant 2008). While these findings are interesting, they leave open the question as to whether more intensive use leads to better skills, or whether the causality is the other way around.

A popular notion is that digital skills can be learned through guided training in computer courses and classes. Empirical findings indicate that this can be true (Lupo and Erlich 2001; Torkzadeh and Van Dyke 2002; Torkzadeh, Chang, and Demirhan 2006). For instance, Torkzadeh, Chang, and Demirhan (2006) showed that students in a 12-week US university course significantly increased their digital skills. Students with less computer anxiety and more favorable computer attitudes benefited more than students with more computer anxiety and less favorable computer attitudes. Despite the existing evidence of a beneficial effect of training, van Dijk (2005) argued that there is another, much more important source of learning digital skills, namely, learning by trial-and-error. De Haan and Huysmans (2002) and van Dijk (2005) presented survey data indicating that (Dutch) Internet users of different age groups regarded "trial-and-error" as an important source of acquiring digital skills for themselves. Similarly, Mossberger, Tolbert, and Stansbury (2003), in a survey of U.S. Internet users, showed that about 67% had positive attitudes about methods of self-learning, and men liked do-it-yourself methods of learning even more than women. Other scholars studying pupil acquisition of digital skills also reasoned that the use of the Internet at home would be especially valuable for learning because it is often private and solitary, with much room for free exploration and experimentation (Kerawalla and Crook 2002; Kuhlemeier and Hemker 2007). Further evidence has been found by Meneses and Momino (2010) in a large-scale study of Catalonian children and young adult Internet users. They showed that within the group of Internet users who claim to have acquired digital skills via self-teaching, as compared to users who claimed to have acquired skills via learning in other contexts, exists the largest proportion of users with adequate specific digital skills, such as knowledge about search engine use, downloading files, chatting, and sending emails. In a multivariate analysis, the association between self-learning and digital skills is stronger than the association between digital skills and learning in other contexts, such as learning in school, via friends, and so on.

While these findings are promising for the do-it-yourself approach, they still leave open the question of causality. For instance, with respect to the findings of Meneses and Momino (2010), it cannot be ruled out that Internet users with more initial digital skills became more motivated to experiment with trial-and-error. Even if this trial-and-error experimentation does not increase their skills, it would nevertheless result in the association between skills and self-learning that the authors found in their data. This, however, is not evidence for an effect of self-learning. Therefore longitudinal analyses are needed. To the best of our knowledge, there is only one field study that analyzed changes over time in digital literacy. In a study on Israeli Internet users, Eshet-Alkalai and Chajut (2009) showed that after five years of use of the Internet, users acquired more skills. Older users, who had less skills at the start of the study, learned more than younger users, who had more skills at the start. Additional analyses suggest that the differential growth in skills was not an effect of age per se. The authors argue, in contrast, that it was an effect of increasing familiarity with the technology. Older users were less familiar with the Internet at the beginning of the study, and thus, they were able to reduce this shortcoming during the five years of Internet use. Unfortunately, the study leaves open the question as to whether users increased their digital skills through trial-and-error, guided training via friends, computer courses, or a combination of these.

Van Dijk (2005) added that learning by trial-and-error does not exclude learning in classes and via guided tutorials. On the contrary, he seems to be of the opinion that learning by trial-and error is useful only until a certain threshold of skills has been reached, as he argued that "[o]perational skills will remain incomplete when they are only learned by trial-and-error" (ibid, 92). For users to learn "better" skills, appropriate didactics are useful and needed. The reader should note that the latter argument implies that in the long run the do-it-yourself approach on its own leads to reduced differences in digital skills. According to this argument, only a certain threshold of skill level can be reached with this approach, after which it does not add any more skills. Therefore, those with better skills would not profit anymore. This prediction differs from claims of other authors suggesting a “rich-get-richer” development in other contexts (e.g., Warschauer 2000; 2003; Norris 2001). (Of course, there are other differences between skilled and unskilled users with respect to quality of access or early adopter benefits, both of which may remain unchanged.) We put this line of argument to the test using two hypotheses.

