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Digital inequalities in the Internet of Things: differences in attitudes, material access, skills, and usage

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ABSTRACT

The Internet of Things (IoT) is more complex and abstract than previous information and communication technologies as there are many connections occurring. New challenges for users arise from increased amount of data, decisions made automatically, less visibility and more ambiguity, and magnified security and privacy risks. There is a fair chance that only a selective group will benefit, making it important to study IoT from a digital inequality perspective. The current study focused on health, home, and security related IoT by conducting a survey among a representative sample of the Dutch population. The study was guided by resources and appropriation theory. IoT attitudes and material access as well as educational and income differences play an important role. Those with higher education and those with higher incomes have more positive attitudes and are the first to actually buy IoT. This also means that they are the first to develop the required skills and to engage in a diverse IoT use. The results suggest that to make the IoT attractive for larger parts of the population, clear terms of use and user-friendly IoT should be an important objective. Stimulating positive attitudes towards IoT will increase the likelihood of IoT ownership, development of IoT skills, and, eventually, a wider diversity of IoT use. Policies should aim to stress the potential outcomes IoT has to offer and should promote transparency and disclosure of how personal data is used as well as better privacy, security practices and regulation.

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Internet of Things; digital divide; digital inequality; digital skills

Introduction

The Internet of Things (IoT) is a system containing everyday devices that have microprocessors and sensors (e.g., sound, movement, and temperature) that are connected to the Internet. The IoT is finding wide applicability and is expected to deliver profound benefits to its users (Atzori, Iera, & Morabito, 2010; Gubbi, Buyya, Marusic, & Palaniswami, 2013). Popular consumer solutions deliver benefits ranging from better healthcare to less energy consumption and a safer living environment. Expectations are that major challenges related

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to delivering care will be solved and a more equitable healthcare system will emerge (Gubbi et al., 2013). Examples of IoT solutions include physiological sensors (often wearable) that monitor body temperature, blood pressure, or breathing activity and warn medical staff upon the detection of a health issue (Paschou, Sakkopoulos, Sourla, & Tsakalidis, 2013). The reduction of resource consumption (electricity, water, and gas) and the increase of living environment satisfaction are often discussed in relation to smart homes. For example, the IoT can adapt a room's heating or lightning based on personal preferences or weather conditions. Appliances such as smart eye locks, cameras, and alarm systems, are important consumer IoT applications as they increase safety and security.

Although popular media particularly stress techno-utopian promises (Bibri, 2015), the ability to realize the potential benefits depends in part on the knowledge, skills, and informed use of individuals (Van Deursen & Mossberger, 2018). The IoT is more complex and abstract than previous information and communication technologies, as there are many connections occurring. There are user-device interfaces, devices communicating with other devices and with third-parties (often with organizations that are unknown to the user), and then there are the user, device, and third-party responses to the data. In comparison with previous waves of Internet use, several features present new challenges for users, i.e., the increased amount of data, decisions being automatically and secretly made, less visibility and more ambiguity, and magnified security and privacy risks (Van Deursen & Mossberger, 2018). The question arises regarding how these features add new complexities to the research on digital inequalities.

Digital inequality research has evolved rapidly over the past decades, and scholars have explored multiple aspects to explain people's use of technology. Typically addressed are motivations and attitudes, physical and material access, skills, and usage (e.g., Blank & Groselj, 2014; Helsper, 2012; Ono & Zavodny, 2007; Van Deursen & Van Dijk, 2015; Zillien & Hargittai, 2009). Recent studies suggest that differences in these types of access reinforce existing inequalities, as human capital carries over to the online world; technologies offer more capital-enhancing opportunities for those of higher socioeconomic status (DiMaggio & Garip, 2012; Helsper, 2012; Mossberger, 2009; Robinson et al., 2015; Sparks, 2014; Witte & Mannon, 2009). The potential benefits of the IoT (including health, comfortable lives, energy savings, and a secure living environment) and the increased complexity of the IoT suggests that inequalities in IoT access have the potential to further exacerbate social inequality. Unfortunately, even though the IoT as a research topic has attracted attention from both academia and industry, the literature is underdeveloped. The expected impact is often based on the technical possibilities of the IoT (Atzori et al., 2010; Dornberger, Inglese, Korkut, & Zhong, 2018; Riggins & Wamba, 2015; Shakiba, Zavvari, Aleebrahim, & Singh, 2016), while important user characteristics, such as motivations or skills, are neglected.

In the current contribution, we provide an empirical investigation of the inequalities in IoT access in the Netherlands. Here, Internet connection rates are high (98% in 2019) and the IoT is available for the general public, especially in relation to health, home, and security appliances. Utility companies have introduced smart thermostats to entire cities, and consumer health, home, and security products are generally available for consumers in stores. It is increasingly difficult for people to opt out of the IoT. We will start by overviewing IoT attitudes and the actual ownership of (health, home, and security) IoT devices in the Netherlands. To study the inequality in the IoT, we utilize perspectives from resource and appropriation theory (Van Dijk, 2005), which, at its core, proposes four successive phases of technology appropriation. The first phase is attitude, which is followed by material access or ownership. In both phases, the differences among segments of the *general population* will be studied. After attitude and material access, Van Dijk frames the concepts of skills and usage. Among *IoT users,* which are those already owning IoT devices, we apply the priority of IoT attitudes, skills, and usage and test them simultaneously. Then, we will study how important determinants are associated with all access types.

Theoretical background

The Internet-of-Things

Over the years, the nature of Internet use has become more complex. Web 1.0 allowed users to read content; Web 2.0 enabled users to contribute to the web by creating, storing, and sharing content; and Web 3.0 introduced semantics that facilitate smoother communications between humans and machines and enable improved information searching and data sharing. Web 4.0 has arrived, and it involves connections between the web and other users anytime and anywhere, as well as personalized services based on continuously obtained data. The most prominent development is the IoT, which implies an objectification of three characteristics: ubiquity, identity, and connection. Van Deursen and Mossberger (2018, p. 3) define the IoT as

> systems that contain ubiquitous everyday objects (e.g., smartphones, cars, wearables, home appliances, etc.) that are accessible through the Internet. The objects are equipped with sensing, storing, and processing capabilities that allow them to understand their environments, and with identifying and networking capabilities that allow them to communicate information about themselves. The systems involve object-object, object-person, and person-person communications and make autonomous decisions.

