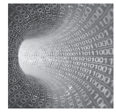

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The digital divide shifts to differences in usage

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Abstract

In a representative survey of the Dutch population we found that people with low levels of education and disabled people are using the Internet for more hours a day in their spare time than higher educated and employed populations. To explain this finding, we investigated what these people are doing online. The first contribution is a theoretically validated cluster of Internet usage types: information, news, personal development, social interaction, leisure, commercial transaction and gaming. The second contribution is that, based on this classification, we were able to identify a number of usage differences, including those demonstrated by people with different gender, age, education and Internet experience, that are often observed in digital divide literature. The general conclusion is that when the Internet matures, it will increasingly reflect known social, economic and cultural relationships of the offline world, including inequalities.

Keywords

Digital divide, digital inequality, knowledge gap, online activities, usage gap

Introduction

This article reports an observation in a recent Dutch survey of Internet use and tries to explain and frame this observation. We found that people with a low level of education use the Internet more hours a day in their spare time than people with medium and higher education levels. Furthermore, disabled people use the Internet more hours a day in their spare time than employed people. This finding is interesting because it is not in accordance with general results of digital divide research. In the first three decades of its history, the Internet was completely dominated by people with a high or medium level of

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education, both inside and outside work and school. Today, lower educated and disabled people are considered as digitally falling behind (e.g. Dutton et al., 2011). It is often shown that they are less likely to use the Internet overall, in any environment, than people that are employed or high educated. With recent observations such as the one above, one might argue that the digital divide has finally closed. This makes it interesting to report on this development in detail and to frame it in digital divide theory.

Several conceptualizations of the digital divide exist (e.g. DiMaggio and Hargittai, 2001; Katz and Rice, 2002; Mossber et al., 2003; Norris, 2001; Warschauer, 2003). Most conceptualizations generally identify four areas of importance: attitudes, access, skills and types of usage. Usage access is the focus of this study and encompasses the purpose of the whole process of technology appropriation. Having sufficient motivation, physical or material access and skills to apply digital media are necessary but not sufficient conditions for actual use (Van Dijk, 2005). Even if differences in terms of physical access have diminished, significant differences may remain in terms of differential skills and the nature of Internet use (e.g. Brandtzæg, 2010; Chen and Wellman, 2005; DiMaggio et al., 2004; Hargittai and Hinnant, 2008; Selwyn, 2004; Van Dijk, 2005; Zillien and Hargittai, 2009).

Internet usage has its own grounds or determinants. It can be defined in terms of content (broadband or narrowband, active and creative or consumptive), frequency, length of time the Internet is used and the type of activities performed. To address the observation described, we focus on the amount and type of usage. More specifically, we are interested in why the lower educated have become the most frequent users of the Internet in terms of hours of use in spare time and what lower educated people are doing on the Internet. These interests lead to the first two research questions:

1. *How do socio-demographic variables relate to the amount of Internet use?*
2. *How do socio-demographic variables relate to types of Internet usage?*

To answer the second research question, a classification of different usage activities is required. Therefore, we will propose a distinction of seven usage types, validated in previously established Uses and Gratifications Theory. Countries with high levels of Internet access, such as the Netherlands, provide the best setting for these types of analytic distinctions because here, Internet access and use are maturing and social distinctions of Internet use are articulating. It becomes possible to identify the most likely categories for Internet usage.

After proposing the classification of usage activities, several demographic groups can be investigated. As there is some variation to the scale of difference, the segments of the population that are most likely to differ in their Internet use can be defined in terms of gender, age, education, Internet experience, employment status, income and residence (*Socio-demographic categories and Internet usage* section).

Theoretical background

From knowledge to usage gap

Although our research questions are descriptive, they have a theoretical relevance that can be found in the so-called knowledge gap and the usage gap hypotheses. The knowledge gap hypothesis is a 40-year-old theory of media that mainly considers traditional media but is often observed as a forerunner to the digital divide concept. Tichenor et al. (1970) suggest that when the infusion of mass media information into a social system increases, segments of the population with higher socio-economic statuses tend to acquire this information at a faster rate than lower status segments, adding the value judgement that more information is better. It is not possible to apply the knowledge gap directly to the Internet. The use of the traditional mass media – on which the knowledge gap focuses – is relatively straightforward and uniform compared to Internet use (Bonfadelli, 2002). The latter requires a broad range of skills enabling navigation through a vast amount of information rather than simply reading newspapers or watching television. Relative to print media and television, Internet usage requires not only enabling technologies but also users with sufficient skills to use the Internet (Bonfadelli, 2002). The characteristics of traditional media (e.g. low potential of selectivity and accuracy of information) create relative passivity in its use (Stern, 1995). In this respect, traditional media usage is different from predominant Internet use (e.g. Stern, 1995). While traditional media enables active mental processing, the Internet requires users to interact with interfaces, frequently cited as the main distinguishing attribute of the Internet (Leckenby and Lee, 2000). A minimum level of active engagement with the medium is required, and interactions, transactions and interpersonal communication are made possible.