Hypothesis 1: The more often somebody makes use of the Internet for private purposes, the more the user's digital skills will grow in the future.

Hypothesis 2: The digital skills of users with lower initial skills will grow more than the digital skills of users with higher initial skills.

The two hypotheses capture only one part of the vicious circle between the lack of digital skills and intensity of Internet use (Mossberger, Tolbert, and Stansbury 2003). The second part is captured by the idea that an important barrier to Internet use is a lack of digital skills (Eastin and LaRose 2000). More abilities would make it likelier that users perceive a relative advantage and ease of use of the Internet, which would lead to a more frequent use of the Internet (Chen 2008). We examine this line of argument by testing the following hypothesis.

Hypothesis 3: The more initial digital skills somebody has, the more often the user will make use of the Internet for private purposes in the future.

Research design, measurements, and method of analysis

Design

As the discussion has shown, to examine the causality between intensity of Internet use and level of digital skills, a longitudinal study is necessary. Contrary to cross-sectional studies, a longitudinal study measures the intensity of Internet use and the level of digital skills more than once. In line with previous research (Chen and Wellman 2005; Goldfarb and Prince 2007; Katz, Rice, and Aspden 2001; Rainie et al. 2003; Norris 2001), our analysis controls for factors like gender, age, education, and income that are related to digital skills. By using lagged multiple regressions together with control variables such as gender, age, and education, the two hypotheses can be tested separately, providing more insight into the effectiveness of the do-it-yourself approach.

Our study makes use of data from two measurements of the same respondents. The data consists of a random sample of Internet users in a large Dutch city. In November 2007 adult household members with Internet access were first approached by means of a computer-assisted telephone interview (n=885, response rate = 29.31%). Of these, 484 people were willing to cooperate in a second interview, this time via a web survey to which they were invited by email. Out of 484 email addresses provided by the respondents, 57 were invalid. After seven months, 195 respondents participated in an additional web survey (n=195, response rate 195/427$\approx$ 46%) in June 2008. A first examination of the data showed that 22 forms were not filled in by the same person who answered the questions during the first survey. These were excluded from the analysis. Finally, 158 responses were valid without missing values and could be included in the multivariate analyses.

Measurements

We used the same items in both surveys for measuring our key concepts of digital skills and frequency of Internet use. Digital skills are measured with an updated version of a scale proposed by Hargittai (2005; 2009). The scale score consists of the sum of values corresponding to answers to nine items that ask respondents to provide self-assessments. Respondents were presented the following nine questions and instructions.

"How familiar are you with the following computer- and Internet-related items? Please choose a number between 1 and 5, where 1 represents no understanding and 5 represents full understanding of the item."

"Scroll on a website / refresh & re-load a webpage/ Use a search engine / Preference setting / Open and send email / Add an attachment to an email / Download a data file / Configure a spam filter / Configure a virtual domain on an http server."

With this list of items we aim at covering different levels of difficulty and sophistication of digital skills. The activities mentioned in the items presuppose a mixture of skills that are needed for successful use of Internet-related software and for successful information searching. In that sense, they presuppose a mixture of operational and informational skills. The scale used in the analyses has a sufficient reliability of α=0.827 in the sample from the first wave in November 2007 and a reliability of α=0.871 in the sample from the second wave in June 2008. However, relying on self-assessments comes with problems. With respect to self-assessments in general, we know that people with weak skills tend to overestimate their expected performance, and well-performing people tend to underestimate their expected performance (Dunning et al. 2003). Moreover, Hargittai and Shafer (2006) found that women tend to underestimate their digital skills. Nevertheless, there are good reasons to use self-assessments in our study. First of all, in our multivariate longitudinal analyses, we are *not* interested in differences in skills *between* individuals. Rather, we are interested in *changes within the same individual*. Even if differences in self-assessments between men and women or between low and high performers may exist, we control for them by measuring their initial level of digital skills. We also control for gender, educational, and other differences. Another important argument is that less subjective tests require laboratory research, as no better tests for use in population surveys are currently available (van Deursen and van Dijk 2010). Furthermore, earlier work has found that asking people to rate their level of understanding of Internet-related items serves as a better proxy for actual online skills rather than other traditional measures (Hargittai 2005). Finally, in our data, there were indicators of face validity for our measurement. The more often respondents use the Internet in November 2007, the stronger their skills were (bi-variate $r=.46$, $p<=.000$, $n=158$), and the older the respondent was, the weaker the skills were (bi-variate $r=-.31$, $p<.000$, $n=158$).

