

E-governance diffusion: Population level e-service adoption rates and usage patterns

Mihkel Solvak^{a,*}, Taavi Unt^{a,b}, Dmitri Rozgonjuk^{a,c,d}, Andres Võrk^{a,e},
Märten Veskimäe^a, Kristjan Vassil^a

^a Johann Skytte Institute for Political Studies, University of Tartu, Lossi 36, Tartu 51003, Estonia

^b Institute of Mathematics and Statistics, University of Tartu, Liivi 2, Tartu 50409, Estonia

^c Institute of Psychology, University of Tartu, Näituse 2, Tartu 50409, Estonia

^d Department of Psychology, University of Toledo, 2801 W. Bancroft St, Toledo, OH 43606, USA

^e School of Economics and Business Administration, University of Tartu, Liivi 4, Tartu 50409, Estonia

ARTICLE INFO

Keywords:

E-governance
E-government
E-services
Diffusion
X-Road
Log data

ABSTRACT

This paper investigates how e-governance diffuses in population. Specifically, the cumulative and peak adoption rates of e-governance, the usage patterns of duration (number of days services were used) and depth (number of services used) of usage were analyzed. The data comprised 2.1 billion rows of anonymized service call log data of the entire Estonian e-governance ecosystem, the X-Road, from 2003 to 2015. The results showed that e-governance diffusion was linear, not sigmoid-shape, as literature suggests. In general, cumulative adoption rate grows faster and peak adoption rate increases as user age decreases, and is higher among women. E-service usage duration does not increase faster than usage depth. Usage depth and duration increased with age, though not linearly, and were higher in women. This is the first study to use the behavioral data logs of the entire population across more than 10 years to study technology diffusion on the example of e-governance. The results complement the contemporary technology adoption and diffusion theories, and this study could be of practical relevance to other nations implementing their own e-services for governance.

1. Introduction

E-governance, or electronic government (e-government), is defined as government's use of web-based technologies and applications, or e-services, that enhance the access and delivery of governmental services and information to the government's citizens, residents, business, governmental, and other relevant entities (Layne and Lee, 2001). E-governance and its services could empower new forms of citizen-government interactions (Chadwick, 2016; Pardo et al., 2011). The 2016 World Bank World development Report “Digital Dividends” highlights effective government service delivery as one of the key dividends when discussing the impact of digital technologies on economy and society at large (World Bank Group, 2016). Yet, the number of services states offer online is in most countries still limited (Chen, 2010), and these services typically include a few state's core business services such as e-customs, financial and tax management, e-procurement systems, or e-voting (Vassil et al., 2016; World Bank Group, 2016).

As of now, still a very small number of states can claim to run a proper e-government, e.g., a government that renders most of its services also online. Consequently, we also lack knowledge on how an e-government would actually diffuse among its population:

* Corresponding author.

E-mail address: mihkel.solvak@ut.ee (M. Solvak).

<https://doi.org/10.1016/j.tele.2018.11.005>

Received 24 August 2018; Received in revised form 12 November 2018; Accepted 13 November 2018

Available online 14 November 2018

0736-5853/ © 2018 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

who, at what speed, and following which patterns would actually choose to interact with the state by switching from analog to online channels of communication? Having this information would allow for more effective strategy of maximizing the “digital dividends” that online services are expected to bring.

Digital technologies, such as the Internet, computers, and smartphones seem to be adopted by the population of Earth in an increasing rate. As of January 2018, the worldwide Internet penetration has passed the 50% mark; the proportion of people with a mobile phone is even higher with more than five billion people in the world owning a device (We Are Social Inc, 2018). Therefore, it may be logical to assume that, over time, the need for e-services from governments will be in higher need. However, to this day, there are no studies that have used objectively measured population-level behavioral data of e-governance usage. Moreover, there seem to be no literature on empirically described evolution of e-governance from the first days of implementation to fully-functional e-ecosystem. In addition to providing insights into e-governance usage evolution, this kind of research could provide knowledge on how e-governance usage conforms with (or parts from) contemporary technology adoption and diffusion theories and models.

The current paper will look at how e-government is being “picked up” by its citizens. More precisely, we will demonstrate empirically the cumulative and peak adoption rates of e-government, defined as a large bundle of e-services, over a more than 10 year period for the whole population of a country. We will also examine how the usage patterns of e-services, defined as duration and depth of usage, have developed among the population over that time period, outlining different patterns according to user characteristics. We do so by using a unique dataset on Estonia, a country with a highly developed e-government, from the period of 2003–2015 comprised of all individual e-service call logs with more than 2.1 billion rows of observations. The data consists of process generated logs, e.g., parameters recorded for analysis when a person uses any e-service, and it covers all these individual usage instances in Estonia between 2003 and 2015.