There are four IoT features that present new challenges for users (Van Deursen & Mossberger, 2018). First, in the complex and omnipresent IoT system, the ubiquity of devices vastly increases the *amount of data* being generated. Second, because devices often go unnoticed and make autonomous decisions, the result is *less autonomy* from the user perspective. In contrast to former technologies in which fully conscious users were required, in the IoT, humans are mostly unaware of what is happening. They become more passive and, to a large extent, abandon their decision-making power. Third, there is *less visibility and more ambiguity*. IoT use takes place in a large social system. Unintended consequences may develop through the decisions that are made by devices or organizations that may be distant from the individual and difficult to observe. As a result, users may not be aware of the data collection, let alone able to predict the resulting consequences. Finally, online *security and privacy risks are magnified*. As security measures vary, there is always the threat that data can be intercepted by unauthorized parties. For users, it will often be unclear exactly what data are being collected, how these data are being used, and with whom they are shared. The amount and diversity of the collected data enable detailed habit profiles, demographics, and well-being. The four IoT features will bring new challenges for users since they are not only confronted with devices and software but also with hard to understand systems. While the potential outcomes are substantial, it is unclear for whom these outcomes are attainable.

Figure 1. Resources and appropriation theory (simplified), Van Dijk (2005).

Inequalities in IoT access

To get a comprehensive view of the inequalities in the IoT, we utilize perspectives from resource and appropriation theory (Van Dijk, 2005). This theory understands technology acceptance as a sequential process, which is called appropriation. Technology appropriation occurs in four access stages, namely, attitude, material access, skills, and usage. This process is based upon the precondition that one should first have a favorable attitude towards a technology in order to move towards the actual acquirement of material access and next to develop the necessary skills and use the technology. The core argument of the theory is that personal (e.g., age, gender, ethnicity, intelligence, personality, and health) and positional (e.g., labor position, education, household composition, and nation) differences across people produce inequalities in the distribution of resources (e.g., income, social network, intelligence, and status) which cause inequalities in the four stages of appropriation. The outcomes of this process cause more or less participation in society in several domains (e.g., economic, social, political, and cultural). The backbone of the theory is presented in Figure 1.

Appropriation of the Internet of Things

The first stage in IoT appropriation is developing a positive *attitude,* which directly relates to how people feel about IoT technology. Theories of technology adoption suggest that one's attitude towards technology is crucial for owning it (Venkatesh, Morris, Davis, & Davis, 2003). Negative attitudes decrease the likelihood that an individual will access the IoT (Reisdorf & Groselj, 2017; Van Dijk, 2005). On the one hand, negative attitudes might develop because of the hidden complexities of the IoT system, its inclination to take control, or privacy concerns. On the other hand, positive attitudes might develop because of the potential benefits the IoT offers.

Next, Van Dijk (2005) frames the concept of *material access*, which involves the opportunities and means to access the IoT. Material access concerns physical access or IoT ownership. While physical access in terms of Internet connections is rapidly increasing in developed countries, the IoT is just at the dawn of its development. Furthermore, material access involves the differences in the technical characteristics of the devices that are used (Van Dijk, 2005). Although the notion of material access is broader than physical access, we focus on the latter in this early stage of IoT diffusion.

After having a positive attitude and acquiring IoT devices, one must require several IoT *skills*. Preferences and needs need to be translated to the IoT system in a distributed, cooperative manner so that appropriate decisions about the resources being controlled (e.g., switching off lights) are made (Van Deursen & Mossberger, 2018). Furthermore, skills are required to decide how the collected data will be used. These data potentially reveal intimate user information of interest to third parties, such as (insurance) companies, creditors, and law enforcement. This requires users to be critical, to maintain their autonomy, and to be suspicious of actors that might manipulate the IoT system for their own benefit.

The final stage is *usage*, which can be defined in terms of frequency and the types of activities that are performed. The latter is increasingly the focus of attention when studying how people in different social groups use the Internet (Blank & Groselj, 2014). The types of activities are also more interesting in relation to the IoT. Combinations of connected devices that all have their own specific applications and that continuously collect user data enable a wider variety of activities. The more IoT devices that one uses, the more activities that can be tracked, and the more outcomes that are potentially gained. For example, a combination of an activity tracker, a smart blood pressure meter, and a sleep tracker provides more information than the activity tracker alone, thus increasing the chance of improved health.

Resource, personal, and positional inequalities

In the current contribution, we focus on two resources that are often considered in digital divide research: income and social support (see Scheerder, Van Deursen, & Van Dijk, 2017). *Income* is the most prominent economic resource and is required to afford the costs of material access (Chinn & Fairlie, 2006; Goldfarb & Prince, 2008; Martin & Robinson, 2007; Ono & Zavodny, 2007). Studies concerning the Internet revealed that those with lower income exhibit relatively negative Internet attitudes (Barzilai-Nahon, 2006), use the Internet less efficaciously, employ the Internet less productively and, thus, are at a greater economic disadvantage (DiMaggio, Hargittai, Celeste, & Shafer, 2004). A recent study revealed that people with higher incomes are more likely to use the IoT (Van Der Zeeuw, Van Deursen, & Jansen, 2019). This enables them to subsequently develop IoT skills, thus resulting in a greater diversity of IoT use. In addition to income, we expect the social resource of *social support* to be important for gaining IoT access. Social support is a general indication of social capital and is the accumulated sum of mutual acquaintances that, due to its durability, is a structural resource that is embodied by one's social network (Bourdieu & Wacquant, 1992). For example, people with many social relationships are more likely to obtain technology and to receive support when materials are purchased or in the event that it malfunctions (Van Dijk, 2005). Most evidence from Internet research suggests that a lack of social support might have a negative impact on the use of the IoT (Scheerder et al., 2017). For example, those with less social support are less likely to engage in a wider variety of Internet use (e.g., Neves & Fonseca, 2015). Van der Zeeuw et al. (2019) found that social support positively determined sharing IoT data.

Factors driving the distribution of resources and IoT access are positional categories commonly falling under education, work, and household. *Educational level of attainment* is a consistent determinant in the digital divide research (e.g., DiMaggio et al., 2004; Scheerder et al., 2017). A positive relation between education and Internet use results from greater awareness, better training, and greater abilities to evaluate content (Rice, MacCreadie, & Chang, 2001). People with lower educational levels have less material access (Van Dijk, 2005), lower levels of Internet skills (e.g., Correa, 2016; Hargittai, 2010; Scheerder et al., 2017), and use the Internet in less beneficial ways (e.g., Blank & Groselj, 2014; Hargittai & Hinnant, 2008; Scheerder et al., 2017). Those with higher levels of education and those who are *employed* are more digitally engaged and will benefit more from technology in their everyday lives (Clayton & Macdonald, 2013; Scheerder et al., 2017). In the household context, digital divide research often reveals an independent effect of *marital status* (Scheerder et al., 2017).