The indicator of frequency of Internet use is calculated by combining two variables. The first variable measures how many days per week the respondent has used the Internet for private purposes during the past three months. The second variable measures how many minutes (with eight categories) per usage day, on average, the respondent has used the Internet. The two variables are multiplied and the square root of the result is taken to reduce the skewness of the distribution.

To test whether Internet users with less skills profit more from trial-and-error, we constructed an interaction variable. We multiplied the indicator of frequency of Internet use with a dichotomous variable indicating whether the respondent has weaker skills. "Weaker" means belonging to the weakest third of respondents. Furthermore, for the multivariate longitudinal analyses, we include a number of control variables, namely, gender, age, educational level, and occupational status. Educational level is measured on a nine-point scale, ranging from no education at all to a post doctorate level. Occupational status measures whether the respondent is working or follows an education versus being unemployed, retired, or a househusband/housewife.

Data analyses

We used lagged multiple regression analyses as the main method of data analysis. To test the first two hypotheses, we utilized digital skills[1] as measured in June 2008 as the dependent variable. Frequency of Internet use as measured in November 2007, digital skills in November 2007, and the interaction between frequency of Internet use and weak digital skills were the most important independent variables. We thus analyzed the effect of frequency of Internet use on changes in digital skills, and we tested whether this effect differs between individuals with weak versus strong initial skills. Furthermore, we controlled for gender, education, age, and occupational status

[1] We used a transformed variable to avoid heteroskedasticity. We utilized a so-called Box-Cox transformation $\{Y'=(Y^{\lambda}-1)/\lambda\}$, with $\lambda=2.51$ (Hamilton 2004). The conclusions, however, do not change when we used the original variable.

of the respondents. To test Hypothesis 3, we utilized frequency of Internet use as measured in June 2008 as the dependent variable (see Figure 1) and took the initial digital skills and frequency of Internet use in November 2007 as the most important independent variables. Again, we used gender, education, age, and occupational status as control variables. The design addresses the problem caused by the vicious circle and makes possible the separate testing of the two hypothesized directions of causality. However, as the general discussion of the findings below indicates, there are still other difficulties persisting with regard to the assessment of causality.

(Figure 1 here)

Results

Descriptive findings

The data from the survey come from a random sample of 885 respondents from the area of Eindhoven, a large Dutch city with 200,000 inhabitants. We examined Internet use in the region of Nuenen and one particular area in Eindhoven called Tongelre. A typical respondent in our sample was of Dutch origin, about 50 years of age, had a college education, and resided in a household with 2.7 other members. (S)he was employed in a permanent or part-time fashion and had an average annual income of €36,157. The demographic sample characteristics did not differ from characteristics of the Eindhoven population except for age and Dutch origin. As Table 1 reveals, in the sample, respondents were older, and the percentage of foreigners was lower as compared to the Eindhoven population.

(Table 1 here)

Overall, 158 respondents filled in both surveys. In the following, we examine to what extent this group differs from those respondents who only filled in the first survey. We found that both groups did not differ with respect to gender (t=.98, df=231.07, p=.33), age (t=.37, df=261.56, p=.72), and occupational status (t=.73, df=867, p=.47). However, there were small differences with respect to frequency of Internet use (t=1.98, df=860, p=.05) and education (t=2.07, df=269.22, p=.04). Those who filled in both surveys are slightly more educated ($\overline{X}_1$=6.3 vs. $\overline{X}_2$=6.5 on a 9-point scale) and use the Internet slightly more often ($\overline{X}_1$=4.01 vs. $\overline{X}_2$=4.28 on a scale from '0' to '7.5'). More importantly, those who filled in both surveys did *not differ* from other respondents *with respect to their digital skills* (t=1.56, df=303.39, p=.12).