The difference in functionality of print media, radio, television and telephone is small compared to the Internet. Therefore, the Internet may create a usage gap that is different from the knowledge gap. While the knowledge gap is about the differential derivation of knowledge from the mass media, the usage gap is a broader thesis that potentially is more relevant for society with regard to differential uses and activities in all spheres of daily life, not just the perception and cognition of mass media. The background of the usage gap lies in a combination of societal tendencies and technological characteristics. The social tendencies are sociocultural differentiation or individualization in (post)modern society, rising socio-economic inequality in income, employment and property worldwide, and commercialization (privatization and liberalization) of formerly public information and communication facilities that increase conditional access, which may be costly. Technological characteristics include the complexity, expensiveness and multifunctionality of computer and Internet technology, which invite different uses (Van Dijk, 2005).

Behind the concept and thesis of a usage gap a clear normative account comes forward. The assumption is that some Internet usage activities are more beneficial or advantageous for Internet users than others. Some activities offer users more chances and resources in moving forward in their career, work, education and societal position than others that are mainly consumptive or entertaining (e.g. DiMaggio et al., 2004; Hargittai and Hinnant, 2008; Kim and Kim, 2001; Mossberger et al., 2003; Van Dijk, 2005; Wasserman and Richmond-Abbott, 2005; Zillien and Hargittai, 2009). In terms of capital and resources theory, inspired by Bourdieu (1984), one could also say that users build more economic, social and cultural capital and resources. The same normative background could also be found in the knowledge gap thesis; knowledge was considered more important than other benefits, such as consumption and entertainment. Zillien and

Hargittai (2009: 278) concluded that ‘the knowledge-gap theory and digital divide research provide a theoretical basis that points to a relationship between social status and patterns of media use.’

Usage classifications

Proper observation of differences in usage requires a classification of Internet usage types derived from the most important contemporary Internet activities. There are several candidates for such a classification. Some are based on a particular theory, while others use a descriptive and inductive approach deriving classifications from factor analyses of the steadily growing list of Internet activities. Most theoretical classifications take the uses-and-gratifications approach (Katz et al., 1974) as a starting point. The first step of this approach is an examination of a medium to derive a list of motivations and gratifications inherent in its use. The uses-and-gratifications approach and the related Expectancy-Value Model (Palmgreen and Rayburn, 1979) explain the way people adopt and use communication media as a function of their psychological needs. For example, some gratifications found are problem solving, persuading others, relationship maintenance, status seeking and personal insight (Flanagin and Metzger, 2001).

Other potential theoretical backgrounds include the Technology Acceptance Model (Davis, 1989) and Social Cognitive Theory, the latter of which has, among others, produced the Model of Media Attendance (LaRose and Eastin, 2004). The first model posits perceived usefulness as an important explanatory variable for use but has not yet produced a list of perceived useful Internet applications. The second claims that expected outcomes are a direct cause of web usage: activity outcomes (playing games, entertainment, cheering-up), monetary outcomes (shopping and prize comparisons), novel outcomes (news and information), social outcomes (talk and support), self-reactive outcomes (pass time and relaxation) and status outcomes (improve life prospects and familiarize oneself with new technology) (LaRose and Eastin, 2004).

Then, there are studies that account for differences in usage by grouping Internet users into use typologies (e.g. Brandtzæg, 2010; Egea et al., 2007; Livingstone and Helsper, 2007). These studies utilize descriptive and inductive research to identify categories of usage types (Kalmus et al., 2011). The result is a variety of classifications that can be advanced to plot Internet usage. Kalmus et al. (2011) suggest that classifications can be used to differentiate between the use of online social, leisure and information services (Amichai-Hamburger and Ben-Artzi, 2000), between social, leisure and academic Internet use (Landers and Lounsbury, 2006), between technical, information exchange and leisure motives (Swickert et al., 2002) or between ritualized and instrumental use (Papacharissi and Rubin, 2000). Kalmus et al. (2011) evaluated the number of motives for Internet use from a list of Internet applications using exploratory factor analysis. They clustered their motivational items into two groups: social media and entertainment, as well as work and information. These researchers correlated these clusters not only with socio-demographic variables, but also with personality traits and indicators of habitus and lifestyle, trying to explain Internet use at large. Their aim was broader than ours, as we focus solely on socio-economic variables and on differences in usage. Furthermore, we take an approach in which we clarify the distinction between motives and actual use, which are two different concepts. We use theoretical accomplishments in uses-and-gratifications research to propose classifications of usage activities. This is further explained in the *Data analysis* section. The purpose of this operation is to relate validated usage clusters with socio-demographic variables to investigate whether differences in usage exist.