The most commonly observed individual characteristics are gender and age (Scheerder et al., 2017). Although the physical Internet access *gender* gap has disappeared in many developed countries, men use the Internet more than women because they have more prior exposure to technology and work-related requirements (e.g., Meraz, 2008). Furthermore, prior research revealed that men and women differ in what they do online (e.g., Zillien & Hargittai, 2009). Of all *age* groups, older adults tend to experience the least positive Internet attitude levels (e.g., Marquié, Jourdan-Boddaert, & Huet, 2002) and make the least use of digital devices (e.g., Zickhur & Madden, 2012). Because of earlier exposure and training, peer use, and greater comfort with new technology, younger people exhibit the highest Internet skill levels and the highest variety of Internet use (see Scheerder et al., 2017).

IoT appropriation: hypotheses for attitude and material access

To study what differences in IoT attitudes and in material (health, home, and security) IoT access exist, we will start by posing hypotheses that concern the whole population (including IoT users and non-users). We consider the aforementioned resources, positions, and personal characteristics. Furthermore, following the process of IoT appropriation, we expect that IoT attitude is also associated with material IoT access. We hypothesize the following:

H1. IoT attitude (positive) is associated with having material IoT access

H2. The resources of (a) Income (high) and (b) Social support, the positions of (c) Education (high), (d) Employment (employed), and (e) Marital status (married / relationship), and the personal characteristics of (f) Gender (male), and (g) Age (younger) are associated with IoT attitude

H3. The resources of (a) Income (high) and (b) Social support, the positions of (c) Education (high), (d) Employment (employed), and (e) Marital status (married / relationship), and the personal characteristics of (f) Gender (male), and (g) Age (younger) are associated with having material IoT access

Hypotheses for IoT attitude, skills, and usage among IoT users

The second set of hypotheses concern those who own IoT devices. We are interested in how IoT attitude, skills, and usage interrelate and what the determinants are for each stage. We expect that IoT attitude facilitates the acquisition of the required IoT skills that in turn enable more diverse IoT use. Prior research suggests that in the process of Internet appropriation, attitudinal access remains relevant for the acquisition of skills (Van Deursen & Van Dijk, 2015). Furthermore, we expect IoT skills to be relevant for IoT usage since a higher skill level allows for a wider range of activities (Van Deursen, Helsper, Eynon, & Van Dijk, 2017). Several multifaceted considerations of the digital divide have revealed strong effects of skills on types of use (e.g., Pearce & Rice, 2013). We hypothesize the following:

H4. IoT attitude (positive) is associated with IoT skills

H5. IoT skills (positive) are associated with IoT usage

To study differences among those who already have material IoT access, we consider whether the same resources and positional and personal categories that are discussed play roles, this time in relation to IoT attitude, skills, and usage. Research among Internet users has long revealed that determinants for having or not having access remain important after an Internet connection is established (Scheerder et al., 2017). We hypothesize the following:

H6. The resources of (a) Income (high) and (b) Social support, the positions of (c) Education (high), (d) Employment (employed), and (e) Marital status (married / relationship), and the personal characteristics of (f) Gender (male), and (g) Age (younger) are associated with IoT attitude

H7. The resources of (a) Income (high) and (b) Social support, the positions of (c) Education (high), (d) Employment (employed), and (e) Marital status (married / relationship), and the personal characteristics of (f) Gender (male), and (g) Age (younger) are associated with having IoT skills

H8. The resources of (a) Income (high) and (b) Social support, the positions of (c) Education (high), (d) Employment (employed), and (e) Marital status (married / relationship), and the personal characteristics of (f) Gender (male), and (g) Age (younger) are associated with IoT usage

Method

Sample

We relied on a data set that was collected in February of 2018. The sampling and fieldwork were performed using PanelClix in the Netherlands. Respondents were recruited from an online panel containing over 100,000 people comprising a highly representative sample of the Dutch population. The members received a small monetary incentive for every survey in which they participated. We conducted our survey in the last week of January and the first week of February 2018 in two parts among the same panel of respondents. The first part concerned general Internet use and covered most determinants, whereas the second part covered specific questions regarding IoT use. In total, 1,356 respondents finished both surveys. In terms of gender, age, and educational level, the sample was highly consistent with the official statistics, and only a slight weight was needed post hoc to match the representativeness to the standards of Statistics Netherlands (CBS), a Dutch governmental statistics agency. See Table 1 for the demographic profiles of the total sample and of the IoT users.

Measures

The IoT survey was pilot tested with eight users over two rounds. Modifications were made based on the feedback that was provided. In the second round, no major comments were made. The survey started with an introduction and explanation of what we

Table 1. Demographic profiles.

	Overall		IoT users	
	N	%	*N*	%
Gender				
Male	705	52.0	297	52.8
Female	651	48.0	266	47.2
Age				
18–35	277	20.4	162	28.8
36–50	267	19.7	137	24.3
51–65	381	28.1	154	27.4
66+	431	31.8	110	19.5
Education				
Low	956	70.5	380	67.5
High	400	29.5	183	32.5

considered the IoT (smart everyday devices connected to the Internet that can be controlled by apps such as smart thermostats, smart meters, Fitbits, smart cameras, etc.). The time needed to answer the survey questions varied due to the number of IoT devices that the respondents owned. On average, it took 20 min to complete the survey.

IoT attitude was measured by adapting eight items of the Internet Attitude Scale (Durndell & Haag, 2002) to the IoT. All the items were balanced for the direction of the response and averaged together to create a single construct ($M = 3.21$; SD = 0.69; α=.76; 5-point agreement Likert scale). See Table 2.

Material IoT access was measured by asking respondents to indicate what IoT devices they owned. An extensive list of 27 health, 20 home, and 10 security appliances was provided (all available to the public in shops). Because in the IoT system, multiple devices are often combined, access and use are somewhat conflated. As material access concerns IoT in its totality, we considered owning any of the devices and created binary variables for each domain: health (46%), home (43%), and security (32%). See Appendixes A, B, and C.

Table 2. Items used for measuring IoT attitude and skills.

	M	SD
IoT attitude ($\alpha = .76$)		
Using Internet-of-Things …		
makes life less social (*R*)	2.41	1.05
makes people servants of technology (*R*)	2.35	.97
will control our lives (*R*)	2.42	1.02
makes people too dependent (*R*)	2.50	.99
is inflicted on us (*R*)	2.60	1.05
dehumanizes society (*R*)	2.69	1.01
makes it difficult to protect my privacy (*R*)	2.34	.98
causes mental instability (*R*)	3.02	.93
IoT skills ($\alpha = .93$)		
I know how to connect smart devices to the Internet	3.39	1.31
I know how to share information from smart devices on the Internet	3.26	1.30
I know how to operate smart devices by using applications	3.46	1.34
I know how to interpret data from smart devices	3.32	1.30
I know how to connect smart devices to my WiFi-network	3.39	1.35
I feel confident operating smart devices	3.15	1.22
I know how to change on a smart device with whom I share data	3.00	1.27
I know how to read data from smart devices	3.30	1.26
I know how to change how often data is gathered by smart devices	3.01	1.27

Note: *R* = reversed.