The next section gives a brief introduction to Estonian e-government, the theoretical background of technology adoption, and the data of the study. This is followed by a section on theoretical expectations, sections on empirical analysis, and discussion.

1.1. Estonian e-governance and the X-Road

The Estonian e-governance rests on four key infrastructural elements. First, an electronic identification system (eID) for citizens. Two main solutions are currently most popular, one with a smart card (ID-card) that also doubles as a physical ID, and the other with a SIM card (Mobile-ID), both support public key infrastructure. The eID can be used for two purposes: secure digital authentication and digital signature. The second key ingredient is a data exchange layer called the X-Road, on which we elaborate more below. A third element is a semantic asset repository system called RIHA, which acts as the e-service catalog/registry. And finally, the fourth element is the state portal (www.eesti.ee), which is the citizen gateway to available online services.

Together, these four elements form a platform that enhances the efficiency and easy scalability of e-services built by both public and private sector institutions. The state essentially guarantees the availability of a secure client identification system and information exchange platform, making e-service development cheaper for other actors.

The heart of the system and source for the data we use in this study is the X-Road, in essence, an organizational method of a distributed data exchange system. It connects data registers (e.g. the Population Register, Health Insurance Register, etc) with service providers over the web. X-Road establishes data exchange rules and communication security standards and monitors that users adhere to these. Every “member” of the X-Road has to route their designated traffic through an adapter and security server and the data exchange happens using encrypted communications over the internet directly between these members. Most services rendered over the X-Road involve information exchange between data registers and service owners such as state institutions which provide some of their customer services online.

This mechanism could be illustrated on the example of e-prescription. When a citizen goes to the doctor to get a prescription medicine, the doctor enters the prescription information through a portal into a data registry run by the eHealth Foundation. The patient then goes to the pharmacy, where upon authentication the dispensing chemist in the pharmacy checks that the given prescription is assigned to that person in the prescription registry and enters the sales information. All these transactions take place over the X-Road and are in essence encrypted transactions between service consumers (doctor, patient, pharmacy) and a data repository (prescription registry) mediated by the service provider (eHealth Foundation) through a mini information system portal (MISP) for human clients to enter and view data. A typical use case of an e-prescription from issuing until purchasing the medicine involves slightly over a dozen service queries between service consumers and the prescription data repository. Although patients can still request a paper prescription, the system is completely paper free. For instance, 99% of all issued prescriptions were e-prescriptions in 2015 (Estonian Health Insurance Fund, 2018). It has brought functionalities hitherto unavailable with paper-based prescriptions, such as the possibility for patients to go online through the state portal and see their prescription portfolio with purchasing history and even if any medical professional has looked at their data. Doctors, on the other hand, can view if their patients did, indeed, purchase the prescribed medicine that, in turn, serves as a proxy measure for patients taking the drug, itself clearly relevant information during treatment. All these queries are being again processed over the X-Road.

All the described traffic is being logged by the X-Road Center administered by the State Information System Authority (www.ria.ee). The Center itself does not exchange data between members, but monitors traffic, admits new members, provides trust services and maintains the system. The given study uses the central log of the X-Road, which contains all service call queries processed over the X-Road between 2003 and 2015; altogether, more than 2.1 billion log entries are analyzed. The service call logs contain the service name, a timestamp, the service provider and the service consumer plus some less relevant technical information. If the service consumer was a human, we also have a unique ID and the gender and date of birth of that person. It should be noted that these data did not contain any additional, identifiable information about individuals, making it impossible to identify the users. In other words,

for human-machine or human-human interactions over the X-Road we know what kind of interaction it was, when did it happen and how old and what gender the service call initiator was.

Access to this central log data for research purposes is limited, strictly regulated and all requests are subject to the approval of the Estonian Data Protection Inspectorate (see <https://www.aki.ee/en> for additional information). Data judged to contain sensitive personal information with a potential to identify the person cannot by law be shared; however, it should be noted that gender and date of birth *per se* are not considered sensitive personal information in Estonian legislation (Riigi Teataja, 2008).

The relevancy of this log information can hardly be understated. It represents behavioral information on an individual level for the whole population given that 99% of prescriptions are digital (Estonian Health Insurance Fund, 2018), 95% tax declarations are filed electronically (e-Estonia, 2017), and 30% of votes in elections are given remotely over the internet (Solvak and Vassil, 2016), just to name a few more prominent e-service examples.¹ Analyzing these behavioral data is clearly an advantage over other studies that have investigated the diffusion and/or the impact of e-governance with other measures, e.g., surveys (Chen, 2010; Deng et al., 2018; Szopiński and Staniewski, 2017). The logs give unprecedented detailed information on what client groups use online services, when and with what speed did they start to consume e-services and how have usage patterns of services evolved over time. They provide a complete snapshot of how an e-state has developed and service usage diffused among the population. We can observe when individuals picked up certain e-services and what other services they consumed in conjunction. On the downside, the logs are simply observations of service calls, we do not know anything else, like the motivation of the person, nor any other background and contextual information that might drive the observed behavior. Yet, as mentioned, the data derived from the X-Road logs could significantly help to understand how technology use, on the example of e-governance, evolves in a state's population.