Socio-demographic categories and Internet usage

There are several socio-demographic variables that explain individual differences in Internet use. Several studies suggest *gender* differences (e.g. Fallows, 2005; Jackson et al., 2001; Meraz, 2008; Subrahmanyam et al., 2001; Valkenburg and Peter, 2007; Wasserman and Richmond-Abbott, 2005; Zillien and Hargittai, 2009). There is, for example, evidence that adult females are more likely to use the Internet's communication tools, whereas adult males are more likely to use the Internet for information, entertainment, commerce (Jackson et al., 2001; Subrahmanyam et al., 2001; Valkenburg and Peter, 2007; Zillien and Hargittai, 2009) and online gaming (e.g. Schumacher and Morahan-Martin, 2001).

Age appears to be one of the most significant variables that effect Internet use (e.g. Bonfadelli, 2002; Fox and Madden, 2005; Zillien and Hargittai, 2009). Presently, it appears that young adults take the lead with the use of communication tools, such as instant messaging and chatting, and are more likely to pursue entertainment and leisure activities, such as downloading music or surfing for fun (Dutton et al., 2011; Fox and Madden, 2005; Jones and Fox, 2009). In contrast, buying products online, emailing, and searching for health-related information are more popular among older users (Jones and Fox, 2009).

In addition, socio-economic status indicators have a significant impact on Internet use (e.g. Zillien and Hargittai, 2009). DiMaggio et al. (2004) argued that persons of higher socio-economic status employ the Internet more productively and to greater economic gain than their less privileged, but nonetheless connected, peers. There is evidence to suggest that people with lower levels of socio-economic status tend to use the Internet in more general and superficial ways (Van Dijk, 2005). Here, socio-economic status is considered as a multi-faced concept incorporating educational level of attainment, employment status and income.

The traditional knowledge gap hypothesis and most versions of the usage gap hypothesis suggest that education is the most important predictor for explaining the types of online activities a person will pursue (Robinson et al., 2003; Van Dijk, 2005). Howard et al. in 2001 already revealed that people with higher levels of education use the Internet for health information, financial transactions and research, while people with a lower level of education use the Internet for casual browsing, playing games or gambling online. Madden (2003) discovered that people with a higher level of education are less likely to download music or use instant messaging but that they are more likely to use the Internet for news, work, travel arrangement and product information. Hargittai and Hinnant (2008) found that those with higher levels of education use the Internet for 'capital-enhancing' activities, which includes seeking political or government information, exploring career opportunities and consulting information about financial and health services. Helsper and Galacz (2009) revealed that the lower educated are least likely to use the Internet for educational and economic purposes, even when they have similar levels of Internet access and skills.

With regard to employment status, we will find in this contribution that disabled people use the Internet for longer periods of spare time daily than people at work or in school. Obviously, the employed and students use them more at work and at school. Still, the finding is remarkable because it is often shown that students and workers are more likely to use the Internet overall, in any environment, than people that are disabled.

Income is a variable with a strong correlation to educational level attained. However, there are studies that show an independent effect of income on, for example, physical and material Internet access (e.g. Katz and Rice, 2002). Concerning types of online activities, Madden (2003) revealed that those with a higher household income are less likely than those with less income to use instant messaging or download music. However, they are more likely to seek news and product information or arrange for travel online and typically use the Internet for work.

Internet experience is often mentioned as a direct competitor to the effect of education in predicting Internet usage types (e.g. Eastin and LaRose, 2000; Gil-Garcia et al., 2006; Hargittai and Hinnant, 2008; Livingstone and Helsper, 2007). Length of experience appears to be a useful predictor of which activities people engage with online (Howard et al., 2001; Zillien and Hargittai, 2009). People experienced with the Internet are most likely to engage in personally advantageous activities.

Since Internet patterns mirror aspects of social structures (Graham, 2008; Van Dijk, 2005), the final factor accounted for is *residency*. People in rural areas have less Internet access given their lower levels of education and income and lower levels of access to broadband connections (Hale et al., 2010). However, few researchers have examined residency differences concerning type of activities.

Method

Sample

We relied on a data set collected in September 2011. Sampling and fieldwork were done by PanelClix in the Netherlands. Respondents were recruited from their online panel, which includes 108,000 people and is believed to be a largely representative sample of the Dutch population, although migrants are slightly underrepresented. Members of the panel receive a small incentive of a few cents for every survey they participate in. Panel members are invited to participate in a study by being sent an email explaining the topic of the survey and how much time it will take to complete. In total, 2850 people were randomly selected to reach a sample of about 1200 persons. During the data collection, amendments were made to be sure to represent the Dutch population in the final sample.