IoT skills was measured among those with material IoT access by using a set of items that was constructed by De Boer, Van Deursen, and Rompay (2019) who proposed an instrument that was inspired by the Internet Skills Scale (Van Deursen, Helpser, & Eynon, 2016). To respond to the items, a 5-point Likert-type scale was used that ranged from one, 'Not at all true for me', to five, 'very true for me', with 'neither true nor untrue for me' as the neutral response. When respondents did not understand the item, they could respond with 'I don't understand this statement', which was coded as 0, thereby creating a 6-point Likert scale. The set of nine items in total covered respondents' knowledge of how to address smart devices and how to deal with the information that they gather ($M = 3.39$; SD = 1.05; $\alpha = .97$). See Table 2.

IoT usage was measured among those with material IoT access. We first checked whether the IoT devices that were owned were also used in an IoT manner, which means that they were connected to the Internet and controlled by an app. We then summed the number of unique IoT devices that people use. The underlying idea is that the number of devices corresponds with more activities being performed. We differentiated between three types of IoT usage: health, home, and security. For each type, dichotomous items were summed into a single scale that reflected the number of IoT devices that were used for health ($M = 1.43$; SD = 1.59), home ($M = 0.90$; SD = 1.26), and security ($M = 0.37$; SD = 0.77) activities.

Income was initially coded as a categorical variable that reflected the total annual family income in the last twelve months. There were three categories of low (<30,000 Euro), middle (30,000–60,000 Euro), and high (>60,000 Euro).

For *social support*, we used the medical outcomes social support survey (Sherbourne & Stewart, 1991) to evaluate support availability. The respondents completed 12 items covering emotional (e.g., 'Someone you can count on to listen when you need to talk'), informational (e.g., 'Someone to give you good advice about a crisis'), and tangible (e.g., 'Someone to help you if you were confined to bed') support. All the items were rated on a 5-point scale with the anchors none of the time (1) and most of the time (5). We computed an aggregate measure of support availability for all items ($\alpha = .97$; $M = 3.75$; SD = 1.07).

The data on *education* were collected by degree as one of eight categories. These data were subsequently divided into three groups of low, middle, and high educational levels being attained. *Employment status* was coded as dummy variables into the following categories: employed (53%), retired (23%), disabled (8%), homemaker (6%), unemployed (4%), and students (6%). *Marital status* was coded into dummy variables, as follows: single (35%), married or living together in a relationship (50%), divorced (9%), and widow(er) (6%).

Gender (male: 49%) was included as a dichotomous variable. *Age* was computed by subtracting the reported year of birth from the survey year and was subsequently categorized into the age groups of 18–35, 36–50, 51–65, and over 66.

Data analysis

To test hypotheses H1-H3, we conducted a linear regression analysis for IoT attitude and a logistic regression for material IoT access in general and for health, home, and security IoT.

To test hypotheses H4-H8, we applied path analysis using Amos 23 to the subsample of those with material IoT access. To obtain a comprehensive model fit, we included the indices that were suggested by Hair (2006): the χ^2 statistic, the ratio of the χ^2 to its degree of freedom (χ^2/df), the standardized root mean residual (SRMR) (<.08), the Tucker-Lewis index (TLI) (>.90), and the root mean square error of approximation (RMSEA) (<.06). These fit indices are typically used to represent the three categories of model fit: absolute, parsimonious, and incremental.

Results

The general population: resource, positional, and personal differences in material and attitudinal IoT access

Overall, 44.7% of the Dutch adult population owns at least one IoT device. For *health* specifically, 31.3% use at least one IoT device. See Figure 2 for an overview. The most popular devices are activity trackers (10.5%), heart rate monitors (10.2%), and sports watches (8.8%), followed by smart blood pressure monitors (6.7%), sleep trackers (5.9%), scales (4.4%), and thermometers (4.0%). IoT devices for improving living conditions in the *home* are used by 24.3%. Figure 3 shows the devices that people own, the most popular one being the smart thermostat (11.4%), which is followed by smart lightning (6,6%), smart central heating (5.1%), and smart energy meters (5.0%). Concerning the IoT for *security* purposes, a total of 11.7% own at least one device. Figure 4 shows that most popular devices are smart cameras (4.7%), followed by smart security systems (3.7%), smart smoke detectors (3.2%), and smart motion sensors (1.7%).

Table 3 reveals that IoT attitude is an important contributor to all types of material IoT access, supporting hypothesis H1. IoT attitude among the general

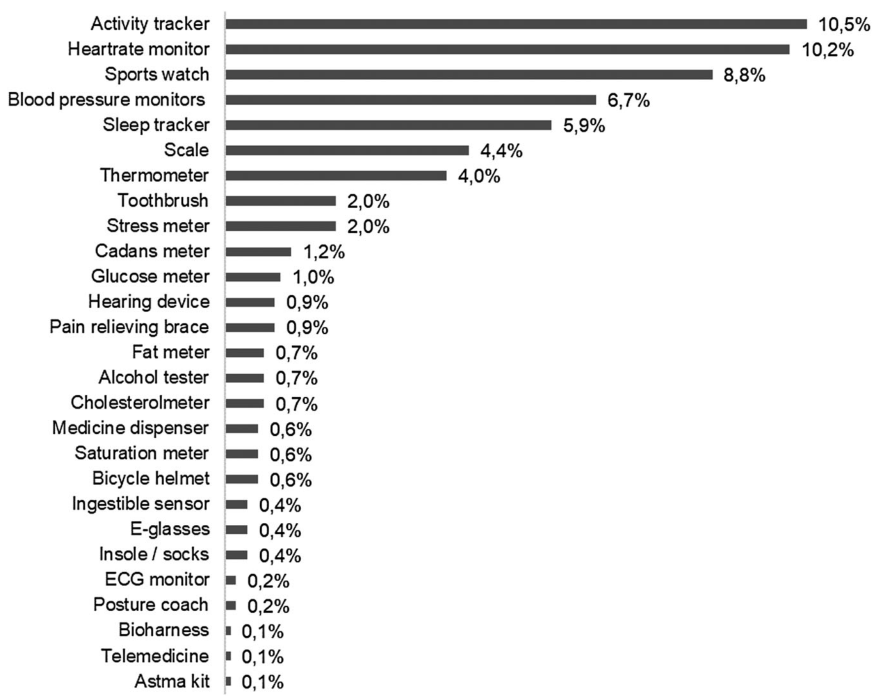

Figure 2. IoT devices (smart) used for health purposes (% of Dutch adult population).