1.2. Aims and hypotheses

This study is the first to provide a detailed descriptive overview of the evolution of a state's whole e-governance ecosystem. In addition to providing insights into the dynamics of e-governance development, the goal of this study is, to some extent, also to compare the empirical findings of technology adoption patterns with contemporary renowned technology adoption and diffusion theories. We will use the two common elements of mentioned technology adoption and diffusion theories (see the Theory section), the sequential nature and user expectations, to arrive at theoretical expectations regarding our factors of interest. These wider commonalities in technology adoption theories hint also what to expect and what caveats to keep in mind when examining actual e-services usage log files of a developed e-government.

We will first of all have to limit our ambitions. What precisely drives technology adoption by citizens or institutions is notoriously hard to identify given that the phenomenon can be equally explained by very different factors (Granovetter, 1978). Subsequently, we focus on two aspects of technology acceptance – the adoption rate and usage practices – and provide here a concise discussion on what to expect of the data given prior theoretical and empirical knowledge of these general problems in technology studies.

The change in usage patterns starts to form over time as the acceptance stage is followed by a post-acceptance stage usually distinguished by more intensive and effective usage of the given technology (Burton-Jones and Straub Jr, 2006; Li et al., 2013; Po-An Hsieh and Wang, 2017; Sorgenfrei et al., 2014). The nature of continued usage might, of course, change over time, the original motivation might be substituted by pure habit (Limayem and Cheung, 2007), in which case future usage becomes automated and follows the same practices as the original motivated usage; then again, usage motivations and intentions might change over time (Sorgenfrei et al., 2014; Venkatesh et al., 2011), which tends to bring about new usage practices (Bhattacharjee, 2001; Jaspersion et al., 2005).

Our aim is twofold. Firstly, to examine the adoption patterns and adoption speed of e-services delivered by the Estonian state, and, secondly, to investigate the actual usage patterns of services and how they have evolved over time. In this study, we operationalize adoption rates as the usage of any e-service by a person for the first time, and examine the cumulative nominal and relative rates of these adoptions over time.

Both theoretical approaches mentioned in the Theory section (e.g., Bass, 1969; Rogers, 2003), therefore, indicate that we should first see a latency period followed by rapid growth of adoption rate over time, with growth easing again as a possible saturation level is reached. This leads to the first hypothesis.

H1: *Cumulative adoption rate of e-services has a sigmoid shape with slow initial growth and increasing growth rate as time passes.*

The theories also indicate that we should see different adoption rates according to sociodemographics, either driven by non-random adoption thresholds in the population or the imitation mechanism in peer groups. This leads to the second and third hypothesis.

H2: *Cumulative adoption rate grows faster and peak adoption rate increases as user age decreases.*

H3: *Cumulative adoption rate grows faster and peak adoption rate is higher among males.*

Our expectations regarding usage practices are the following. First, as the acceptance stage morphs into the post-acceptance stage service, usage should go up along all dimensions, both in depth (measured as number of services used) and duration (measured as number of days services were used).

¹ All this means that Estonian e-services infrastructure has become critical for the state. Ensuring the defense of these from cyber threats is the responsibility of the State Information System Authority. E.g., they have recorded a total of 3126 cyber incidents compromising service integrity, confidentiality and availability in 2017 alone with 122 judged to be high priority incidents. The most common incidents involved either malware, ransomware or phishing (Information System Authority, 2018).

H4: Over time, usage duration and depth increase.

It is safe to assume that in the beginning e-service usage is limited and characterized by minimal complexity, services can be used independently. As time passes and new functionalities and new services are added, complexity is increased and interdependent services usage patterns develop. It is then likely that we will first see an increase in usage duration before in usage depth.

H5: E-service usage duration increases faster than usage depth. Empirically, this would mean that a limited number of services is simply being used more often, but no new services are being taken up. Paradoxically, this would also indicate a habit formation as some work related functionality is being fulfilled well by the given service and the user does not need to take up cross-usage.

With regard to the age and gender structure, we expect a negative association between depth and duration of e-service usage and age, with older groups having lower values on both indicators.

H6: E-service usage depth and duration increases as user age decreases.

Finally, with regard to gender we should see males to be more active and persistent users of e-services given that women have been shown to be more tech-averse (Ahuja and Thatcher, 2005).