Several measures were taken to increase response rate. The time needed to answer survey questions was reduced to approximately 15 minutes. The online survey used specific software that checked for missing responses even when users were prompted to answer them. Pretesting of the survey was conducted with 10 Internet users in two rounds. Amendments were made at the end of every round based on provided feedback.

The 10 respondents in the second round gave no major comments and the survey was deemed ready for posting. The survey lasted for two weeks.

Background variables of the respondents are compared with the latest data from Statistics Netherlands. Given that our final sample is drawn from a representative sample, and that amendments were made to be sure to represent the Dutch population in the final sample, analyses showed that the gender, age and formal education of our respondents did match official statistics. As a result, only a very small correction was needed post hoc.

Measures

Amount of Internet use was measured as the number of hours in a day respondents spent online in their free time.

The respondents were asked to indicate to what extent they use the Internet for several *activities*. In total, 20 popular activities that regularly appear in recent scientific and market research of Internet applications were added to the survey. Respondents were asked with what frequency they engage in the activities, by using a five-point scale ranging from 'never' to 'daily' as an ordinal-level measure.

Motivations for using the Internet were comprised of 24 items. Respondents indicated their level of agreement with reasons for accessing the Internet. Possible responses ranged from (1) strongly disagree to (5) strongly agree. Items included in the study cover motivations that can be directly related to types of usage. The motivational items included in the study are based on motivations relating to *information seeking* (Papacharissi and Rubin, 2000; Song et al., 2004), *career* (Charney and Greenberg, 2001), *personal development* (Choi et al., 2004; Parker and Plank, 2000), *transaction*, leisure-related activities, such as *entertainment* and *passing time* (Papacharissi and Rubin, 2000), and items based on constructs of more interpersonally oriented needs (Papacharissi and Rubin, 2000; Song et al., 2004).

To measure *age*, respondents were asked for their year of birth, which was then transposed to a continuous age variable. *Gender* was included as a dichotomous variable. Data on *education* were collected by degree. These data were subsequently divided into three overall groups of low, medium and high educational levels attained. *Internet experience* was measured as the number of years that people have been using the Internet. *Employment status* was coded as dummy variables of the following groups: employed, retired, disabled, housemen or -wives, unemployed and students. *Income* was measured as total family income in the last 12 months, in eight categories of 10,000 Euros and 80,000 Euros or more. Finally, residency was included as a dichotomous variable, urban and rural.

Data analysis

We took three steps to create a validated classification of Internet usage activities that can be used to identify usage gaps. In the first step, we created a list of 20 Internet activities and subsequently used principal component analysis with varimax rotation to identify the underlying clusters. Factor loadings were used at 0.5 and above for each item

(Hair et al., 2006). All items were used for the factor analysis, which extracted seven factors. It was observed that two items were not loaded on any of the factors. These items were deleted from the original list. Factor analysis was repeated using 18 items (Table 4). There were no items that loaded on two factors. Seven factors showed eigenvalues above the acceptable 0.7 (Jolliffe, 1972) and were retained. Internal consistency of the factors for each usage cluster reveals a reliable factor solution. Cronbach's α coefficients ranged from 0.64 to 0.75.

Secondly, we conducted a confirmatory factor analysis of motivational items, derived from Uses and Gratifications Theory. In uses-and-gratification studies, respondents are typically asked to indicate for what purpose they use the Internet. A confirmatory principal component analysis with varimax rotation was used to identify the underlying motivations for Internet use. All 24 items were used for the factor analysis and confirmed eight motivational clusters, with eigenvalues above the acceptable 0.7. Internal consistency of the factors for each motivation cluster ranged from 0.66 to 0.87.

Thirdly, we compared the results of the *confirmatory* factor analysis of motivations for using the Internet with new clusters of actual usage derived from the *exploratory* factor analysis of Internet activities. Here, the goal is to prove the assumption that high measures of statistical association exist between neutrally labelled usage activities and clusters labelled with motivations derived from established theory. Therefore, the correlations between the confirmed motivation clusters and the newly created usage clusters were determined. If the Pearson's correlations are highest among related clusters, then we appear to have created a usage classification that is validated by the previously established Uses and Gratifications Theory.

The purpose of the three steps described above is to relate the validated usage activity clusters with socio-demographic variables to investigate differences in usage. To decipher what exactly may be the cause of the association of people's background characteristics and the frequency of several Internet activities people engage in, we performed linear regression analyses with newly created usage clusters as dependent variables. The regression models included the independent variables of gender, age, education, Internet experience, employment status, income and residency.