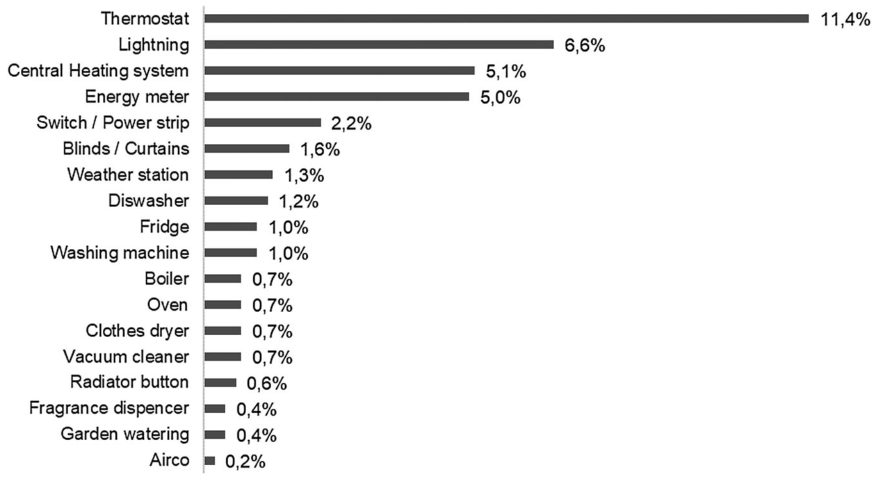

Figure 3. IoT devices (smart) used for home purposes (% of Dutch adult population).

population is determined by income, supporting hypothesis H2a (the remaining hypotheses concerning IoT attitude are rejected). Income is also important for material IoT access in general, and specifically for home and security IoT, supporting H3a. The resource of social support contributes negatively to having security related IoT, rejecting hypothesis H3b. Education did not emerge as significant predictor. Those who are employed are more likely to own home IoT devices compared to students, partly supporting H3d. Hypothesis H3e is also supported, as married people or those in relationships are generally more likely to own IoT devices, specifically health and home IoT devices, when compared to single people. Concerning individual characteristics, Table 1 shows that men are more likely to own security-related IoT devices, partly supporting H3f and that age contributes negatively to all material IoT access types, supporting H3g.

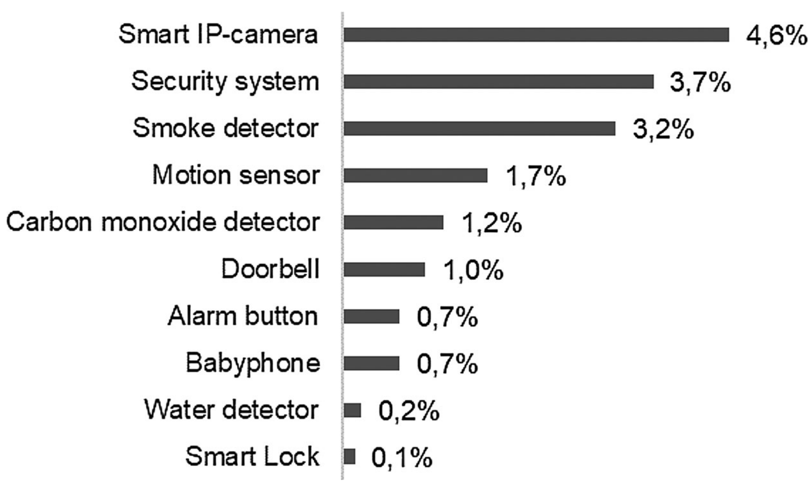

Figure 4. IoT devices (smart) used for home purposes (% of Dutch adult population).

Table 3. Regression analysis to predict attitudinal (OLS) and material IoT access (Logistic).

	IoT attitude (β)	Material IoT access (odd ratio)			
		Any	Health	Home	Security
Gender (M/F)	−.03	0.94	0.93	1.03	0.57**
Age (ref. 18–35)					
36–50	−.07	0.59*	0.67	0.62*	0.70
51–65	−.07	0.38***	0.39***	0.44***	0.59
66+	−.14	0.20***	0.33**	0.13***	0.16**
Employment (ref. employed)					
Unemployed	−.03	0.75	0.75	1.15	0.47
Retired	.04	0.77	0.61	1.48	1.31
Disabled	−.01	0.86	0.89	0.77	0.55
Homemaker	.03	0.60	0.66	0.52	0.67
Student	−.01	0.83	1.37	0.39*	0.57
Education (ref. low)					
Middle	−.03	1.09	1.08	1.21	0.99
High	.01	1.05	1.38	1.17	0.87
Marital status (ref. married)					
Single	.00	0.56***	0.69*	0.54**	0.96
Widow	.03	0.84	0.98	0.63	1.21
Divorced	−.03	0.88	1.05	1.12	1.63
Income (ref. low)					
Middle	.08**	1.31*	1.30	1.57**	1.69*
High	.10**	1.74**	1.51	2.15***	2.30**
Social support	.05	1.02	1.00	0.94	0.83*
IoT attitude		2.03***	1.96***	2.29***	1.56**
Constant		0.20**	0.09**	0.04***	0.19*
Nagelkerke R^2		*.19*	*.16*	*.18*	*.11*
Chi-square		*199.94****	*158.39****	*171.21****	*78.27****
R^2	*.03*				
F	*2.33***				

$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

IoT users: resource, positional, and personal differences in attitude, skills, and usage

To test hypotheses H4-H8, we started by examining the basic assumptions of path analysis. Normality, kurtosis, and skewness did not differ significantly from the acceptable criteria, and there were no outliers or multicollinearity beyond what would be theoretically expected. The fit results that were obtained from testing the validity of a causal structure of the hypothesized model (applied to the subsample of IoT users; $n = 563$) are as follows: $\chi^2(15) = 8.39$, $\chi^2/\mathrm{df} = 2.80$, SRMR = .02, TLI = .81, and RMSEA = .06 (90% confidence interval [CI] = .01, .10). As an improvement, we added one path departing from IoT attitude to Home IoT usage. This addition resulted in a model with a good fit: $\chi^2(19) = 2.44$, $\chi^2/\mathrm{df} = 1.22$, SRMR = .01, TLI = .98, and RMSEA = .02 (90% confidence interval [CI] = .00, .09). Figure 4 provides the hypothesized path model with the coefficients and variances explained.