In 2007 respondents in our sample used the Internet rather frequently. For example, 59% of the users reported in November 2007 that they use the Internet seven days a week for private purposes, and 81% used it at least four days a week (median=7, $\overline{X}$ =5.6). Furthermore, 48% reported using it for more than one hour per usage day. Seven months later, however, the use of the Internet declined significantly (t=4.7, df=157, p=<.00) from a mean value of 4.3 (SD=1.5) to 3.8 (SD=1.5). The user scores on the scale of digital skills in November 2007 ranged from 12 to 45 with a mean value of 32.7 (SD=6.3). This mean value corresponds to a 3.6 score per item on a scale from 1 to 5. Until June 2008, digital skills grew weakly, with a mean value in the measurement of the second wave at 33.4 (SD=7.4), resulting in a marginally significant difference (t=1.78, df=157, p=.08). Furthermore, as shown in the Appendix, those who have higher skills in November 2007 use the Internet more often, are somewhat younger, tend to be male, and are more often working or in education as compared to those with lower digital skills. In addition, those who have higher skills in November 2007 tend to be those who have higher skills in June 2008. Also, respondents using the Internet more often in November 2007 tend to use it more frequently in June 2008. Thus, we have a high degree of stability with respect to frequency of Internet use and digital skills. While frequency of use somewhat decreased, digital skills slightly increased within the seven months of our study. The finding of increasing skills is in line with the results of Eshet-Alkalai and Chajut (2009), who found strong growth in digital skills after five years. An open question is whether the growth of skills is affected by the frequency of Internet use.

Hypotheses testing

Table 2 presents the results of two multiple regressions on changes in digital skills (Model 1) and frequency of Internet use (Model 2). First, we observe a significant and positive effect of digital skills in November 2007 on digital skills in June 2008 (see Model 1). With respect to the first hypothesis, we find that the more often the respondent used the Internet in November 2007, the more his/her digital skills grew leading up to June 2008. In addition, the interaction effect between lower skills and frequency of Internet use in November is non-significant, meaning that the growth in skills for the more intensive users of the Internet does not differ between those with high versus low initial skills. We thus find support for the first hypothesis, though not for the second one. Furthermore, the growth in digital skills is higher for men than for women, meaning that the gender difference in these skills became larger during the seven months under observation. The older the respondents are, the lower are their additional skills. Educational level and occupational status do not affect changes in digital skills. Model 2 shows that apart from the effect of the frequency of Internet use in November 2007 on the frequency of Internet use in June 2008, no other variable has any significant effect on frequency of Internet use in June 2008. Most importantly, digital skills in November 2007 did not affect changes in the frequency of Internet use in June 2008. Accordingly, Hypothesis 3 is not supported. In addition none of the demographic variables predict changes in the frequency of Internet use.

(Table 2 about here)

Discussion: The results provide support for the hypothesis regarding the beneficial effect of the do-it-yourself-approach. More frequent Internet use leads to an increase in the digital skills of users but not vice-versa. The more people use the Internet, the more sophisticated they become. At first glance, it may seem surprising that there is no effect of digital skills on frequency of Internet use, given that such an effect is often supposed (see, e.g., Hargittai and Hinnant 2008; Zillien and Hargittai 2009). We offer the following explanation for this finding. As described above, the respondents used the Internet rather frequently in November 2007. Furthermore, users with high digital skills tended to use the Internet even more frequently, as indicated by the high correlation between digital skills and frequency of use shown in the Appendix. For users with high digital skills, an increase in frequency of use might be difficult because of a ceiling effect. There is a limit to the amount of time one is willing and able to spend on the Internet. It could also be that higher skills make users more efficiently in their use of the Internet for private purposes, thereby counteracting the tendency to expand the usage time. Moreover, it could be that a usage-intensifying effect of skills might have already taken place in earlier periods.