Findings

Respondents

The final response rate was 52%. A total of 1488 responses were received, of which seven were rejected due to incomplete responses. Hence, a total of 1481 responses were used for data analysis. For education, age and gender, our findings are consistent with the segmentations provided by the official statistics of the Netherlands. Table 1 summarizes the demographic profile of the respondents. The mean age of the respondents was 48.2 years (SD = 17.4), with age ranging range from 16 to 87. Almost all respondents had been born in the Netherlands (95%). The average years of Internet experience of the respondents is 11.8 (SD = 4.6). The amount of Internet use is high, with an average of 3.1 (SD = 3.2) hours a day in spare time.

Table 1. Demographic profile.

	N	%
Gender		
Male	771	52.1
Female	710	47.9
Age		
16–29	279	18.8
30–49	460	31.1
50–64	426	28.8
65+	316	21.3
Education		
Low	504	34.0
Middle	570	38.5
High	407	27.5
Employment status		
Employed	723	48.8
Unemployed	63	4.3
Disabled	88	5.9
Retired	371	25.1
Housemen/-wife	104	7.0
Student	132	8.9
Residency		
Urban	877	59.2
Rural	604	40.8

Classifying Internet usage activities

To investigate which usage gaps exist on the Internet, we first need to classify usage activities. As described in the *Method* section, we took three subsequent steps to create such a classification. In the first step, we investigated several Internet usage activities using an exploratory principal component factor analysis. In total, 18 items were retained in a seven-factor structure together accounting for 69.2% of the total variance, which is considered acceptable for research in the social sciences (Hair et al., 1995). The resulting seven-factor solution and the factor's labels are shown in Table 2. The factor labelled 'gaming' is poorly defined, since only one item loads on it. However, the exploratory nature of this study warranted using 'Playing online games' as the only item for the subsequent analysis. Two factors contain two items, which is acceptable since both items are strongly correlated.

In the second step, we conducted a confirmatory principal component factor analysis for the 24 motivational items. The eight factors together accounted for 75.8% of the total variance. All the items were retained for the factor analysis, and all items loaded on the factors obtained. Thus, the factor analysis confirmed the eight motivations for using the Internet. The coefficient alphas reveal a reliable factor solution. The results are shown in Table 3.

Table 2. Rotated factor matrix of usage activities (*How often do you use the Internet for…*).

Factors	Items	Factor loadings	Reliability (Internal consistency)
1: Personal development	Finding online courses and training	0.792	0.77
	Following online courses	0.781	
	Find vacancies/applying for jobs	0.688	
	Independent learning	0.680	
2: Leisure	Downloading music/video	0.777	0.67
	Hobby	0.523	
	Free surfing	0.501	
3: Commercial transaction	Using sites such as ebay	0.820	0.71
	Acquiring product information	0.687	
	Shopping or ordering products	0.679	
4: Social interaction	Using social network sites	0.775	0.69
	Chatting	0.725	
	Sharing photos/videos	0.491	
5: Information	Using search systems	0.808	0.63
	Searching information	0.732	
6: News	News services	0.875	0.67
	Newspapers and online magazines	0.774	
7: Gaming	Playing online games	0.882	

Loadings greater than .50 are shown. The items are sorted by the size of their factor loadings on a respective factor.

In the third step, the seven usage factors are validated by measuring Pearson's correlations with the motivation factors. For content, we would expect there to be a significant relationship between the motivation and usage factor 'information', between the motivation 'career' and the usage cluster of 'personal development', between the motivations 'social interaction' and 'relationship maintenance' with the usage cluster 'social interaction', between the motivation 'shopping' and the usage cluster 'commercial transaction', between the motivations 'entertainment' and 'relaxation' and the usage clusters 'leisure' and 'gaming'. All expected relations are confirmed, since the correlations are highest between the related clusters (see Table 4). This suggests that we obtained a classification of usage activities that is validated by established Uses and Gratifications Theory and can be used to reveal which socio-demographic variables reveal differences in usage.

Investigating differences in usage

Using the validated classification of seven types of Internet usage, we investigate how these types relate to differences in socio-demographic variables. For all categories of

Table 3. Rotated factor matrix of motivational items (*My reason to use the Internet is…*).