The standardized path coefficients in Figure 5 reveals several significant effects. IoT attitude contributes positively to IoT skills, which in turn contributes positively to health and home IoT usage. Hypotheses H4 is supported, and H5 is partly supported. The figure furthermore reveals that IoT attitude contributes indirectly to health and home IoT usage.

Figure 5 furthermore shows several significant direct and indirect effects of the resource, positional, and personal determinants. Direct, indirect, and total effects, as well as an overview of hypotheses H6-H8, are summarized in Table 4. Concerning

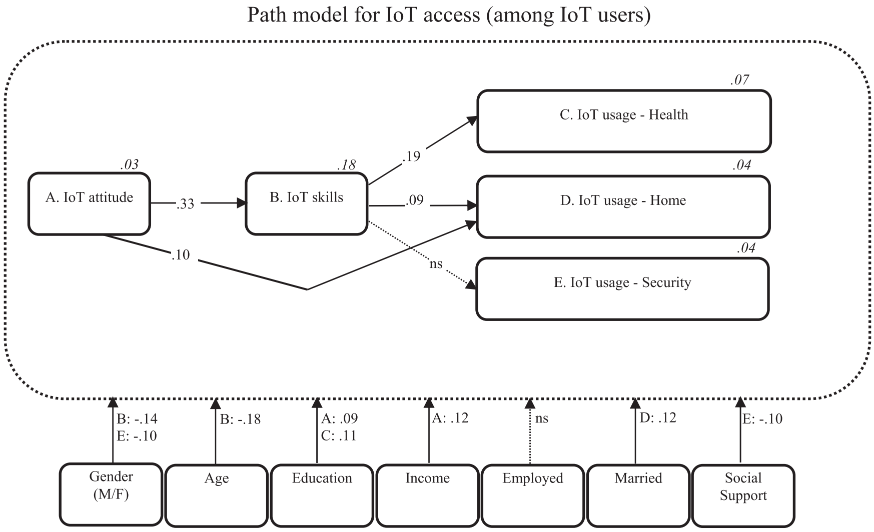

Figure 5. Path model for IoT access (among IoT users).

Note: *n* = 563 IoT users. Paths significant at .05 level; path from attitudinal IoT access to usage IoT access – Home was added to improve model fit. R^2's in italic.

resources, income contributes positively to IoT attitude. Small indirect effects on IoT skills and health and home IoT usage are notable. Social support only (negatively) contributes to security IoT usage and indirectly to IoT skills.

Education directly and positively contributes to IoT attitude and health IoT usage. There are indirect contributions to IoT skills and health and home IoT usage. Those married or in a relationship are more likely to take part in home IoT usage.

Table 4. Significant direct, indirect, and total effects of IoT access determinants.

	Direct effects	Indirect effects	Total effects	Hypothesis*
H6a.Income→IoTattitude	.12		.12	A
H7a.Income→IoTskills	x	.04	.04	PA
H8a.Income→IoTusage–Health/Home/Security	x/x/x	.01/.01/x	.01/.01/x	PA
H6b.Socialsupport→IoTattitude	x	x	x	R
H7b.Socialsupport→IoTskills	x	−.03	−.03	PA
H8b.Socialsupport→IoTusage–Health/Home/Security	x/x/−.10	−.01/−.00/x	−.01/−.00/−.10	PA
H6c.Education→IoTattitude	.09	x	.09	A
H7c.Education→IoTskills	x	.03	.03	PA
H8c.Education→IoTusage–Health/Home/Security	.11/x/x	.01/.01/x	.12/.01/x	PA
H6d.Employment→IoTattitude	x	x	x	R
H7d.Employment→IoTskills	x	x	x	R
H8d.Employment→IoTusage–Health/Home/Security	x	x	x	R
H6e.Maritalstatus→IoTattitude	x	x	x	R
H7e.Maritalstatus→IoTskills	x	x	x	R
H8e.Maritalstatus→IoTusage–Health/Home/Security	x/.12/x	x	x/.12/x	PA
H6f.Gender→IoTattitude	x	x	x	R
H7f.Gender→IoTskills	−.14	x	−.14	A
H8f.Gender→IoTusage–Health/Home/Security	x/x/−.10	−.03/−.01/−	−.03/−.01/−.10	PA
H6g.Age→IoTattitude	x	x	x	R
H7g.Age→IoTskills	−.18	–	−.18	A
H8g.Age→IoTusage–Health/Home/Security	x/x/x	−.03/−.02/x	−.03/−.02/x	PA

*A: accepted; PA: partly accepted (indirect contribution only); R: rejected.

Regarding personal characteristics, men are more likely to possess IoT skills and use security IoT. Indirectly, men also have higher health and home IoT use. Age contributes negatively to IoT skills and home IoT usage. Age also contributes indirectly and negatively to health and home IoT usage. Employment did not contribute to any of the IoT usage types.

Discussion

Main findings

The era of Web 4.0 has arrived and its most prominent development, the IoT, is now widely available for consumers. Almost half of the Dutch adult population owns an IoT device. Although this may sound like the IoT is firmly rooted in people's daily lives, ownership can be ascribed to a relatively limited set of devices: activity trackers, heart rate monitors, sport watches, smart thermostats, and lightning systems. The important features of such appliances are that a large amount of data is being collected, there is less autonomy from a user's perspective, the devices work in the background and are invisible to the user, and there are substantial risks (Van Deursen & Mossberger, 2018). Crucially, the IoT is directed by artificial intelligence, as decisions are not only automatically made by users but – once initial configurations are set – primarily by algorithms. These features have important consequences to the research on digital inequality. For example, although the devices are relatively cheap and daily use of IoT does not require extensive user skills as far as basic operations and functioning is concerned (precisely because IoT operates 'on its own'), the story becomes more complex once these devices become part of an interconnected system in which they are connected to a multitude of other devices. Apart from a more complex process of appropriation (the process might have to be reiterated until a motivational threshold is reached), use might occur without any understanding of how functioning of a particular device influences functioning of other devices, and perhaps more importantly how data gathered in the background are shared across devices within and outside of the network (e.g., physical exercise data being shared with medical specialist or health insurance companies). In other words, although pragmatic use might be easy and straightforward, implications of use are far more complex and hence might require more advanced strategic skills. It is at this point that future research should clarify how such implications will affect (existing notions of) digital inequality. Taking a step back, in the current contribution, resources and appropriation theory was used to study inequalities in the use of IoT in the Netherlands.