What we can conclude from the above is that the supposed vicious circle of lack of skills and infrequent use of the Internet cannot be found in our data. At least among those who use the Internet already with some regularity, more frequent Internet usage leads to better digital skills and not the other way around. The reader should note that for those without Internet access at home (not included our sample) results might be different. It is also remarkable that men increase their skills more so than women, and younger users increase their skills more so than older ones. The negative effect of age seems to not be in line with earlier findings of Eshet-Alkalai and Chajut (2009), who found that older Internet users increased their skills more than younger ones. To reconcile their result with our findings, we again analyzed changes in digital skills to test whether the self-learning effect of the frequency of Internet use differs between different demographic groups (i.e., men vs. women, young vs. old, high- vs. low-educated, working or in school vs. those not working or in school). In Table 3, we report the results of the analyses and also show the standardized effects in order to compare the strength of the effect of self-learning with other effects.

(Table 3 here)

Table 3 demonstrates that there is only one significant interaction effect between the frequency of Internet use and particular demographic characteristics. All other interaction effects are non-significant (not shown here). The effect of the frequency of Internet use in November 2007 is larger for older Internet users (the upper 50% in the sample, cut-off point = 50 years and older) as compared to younger ones, and it is positive for both age groups. Other effects are in line with the findings presented above. The significance of the interaction effect makes our findings consistent with the results of Eshet-Alkalai and Chajut (2009). If older users utilize the Internet more frequently, they are able to reduce the gap in digital skills with respect to younger people, although only slightly. It is remarkable that this interaction effect is significant, as we control for differences in initial digital skills in November 2007. We suspect that the effect of self-learning is larger for older people because our own proxy for digital skills imperfectly removes differences in skills between age groups, with older age still an indicator of a lack of skills. By looking at the standardized coefficients, we can see that the best predictor of digital skills in June 2008 is the respondent's level of digital skills in November 2007. This comes as no surprise. Moreover, we see that the self-learning effect reaches 37% (19/51) of the size of the lagged effect of digital skills. For older respondents, this effect even reaches a remarkable 76% of the lagged effect of digital skills. While self-learning cannot remove initial differences in digital skills, it can reduce it to some extent if older users (with weaker skills) make use of it more often. Two other effects of demographic characteristics caught our attention. First, the positive effect of being male indicates that men learn more than women. Second, the negative and significant main effect of age indicates that older users who rarely use the Internet "lose" more of their digital skills as compared to younger users who rarely use it. Again, these analyses take into account initial differences in digital skills.

There are a number of limitations of our study that additional research should address. The data include only a sample of Internet users of a single city. Further research could use random samples from the whole of the Netherlands (or other countries) to reproduce our findings. Moreover, there is a sampling bias in our data in favor of somewhat older Internet users. While we cannot see at this moment how this could have affected our results, a higher response rate with less bias would have surely been desirable. The limitations in the measurement of digital skills have already been mentioned. Another issue to be taken into account in future research is the change in the mode of data collection between first wave (i.e., the telephone survey) and second wave (i.e., the web survey). However, there is no indication that this could explain the effects discussed above. An important point is whether the results justify the assumption of a causal effect of the frequency of Internet use on digital skills, as is assumed in the literature. The panel design rules out that causality runs in the other direction, which is a crucial advantage of this study as compared to earlier research. Nevertheless, there are other strong assumptions that have to be made in cross-sectional as well as longitudinal studies. We have to assume that there are no other relevant third factors that may have caused a high frequency of Internet use in November 2007 and subsequent growth in digital skills leading up to June 2008. These factors include external events as well as other individual characteristics not measured in the questionnaires. Only a randomized allocation of respondents to conditions of low versus high frequency of Internet use could avoid these assumptions. Such experimental research, however, is hardly possible. Additional research should therefore try to identify other possible factors of influence and include them in future analyses. Furthermore, it could be that other factors interact with self-learning and strengthen its effect on skills. Good candidates might be factors of a motivational and attitudinal nature that facilitate learning and ICT use. For instance, research indicates that an internal locus of control (Broos & Roe 2006) and feelings of high self-efficacy motivate people using ICT and the Internet in general (Selwyn 2003), and especially when they are used for learning purposes (Helsper & Eynon 2010). It might be that the participants in our longitudinal study score high on these concepts and therefore have a strong learning motivation. Future research should clarify to what extent strong motivations are important for self-learning to have effects. Nevertheless, based on our results, we feel confident in proposing a causal effect of the frequency of Internet use on digital skills.