Factors	Items	Factor loadings	Reliability (internal consistency)
1: Information	To find information	0.856	0.66
	To discover things	0.798	
	To investigate things	0.696	
2: Career	To make a career for myself	0.872	0.75
	To improve my chances in the work field	0.842	
	To get a promotion at work	0.777	
3: Personal development	To stimulate my creativity	0.763	0.71
	To learn new things	0.531	
	Develop myself	0.428	
4: Shopping	To order something quickly	0.846	0.87
	To buy a product I heard of	0.818	
	To purchase something	0.751	
5: Entertainment	To entertain myself	0.828	0.71
	To have fun	0.751	
	To find information for amusement	0.727	
6: Relaxation	To feel less hurried	0.805	0.71
	To release stress	0.802	
	To come at ease	0.723	
7: Relationship maintenance	To maintain contact with friends	0.823	0.66
	To have contact with my friends	0.759	
	To send people I know messages	0.741	
8: Social interaction	To participate in chat sessions	0.812	0.71
	To make new contacts	0.589	
	To connect with a group	0.587	

Loadings greater than .50 are shown. The items are sorted by the size of their factor loadings on a respective factor.

usage listed, regression analyses are summarized in Table 5. Firstly, we investigated how differences between gender, age, education, Internet experience, income, employment status and residency are significant when considering amount of use as a dependent variable. Here, the finding addressed in the introduction of this article is shown: in their free time, lower educated individuals use the Internet for longer periods of time than those who are medium and higher educated. The same can be observed regarding employment.

Table 4. Validation of factor analysis of application clusters in terms of drivers of applications by factor analysis of actual motives.

		Usage activity clusters						
		Information	*Personal development*	*News*	*Leisure*	*Social interaction*	*Commercial transaction*	*Gaming*
Motivation Clusters	*Information*	.388***	.093**	.240***	.207**	.093**	.249**	.038
	Career	.145***	.399***	.140***	.251***	.295***	.246***	.167***
	Relationship maintenance	.195***	.180***	.173***	.204***	.454***	.193***	.202***
	Shopping	.294***	.183***	.214***	.284***	.198***	.469***	.135***
	Entertainment	.318***	.193***	.257***	.419***	.354***	.285***	.303***
	Relaxation	.102***	.223***	.100***	.235***	.369***	.242***	.287***
	Social interaction	.089***	.290***	.127***	.267***	.558***	.251***	.255***
	Personal development	.322***	.285***	.246***	.320***	.263***	.306***	.180***

*significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level.

Table 5. Multiple linear regression analysis with amount of Internet use and seven clusters of usage activities as dependent variables.

	Amount of Internet use	*Information*	*News*	*Personal development*	*Leisure*	*Gaming*	*Social interaction*	*Commercial transaction*
Explanatory variables	*B (Std. error)*	*B (Std. error)*	*B (Std. error)*	*B (Std. error)*	*B (Std. error)*	*B (Std. error)*	*B (Std. error)*	*B (Std. error)*
Constant	3.364(0.499)***	4.020(0.108)***	3.173(0.204)***	2.108(0.116)***	3.087(0.146)***	3.130(0.229)***	3.224(0.163)***	2.990(0.133)***
Sex								
Male	0.602(0.208)**	0.049(0.045)	0.278(0.085)***	0.072(0.048)	0.492(0.061)***	–0.216(0.095)*	–0.071(0.068)	0.061(0.055)
Age (reference: 16–29)								
30–49	0.095(0.350)	–0.156(0.076)	–0.086(0.143)	–0.414(0.081)***	–0.296(0.102)**	–0.412(0.161)*	–0.561(0.115)***	–0.083(0.093)
50–64	–0.802(0.372)*	–0.327(0.081)***	–0.542(0.152)***	–0.704(0.086)***	–0.891(0.109)***	-1.128(0.171)***	-1.198(0.122)***	–0.429(0.099)***
65+	–0.610(0.521)	–0.580(0.113)***	–0.807(0.213)***	–0.816(0.121)***	-1.152(0.152)***	-1.057(0.239)***	-1.326(0.170)***	–0.616(0.138)***
Educational level (reference: low educational level)								
Medium educational level	–0.583(0.242)*	0.126(0.052)*	0.096(0.099)	0.025(0.056)	–0.070(0.071)	–0.196(0.111)	–0.114(0.079)	0.017(0.064)
High educational level	–0.816(0.284)**	0.245(0.064)***	0.196(0.120)	0.220(0.068)***	0.030(0.086)	–0.507(0.135)***	–0.211(0.096)*	–0.047(0.078)
Internet experience	0.053(0.022)*	0.021(0.005)***	0.030(0.009)***	0.000(0.005)	0.027(0.007)***	0.002(0.010)	0.008(0.007)	0.003(0.006)
Household income	–0.113(0.059)	0.054(0.013)***	0.078(0.024)***	–0.001(0.014)	0.036(0.017)*	–0.027(0.027)	–0.010(0.019)	0.031(0.016)*
Employment status (reference: employed)								
Unemployed	–0.113(0.532)	–0.062(0.115)	–0.126(0.217)	0.213(0.123)	0.106(0.156)	0.149(0.244)	–0.248(0.147)	–0.037(0.141)
Disabled	1.505(0.422)***	0.154(0.091)	0.305(0.172)	–0.100(0.098)	0.197(0.124)	0.743(0.194)***	0.282(0.134)*	–0.076(0.112)
Retired	0.078(0.082)	0.041(0.018)	0.086(0.033)	–0.034(0.019)	–0.016(0.024)	–0.029(0.037)	–0.011(0.027)	0.016(0.022)
Housemen/-wife	0.151(0.466)	–0.031(0.101)	–0.060(0.190)	–0.071(0.108)	0.011(0.136)	–0.164(0.214)	–0.004(0.152)	–0.094(0.124)
Student	0.301(0.569)	0.242(0.123)*	–0.152(0.232)	0.334(0.132)*	0.357(0.166)*	0.047(0.261)	0.367(0.186)*	–0.010(0.151)
Residency *(reference: rural)*								
Urban	0.478(0.201)*	0.021(0.044)	0.100(0.082)	0.041(0.047)	0.085(0.059)	–0.062(0.092)	0.137(0.066)*	0.010(0.053)
R^2, adj R^2	.064, .050	.151, .139	.092, .079	.218, .207	.283, .273	.148, .136	.339, .230	.076, .063
F	4.816***	12.648***	7.166***	19.730***	27.984***	12.328***	26.074***	5.798***

*significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level.

People that are disabled use the Internet more hours a day than people who are employed. Also, the results show that people living in urban areas use the Internet for longer periods of time than people living in rural areas.

From Table 5, we conclude that the most prominent differences relate to *age*. For all usage clusters, age is an important contributor. Considerable differences for *education* are also observable. Lower educated people make less use of information than medium and high educated people. They also make less use of the Internet for personal development than the higher educated. Conversely, the lower educated use the Internet more for gaming and social interaction than the higher educated. Table 5 also reveals differences over gender, favouring men concerning the activities of news and leisure. Women use the Internet more for online gaming.

Employment status reveals that people who are disabled are more likely to use the Internet for gaming and for social interaction than people who are employed. Students are more likely to use the Internet for information, personal development, social interaction and leisure than the employed.

There are also relatively small, but nevertheless significant, differences in usage regarding Internet experience and income. People that have been using the Internet for longer periods of time are more likely to use the Internet for news, information and music and video. The same goes for people with higher income levels. They also are more active in online shopping. Finally, there is one small difference regarding residency: people living in urban areas make more use of social interaction than people living in rural areas.

Discussion

Main findings

In the last decade, attention in digital divide research has shifted from inequalities of access to digital skills and usage, pointing out the limitations of digital divide research in the beginning of the 21st century that mainly considered binary classifications of haves and have nots. Furthermore, the descriptive inventories of Internet activity use by the most important demographic categories made in the last 10 years now evolve into more analytic considerations. Our analysis of the data from a representative population survey revealed and validated seven clusters of Internet usage: information, news, personal development, commercial transaction, leisure, social interaction and gaming. This classification is used to answer the research questions. We investigated how and by who the Internet is used to explain the observation that currently in their spare time, at least in the Netherlands, people with a low level of education use the Internet more frequently and for more hours a day than people with medium and high levels of education. Low educated people seem to engage more in social interaction and gaming, which both are very time-consuming activities.

Besides education, age and gender are the most salient predictors for differences in Internet usage, whereas Internet experience, income and residency seem to be less relevant than expected. It is important to emphasize that both the knowledge gap and the usage gap thesis are framed in terms of knowledge and usage inequalities related to levels of education. It is a plausible statement that differences in age are partly a temporary phenomenon, not only because the contemporary young will grow old, but also because increasingly present-day older generations adopt Internet activities such as music and video, gaming and social media. The same could occur with gender differences when Internet activities become more equally shared. As with both age and gender, a particular share of inequality will remain that is derived from relatively permanent socio-cultural preferences. It is also plausible that inequalities related to different levels of education are longer lasting as they are deeply engrained in the fabric of our information or knowledge society. Therefore, the suggestion for discussion can be made that ultimately differences in education might be more permanent than differences among age and gender.

Although, at least in the Netherlands, low educated Internet users spent more time online in their spare time, the findings reveal that those with higher social status use the Internet in more beneficial ways. Similarly, Zillien and Hargittai (2009: 287) concluded that ‘those already in more privileged positions are reaping the benefits of their time spent online more than users from lower socio-economic backgrounds.’ The findings suggest that as the Internet becomes more mature, its usage reflects traditional media use in society; Internet use increasingly reflects known social, economic and cultural relationships present in the offline world, including inequalities (e.g. Golding, 1996; Mason and Hacker, 2003; Van Dijk, 2005; Witte and Mannon, 2010; Zillien and Hargittai, 2009). For example, people with lower education and lower income also tend to watch more TV, or read fewer books and newspapers. Such parallels support the comparison between the knowledge gap hypothesis regarding the use of mass media and the usage gap hypothesis regarding the use of the Internet (e.g. Bonfadelli, 2002; Van Dijk, 2005; Zillien and Hargittai, 2009). The effect of education conforms to the thesis of the usage gap, and to previous assumptions that defended the knowledge gap.