Following the appropriation process, we can first confirm the important role of IoT attitude. A positive attitude towards IoT increases the likelihood of IoT ownership and IoT skills and eventually leads to a wider diversity of IoT use. IoT skills, in turn, are important for IoT usage, although we did not find an effect for security related IoT activities. The adoption of security devices and related activities might be undertaken (regardless of skill levels), as they are important to wellbeing of one's self and family members, issues which relate to basic needs. Resource and appropriation theory then argues that inequalities in the appropriation stages are caused by inequalities in resources, positions, and personal characteristics. Income surfaces as an important resource in relation to IoT attitude. People with low incomes that cannot afford IoT devices are less likely to develop favorable attitudes. Income remains important for material IoT access, especially for home-related IoT that appeals to (less basic) hedonic needs that are related to comfort and luxury, and safety-related IoT. The resource of social support only played a role in relation to security. Those with fewer support networks are more likely to buy security related IoT devices, maybe because they feel more insecure.

Among the IoT owners, next to the income resource, the position of educational attainment is associated with IoT attitudes. Education is also important for health related IoT uses. Both income and education were important predictors in Internet research that studied initial attitudes and uptake. As resource and appropriation theory posits IoT attitude at the start of the appropriation process, followed by material access, those with higher incomes and education will be the first to develop the necessary IoT skills and engage in diverse use of IoT devices. They are more likely to benefit from IoT developments. In terms of inequality, those that are already in more privileged positions are the first to further strengthen their resources by using the IoT or, in other words, to improve their health, living conditions at home, and security. Similar conclusions can be drawn for age: younger people tend to have the most material IoT access and have higher levels of IoT skills.

That attitude remains important throughout the appropriation process might be explained by the (hidden) complexity of the IoT system. Even after owning IoT devices and employing IoT skills, it remains difficult for people to understand what is occurring in the IoT system. This suggests that clear terms of use and a user-friendly IoT should be important objectives. Policies that promote the transparency and disclosure of how personal data are used, as well as incorporate better privacy and security practices, could result in more positive attitudes. Note that the findings should not be assumed to suggest that supporting positive attitudes is most important, followed by policies improving material access, and, third, policies supporting skills. Rather we have seen that (their sequential nature notwithstanding) all stages have their own determinants and interact together to shape IoT inequalities. Accordingly, policies could address them simultaneously. In fact, even different IoT appliances behave differently as they have different determinants (suggesting that future studies should be careful and not collapse them so easily). Overall, our findings show that the types of users who were the first to appropriate computers and the Internet are also the first to use the IoT. As the IoT has an increasing number of valuable applications, the use of IoT may be accompanied by widening inequalities, presenting a nontrivial share of users who are unable to take advantage of the IoT at their disposal and who are less empowered to make decisions, which are, instead, governed by unseen forces. Because digital inequality is a critical issue in the contemporary economy, this study furthers our understanding of IoT access among various segments of the population.

The current investigation presented sufficient evidence to support beginning to focus digital inequality research on the IoT. In relation to Internet use, it took a long time before the emphasis started to shift away from having a connection to more elaborate explanations of skills and usage. For studying inequalities in the IoT, we stress that we should start incorporating these steps in research and policy at the start, even though material access rates are far from being saturated. Our results reveal that several inequalities emerge among those already using IoT devices.

Limitations and future research

In the current study, we used resource and appropriation theory to investigate IoT inequalities in the Netherlands. The operationalization of the four IoT appropriation stages has some limitations. Material IoT access was limited to having access to a device. Other technology affordances are ignored and could be added in future studies (Van Deursen & Van Dijk, 2019). For example, not all activity trackers are of the same quality or have the same functionality. IoT skills were measured as a single construct. The instrument that was used (De Boer et al., 2019) was not yet able to statistically confirm the presence of different skills, although the underlying statements covered a broader array, ranging from communication to data protection skills. Future studies should try to disentangle the different IoT skill dimensions that are important in relation to the IoT: for example, operational skills might become less important (due to the autonomy of the devices), while information, data visualizations, and communication skills may become key (see Van Deursen & Mossberger (2018) for a discussion). Finally, IoT usage was considered as the number of IoT devices in a specific domain. The underlying idea is that more devices create a wider diversity of activities and more potential outcomes. However, we did not look at the specific activities that one device might enable.

The current study was conducted among the Dutch population, which is characterized by high levels of Internet access. It would be useful to replicate this study in other developed (and developing) countries. We expect that attitudinal IoT access will be even more important for obtaining material IoT access and improving IoT skills and different types of usage. However, policies ensuring positive attitudes and required materials alone will not guarantee skilled and fruitful IoT use. Furthermore, simultaneously investigating different types of IoT access in other countries might result in different gravities of the access points, in turn demanding different policy initiatives.

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References

Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, *54*(15), 2787–2805. doi:10.1016/j.comnet.2010.05.010

Barzilai-Nahon, K. (2006). Gaps and bits: Conceptualizing measurements for digital divide/s. *The Information Society*, *22*(5), 269–278. doi:10.1080/01972240600903953

Bibri, S. E. (2015). *The shaping of ambient intelligence and the Internet of Things*. Amsterdam: Atlantis Press.

Blank, G., & Groselj, D. (2014). Dimensions of Internet use: Amount, variety, and types. *Information, Communication & Society*, *17*(4), 417–435. doi:10.1080/1369118X.2014.889189

Bourdieu, P., & Wacquant, L. J. (1992). *An invitation to reflexive sociology*. Chicago, IL: University of Chicago press.

Chinn, M. D., & Fairlie, R. W. (2006). The determinants of the global digital divide: A cross-country analysis of computer and Internet penetration. *Oxford Economic Papers*, *59*(1), 16–44. doi:10.1093/oep/gpl024

Clayton, J., & Macdonald, S. J. (2013). The limits of technology. Social class, occupation and digital inclusion in the city of Sunderland, England. *Information, Communication & Society*, *16*(6), 945–966. doi:10.1080/1369118X.2012.748817

Correa, T. (2016). Digital skills and social media use: How Internet skills are related to different types of Facebook use among 'digital natives'. *Information, Communication & Society*, *19*(8), 1095–1107. doi:10.1080/1369118X.2015.1084023

De Boer, P. S., Van Deursen, A. J. A. M., & Van Rompay, T. J. L. (2019). Accepting the Internet-of-Things in our homes: The role of user skills. *Telematics and Informatics*, *36*, 147–156.

DiMaggio, P., & Garip, F. (2012). Network effects and social inequality. *Annual Review of Sociology*, *38*, 93–118. doi:10.1146/annurev.soc.012809.102545

DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital inequality: From unequal access to differentiated use. In K. M. Neckerman (Ed.), *Social inequality* (pp. 355–400). New York: Russell Sage Foundation.