Summary and discussion

This paper contributes to the discussion on whether self-learning by trial-and-error contributes to the development of digital skills and to what extent this approach helps to reduce digital inequality. Some researchers claim that the do-it-yourself-approach is beneficial for one's digital skills and that self-learning is of special value to those users with fewer digital skills (van Dijk 2005). Earlier research often documents a strong association between intensity of Internet use and digital skills (e.g., Hargittai 2003; Howard, Rainie, and Jones 2001; Kuhlemeier and Hemker 2007; Meneses and Momino 2010; Zillien and Hargittai 2009). However, these findings do not identify the causality in this relationship, that is, whether more skills lead to more frequent Internet use or vice-versa. As Mossberger, Tolbert, and Stansbury (2003, 121) indicate, both causal paths are plausible because disadvantaged users may find themselves in a vicious circle of lack of skills leading to infrequent Internet use and vice versa. This study uses panel data of a random sample of Internet users in a large Dutch city to test the two underlying hypotheses about the direction of causality separately. It utilizes questionnaire data about frequency of Internet use, digital skills, and other characteristics of respondents measured at two periods within a time interval of seven months (November 2007 and June 2008).

Our multivariate lagged regression analyses showed the following results. A higher frequency of Internet use in November 2007 increased user digital skills in June 2008, but not vice-versa. That means that our data supported the hypothesis regarding the beneficial effect of the do-it-yourself-approach. However, contrary to expectations in the literature, Internet users with weak digital skills generally did not benefit more from this approach as compared to those respondents with strong digital skills. We propose therefore that self-learning *in general* does not reduce inequality in digital skills. Rather, all users are shifted up independently of their initial skills. However, there was one differential effect of self-learning found in our multivariate analyses, as older Internet users who frequently use the Internet benefit more from self-learning than younger ones who frequently use the Internet. We suppose that the older age of users is an indirect indicator of a lack of digital skills because we were not able to measure the level of digital skills perfectly, and age is correlated with a lack of digital skills in our data. That means that the data may provide limited evidence of a specific inequality-reducing effect with respect to age differences. On this last point, more research is needed.

Future research on the effects of self-learning can build on the results of this study in a number of ways. From a methodological point of view, it is important to test whether the effects of learning by trial-and-error can be found in a laboratory setting and in field studies using less subjective measurements of digital skills. Also, it should be studied whether more abstract digital skills, operational and strategic skills in the terminology of van Dijk (2005), can be enhanced by self-learning. For instance, it is unclear whether self-learning leads to more expertise in evaluating the validity of found information. In addition researchers should try to find additional evidence regarding the beneficial effect of self-learning in other countries and under different conditions. In this study we assumed and tested a causal lag of self-learning on digital skills with about a half-year of delay. This period was chosen for two reasons. On the one hand, the period should not be too long to keep the contact with the panel respondents to avoid a too-large loss of sample size. On the other hand, we had to wait long enough so that initial learning effects would be visible. Testing a longer causal lag may lead to larger learning effects. More theory and cumulative research is needed to inform us about the effects of periods of different lengths. Furthermore, future research should examine which specific forms of Internet use are more beneficial for increasing user digital skills. In the literature a distinction is made between social and non-social forms of Internet use (Zhao 2006), and the latter can be separated into entertaining and informing forms of Internet use (Di Gennaro and Dutton 2008). At the moment, it is unclear whether entertaining forms of Internet use have the same learning value as other forms. Also, different user groups may profit in different ways, or not at all, from specific forms of Internet use. More theoretical analysis is needed that informs us about the effects and causal lags of different forms of Internet use for different user groups. For instance, it might be that the learning effects show up later for older as compared to younger users. Entertaining forms of Internet use may have larger learning effects for younger users because these users grew up with digital games. Such a theory would have important implications for the reduction of digital inequality.