Similarities between participation in the offline and online world are often a topic of debate in discussions concerning social inequality. A decade ago, Compaine (2001) compared the diffusion of television, radio and telephone with the diffusion of the Internet, and concluded that the digital divide is a temporary problem. Most scholars have moved away from such conclusions, but comparing the knowledge gap hypothesis with the usage gap hypothesis might lead to another misinterpretation, namely that differences in education have always been one of the causes of differences in society and opportunities in life and, thus, the Internet is just the next advancement in communication technology with its usage determined by education. The intensive and extensive nature of Internet use among the well-off and well-educated suggests an elite lifestyle from which those with less capital are marginalized (e.g. Van Dijk, 2005; Witte and Mannon, 2010; Zillien and Hargittai, 2009). Although inequalities within society have always existed, the Internet created an even stronger division; the higher status members increasingly gain access to more information than the lower status members. The Internet is not only an active reproducer of social inequality, but also a potential accelerator (Witte and Mannon, 2010). Rather than equalization, the Internet tends to reinforce social inequality and lead to the formation of disadvantaged and excluded individuals (Golding, 1996; Norris, 2001; Van Dijk, 2005). Wei and Hindman (2011), for example, found that socio-economic status is more strongly related to the informational use of the Internet than with that of the traditional media, and that the differential use of the Internet is associated with a greater knowledge gap than that of the traditional media. They therefore suggested that the digital divide matters more than its traditional counterpart. After all, the Internet has more functions than traditional media have.

Information and network society theory both acknowledge the importance of the Internet as a vital resource in society. In political, social, cultural, health and economic domains, more and more information and services are provided online and, often, it is expected that they will be used by all. The results of this and other recent studies reveal that within several domains, current policy directions should be evaluated. There are strong indications that parts of the population will be excluded from several Internet activities. The results of the current investigation suggest that overcoming digital divides is a rather complex challenge that goes beyond improving access or Internet skills. Clearly, this article among others has shown that they are related to individual motivations and socio-cultural preferences. In a free society, such preferences can only partly be changed by, for example, governmental, social and cultural policies in education and community building. Internet activities related to information, career and personal development could be made more attractive for larger parts of the population. Finally, the improvement and spread of positions in education and on the labour market (actually following school or adult education and having an appealing job) might show the most positive contributions to the reduction of differences in usage.

Shortcomings and future research

In this article, we propose seven categories of usage activities. Our classification made a distinction between motives and actual use, which are different concepts. The usage categories are validated by using motivational categories present in Uses and Gratifications Theory. In future contributions, the identified usage clusters can be further improved, for example, by adding more items to the gaming factor.

The validated usage clusters are used to explain the finding that people with low levels of education use the Internet for more hours a day than people with high levels of education. One might argue that high educated populations have less spare time; however, the results do reveal that they use this time online differently. Future studies should investigate whether high educated and employed people use the Internet at work also for private purposes, and if they do, what this private use looks like. This would be to investigate whether the higher educated compensate at work for the activities that the lower educated perform in their leisure time.

Considering the assumed advantages of serious uses of the Internet, it has to be shown that that they actually create more benefits in terms of different types of resources and capital than entertainment uses. This is hard to measure. In fact, this article only shows evidence of unequal use that might have societal results. It would also have to be demonstrated that Internet use increasingly reflects and perhaps even reinforces inequalities in society.

Furthermore, it is not fully clear what the exact implications of the difference between the knowledge and usage gap hypotheses are. Further research should investigate the similarities and differences between usage of the traditional mass media and the Internet, by for example including comparable types of usage in mass media other than the Internet. A comparison of the results could show whether the use of the Internet actually makes a difference, the underlying assumption of all digital divide research.

In this study, we have revealed that differences in usage exist. Structural usage differences appear when particular segments of the population systematically and over longer periods of time take advantage of the serious Internet activities they engage in, while others only use the Internet for everyday life and entertaining activities. Future research should also determine whether there is a growth or a reduction of the multiple differences distinguished in this article in a longitudinal perspective. As suggested, gender and age differences might partly disappear when the technology matures and spreads further across the population, while educational differences increase.

Finally, this study should be replicated in other countries with increasing popular use of the Internet for all everyday activities. Will the same trends of popularization and increasingly unequal use appear as in the Netherlands? Here again, longitudinal replications are required to determine whether the differences discussed are growing or decreasing.

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