Dornberger, R., Inglese, T., Korkut, S., & Zhong, V. (2018). Digitalization: Yesterday, today and tomorrow. In R. Dornberger (Ed.), *Business information systems and technology 4.0 new trends in the age of digital change* (pp. 1–11). Cham: Springer.

Durndell, A., & Haag, Z. (2002). Computer self efficacy, computeranxiety, attitudes towards the Internet and reported experience with the Internet, by gender, in an East European sample. *Computers in Human Behavior*, *18*(5), 521–535.

Goldfarb, A., & Prince, J. (2008). Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy*, *20*(1), 2–15. doi:10.1016/j.infoecopol.2007.05.001

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, *29*(7), 1645–1660.

Hair, J. F. (2006). *Multivariate data analysis*. Upper Saddle River, NJ: Prentice Hall.

Hargittai, E. (2010). Digital na(t)ives? Variation in Internet skills and uses among members of the 'Net generation'. *Sociological Inquiry*, *80*(1), 92–113. doi:10.1111/j.1475-682X.2009.00317.x

Hargittai, E., & Hinnant, A. (2008). Digital inequality differences in young adults' use of the Internet. *Communication Research*, *35*(5), 602–621. doi:10.1177/0093650208321782

Helsper, E. J. (2012). A corresponding fields model for the links between social and digital exclusion. *Communication Theory*, *22*(4), 403–426. doi:10.1111/j.1468-2885.2012.01416.x

Marquié, J. C., Jourdan-Boddaert, L., & Huet, N. (2002). Do older adults underestimate their actual computer knowledge? *Behaviour & Information Technology*, *21*(4), 273–280.

Martin, S., & Robinson, J. (2007). The income digital divide: Trends and predictions for levels of Internet use. *Social Problems*, *54*(1), 1–22. doi:10.1525/sp.2007.54.1.1

Meraz, S. (2008). Women and technology: How socialization created a gender gap. In S. M. P. Pointdexter & A. M. Weiss (Eds.), *Women, men, and news. Divided and disconnected in the new media landscape* (pp. 3–18). New York: Routledge.

Mossberger, K. (2009). Toward digital citizenship. Addressing inequality in the information age. In A. Chadwick & P. Howard (Eds.), *Routledge handbook of Internet politics* (pp. 173–185). New York: Routlegde.

Neves, B. B., & Fonseca, J. R. (2015). Latent class models in action: Bridging social capital & Internet usage. *Social Science Research*, *50*, 15–30. doi:10.1016/j.ssresearch.2014.11.002

Ono, H., & Zavodny, M. (2007). Digital inequality: A five country comparison using microdata. *Social Science Research*, *36*(3), 1135–1155. doi:10.1016/j.ssresearch.2006.09.001

Paschou, M., Sakkopoulos, E., Sourla, E., & Tsakalidis, A. (2013). Health Internet of Things: Metrics and methods for efficient data transfer. *Simulation Modelling Practice and Theory*, *34*, 186–199. doi:10.1016/j.simpat.2012.08.002

Pearce, K. E., & Rice, R. E. (2013). Digital divides from access to activities: Comparing mobile and personal computer Internet users. *Journal of Communication*, *63*(4), 721–744. doi:10.1111/jcom.12045

Reisdorf, B., & Groselj, D. (2017). Internet (non-)use types and motivational access: Implications for digital inequalities research. *New Media & Society*, *19*(8), 1157–1176. doi:10.1177/1461444815621539

Rice, R. E., MacCreadie, M., & Chang, S.-J. L. (2001). *Accessing and browsing information and communication*. Cambridge, MA: MIT Press.

Riggins, F. J., & Wamba, S. F. (2015). *Research directions on the adoption, usage, and impact of the Internet of Things through the use of big data analytics*. System Sciences (HICSS), IEEE, 48th Hawaii International Conference (pp. 1531–1540).

Robinson, L., Cotton, S. R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W., … Stern, M. J. (2015). Digital inequalities and why they matter. *Information, Communication & Society*, *18*(5), 569–582. doi:10.1080/1369118X.2015.1012532

Scheerder, A., van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, *34*(8), 1607–1624. doi:10.1016/j.tele.2017.07.007

Shakiba, M., Zavvari, A., Aleebrahim, N., & Singh, M. J. (2016). Evaluating the academic trend of RFID technology based on SCI and SSCI publications from 2001 to 2014. *Scientometrics*, *109*(1), 591–614. doi:10.1007/s11192-016-2095-y

Sherbourne, C. D., & Stewart, A. L. (1991). The MOS social support survey. *Social Science & Medicine*, *32*(6), 705–714. doi:10.1016/0277-9536(91)90150-B

Sparks, C. (2014). Technological innovation and social change. In J. Servaes (Ed.), *Technological determinism and social change: Communication in a tech-mad world* (pp. 65–86). London: Lexington Books.

Van Der Zeeuw, A., Van Deursen, A. J. A. M., & Jansen, G. (2019). Inequalities in the social use of the internet of things: A capital and skills perspective. *New Media and Society*, In press.

Van Deursen, A. J. A. M., & Helsper, E. J. (2016). Development and validation of the Internet skills scale (ISS). *Information, Communication & Society*, *19*(6), 804–823.

Van Deursen, A. J. A. M., Helsper, E. J., Eynon, R., & van Dijk, J. A. G. M. (2017). The compoundness and sequentiality of digital inequality. *International Journal of Communication*, *11*(2017), 452–473.

Van Deursen, A. J. A. M., & Mossberger, K. (2018). Any thing for anyone? A new digital divide in internet-of-things skills. *Policy and Internet*, *10*(2), 122–140.

Van Deursen, A. J. A. M., & Van Dijk, J. A. G. M. (2015). Towards a multifaceted model of internet access to understand digital divides: An empirical investigation. *The Information Society*, *31*(5), 379–391.

Van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *New Media & Society*, *21*(2), 354–375.

Van Dijk, J. A. G. M. (2005). *The deepening divide: Inequality in the information society*. London: SAGE.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. doi:10.2307/30036540

Witte, J. C., & Mannon, S. E. (2009). *The Internet and social inequalities*. New York, NY: Routledge.

Zickuhr, K., & Madden, M. (2012). *Older adults and Internet use*. Washington, DC: Pew Research Center.

Zillien, N., & Hargittai, E. (2009). Digital distinction: Status-specific types of Internet usage. *Social Science Quarterly*, *90*(2), 274–291. doi:10.1111/j.1540-6237.2009.00617.x