The most important policy conclusion that can be drawn from the findings is that self-learning by trial-and error at home could be promoted in order to increase digital skills. Up to now, self-learning has not received much attention in the public debate about the digital divide and digital inequality. This should change. Public access centers, such as libraries, that offer courses are useful tools (Mossberger, Tolbert, and Stansbury 2003). However, opportunities for learning arise from supporting Internet access at home without a need for any additional funding of courses. The data indicate that even those with weak skills can profit from learning at home if they have a minimum level of skill, the motivation, and positive attitude towards ICT that leads them to experiment with the Internet. Of course, there are other groups that do not fulfill this requirement; thus, resources for guided training might be focused on them. For those who have access at home but do not often use it, special campaigns that cover information and motivation issues deserve much more attention. This is not a plea for a laissez-faire approach that abandons all efforts to teach digital skills and leave users completely on their own. Rather, this study indicates that self-learning may have some important benefits. In addition, there may be other benefits of guided teaching. For instance, Jenkins et al. (2007) argue that guided teaching may be necessary for the development of advanced, abstract skills and the acceptance of ethical standards for online communication. At the moment, it is unclear whether self-learning can contribute to the learning of these skills as well. It remains to be seen what the limits of self-learning of digital skills are. Future research should inform policy makers what mixture of self-learning and guided teaching may be most useful. Nevertheless the results speak for recognizing the power of self-learning, and public information and motivation campaigns can make use of these insights. With relatively little initial investment, such campaigns may induce large learning benefits among all users. These benefits may be of special value for the quality of life for those people with weak skills.

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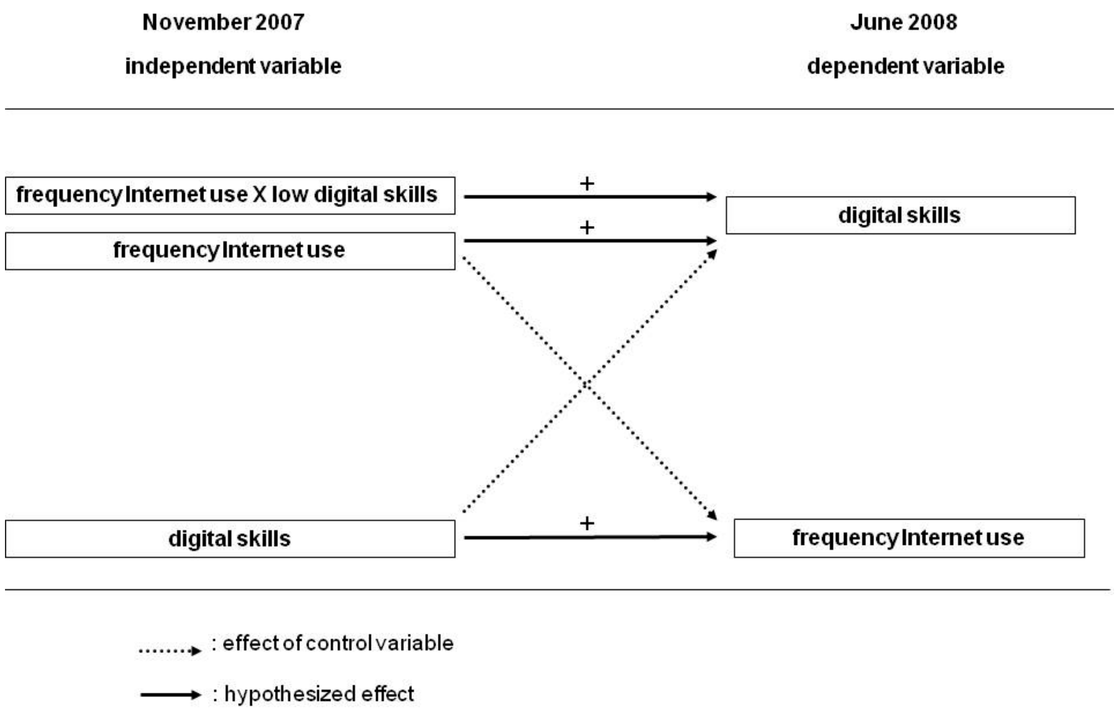
Figure 1: Lagged regression analyses (without demographic control variables)



TABLES

Table 1: Selected sample and population characteristics

Characteristic	Arithmetic mean / proportion	
	sample	Eindhoven
Dutch origin (in percent)	90.22	72.46
Average age (in years)	50.02	39.5
College education (in percent)	65.25	66.03 [b]
Male (in percent)	53.8	50.6
Mean household income (in Euros)	36.157	38.100 [b]
Average household size	2.71	2.25
In labor force	63.86	64.5 [a]

Notes: n=880; data for Eindhoven are from Statistics Netherlands (CBS 2010) for 2007 with the exception of (a) 2006 and (b) 2005.

Table 2: Lagged multiple linear regressions

Variable	**Model 1: Digital skills (time 2)** Unstandardized estimated value (standard error)		**Model 2: Frequency Internet Use (time 2)** Unstandardized Estimated value (standard error)	
Frequency Internet Use (time 1)	250.54***	(56.33)	.67***	(.07)
Digital Skills (time 1)	98.23***	(19.66)	.01	(.02)
Weak Skills X Frequency Internet Use (time 1)	-27.46	(57.99)	___	___
Gender (male=1)	479.63**	(158.15)	-.24	(.20)
Age	-22.45**	(7.47)	-.01	(.01)
Education	18.17	(53.29)	-.02	(.07)
Occupational Status	69.15	(192.02)	-.14	(.24)
*: p<=.05 **: p<=.01, ***: p<.001 (two-sided), n=158, constant not shown	Adjusted R-Square=60.86%		Adjusted R-Square=45.92%	

Table 3: Lagged multiple linear regression of digital skills at time 2

Variable	Model: Digital skills (time 2) Unstandardized estimated value	Standard error	Standardized coefficient (Beta)
Frequency Internet Use (time 1)	173.21**	(60.99)	.19
Digital Skills (time 1)	110.81***	(13.83)	.51
Gender (male=1)	482.54**	(155.48)	.17
Age	-39.21***	(10.34)	-.35
Education	17.81	(51.72)	.02
Occupational Status	62.38	(187.97)	.02
High age X Frequency Internet use (time 1)	119.67*	(52.21)	.20
*: p<=.05 **: p<=.01, ***: p<.001 (two-sided), n=158, constant not shown	Adjusted R-Square=62.13%		

Appendix: Correlations
(Pearson's r and significance values)

	Digital Skills (time 1)	Digital Skills (time 2)	Frequency of Internet Use (time 1)	Frequency of Internet Use (time 2)	Age	Gender	Education	Occupational status
Digital Skills (time 2)	.71***	1						
	.000							
Frequency of Internet Use (time 1)	.46**	.51****	1					
	.000	.000						
Frequency of Internet Use (time 2)	.34**	.41**	.69**	1				
	.000	.000	.000					
Age	-.31**	-.38**	-.13	-.14	1			
	.000	.000	.09	.08				
Gender (1=Male)	.323**	.31**	.18*	.05	.18*	1		
	.000	.000	.03	.55	.03			
Education	.07	.06	-.09	-.08	.00	.05	1	
	.37	.43	.25	.31	.98	.57		
Occupational status	.25**	.28**	.00	-.01	-.58**	.03	.08	1
	.001	.000	.99	.95	.000	.75	.30	

N=158, *: p<.05, **: p<.01 (2-tailed)