H7: E-service usage depth and duration is lower for women.

We will test these hypotheses by graphically examining the usage logs over time and across age and gender. As mentioned, this is the first study to investigate the shape of technology diffusion of e-government on the whole population level by looking at the behavioral usage patterns. These results could have a significant implication to the fields of e-governance and technology adoption studies by allowing to test the hypothesized evolution of technology diffusion in an e-government. Specifically, e-governance adoption patterns on the example of Estonian e-ecosystem could be helpful for other states and nations who are implementing their own e-governance. The findings of this study could serve as a large-scale (in terms of the amount but also the objectivity of data) example of how some technology diffuses in a state's population. Other countries may find this information useful when developing their on e-ecosystems.

2. Material and methods

2.1. Measurements

We described the log data extracted from the Estonian e-ecosystem in the section *Estonian e-government and the X-Road* above. The data were shared with our research group only after obtaining a permission from the Estonian Data Protection Inspectorate. Requesting the permit involved a detailed description of the dataset (including variable description). The Inspectorate concluded that sharing this data (used in the current study) would not mean compromising sensitive personal information. Our *measurement of adoption* is as follows: when a person's ID appears in the log of any e-service, it is recoded as usage of an e-service. The adoption rates are computed separately for age groups and genders by counting the number of individual adoptions within that group in the given year and comparing it with the reference number of the size of the given group in the whole population. The latter number is taken from Statistics Estonia (www.stat.ee). The logs themselves are individual level observations and we could, theoretically, map the adoptions along a time-scale of milliseconds, but we chose the year as our time unit due to the long time period under study.

As for duration and depth of usage we use two measures. The *usage duration* is expressed as the number of days in a given year the person has used any e-service. The *usage depth* is expressed as the number of unique e-services the person has used at least once during the given year. Similar measures of duration and usage intensity have been widely used and suggested in technology adoption studies (Burton-Jones and Grange, 2012; Burton-Jones and Straub Jr, 2006; Iivari, 2005; Sorgenfrei et al., 2014). We use these measures throughout the examined period, even though studies on post-acceptance stage have employed more complicated measures, such as explorative usage and usage of additional system features in work processes (Jasperson et al., 2005; Po-An Hsieh and Wang, 2017; Saeed and Abdinnour, 2013). As we only have service call logs and do not really know to what extent these services are being used in the aforementioned ways, it is reasonable to assume that increase in usage complexity will also be reflected in increase in duration and usage of a larger number of services. The duration and depth measures are computed for individuals and then aggregated to group levels for each year.

2.2. Data analysis

We use descriptive methods for the data analysis. In other words, we provide the aggregated results for the e-services usage operationalized in the previous section in graphical and/or tabular output. Similar approaches have been used in analyzing the behavior of internet voters in Estonia (Unt et al., 2017).

3. Theory

E-services themselves are consumable and there are no clear upper limits or saturation levels for usage. The classical account of diffusion of innovations forwarded by (Rogers, 2003) sees new technology to be adopted by a heterogeneous population whose acceptance threshold has a normal distribution with the cumulative adoption rate taking subsequently the familiar S-shape. The actual adoption thresholds, though normally distributed in the population, are individually non-random with low threshold in first adopters who are clearly different in terms of socio-demographics and attitudes from subsequent adopters, as demonstrated consistently over time and in very different disciplines (Abrahamson, 1991; Bonus, 1973; Duesenberry, 1949; Fliegel, 1993; Greenhalgh et al., 2004; Liebermann and Paroush, 1982; MacVaugh and Schiavone, 2010; Meade and Islam, 2006). A particularly persistent

condition in early technology adoption tends to be younger age of first adopters (Czaja et al., 2006; Meyer, 2009; Morris and Venkatesh, 2000).

An alternative theoretical approach sees adoption being driven by population dynamics with people having an inherent desire to innovate and imitate others. Adoption is driven by a sum of the innate innovation probability and some function of previous adopters (Bass, 1969). The larger the number of previous adopters, the larger the weight of imitation becomes, leading to a non-linear growth in the form of an S-shaped cumulative adoption rate (Meade and Islam, 2006). It is more likely, however, that personal adoption is not driven by the general population adoption rate as individuals are unlikely to have correct perceptions of it, but rather by local influence in the form of share of users in the more immediate social environment (Granovetter, 1978).

With regard to expectations on usage patterns we have to turn to the technology acceptance literature. The list of theories explaining acceptance is long and diverse – theory of reasoned action (TRA; Fishbein, 1979; Sheppard et al., 1988), Theory of Planned Behavior (TPB; Ajzen, 1991), Technology Acceptance Model and its extended version (TAM; Davis, 1985; Venkatesh and Davis, 2000), Diffusion of Innovation theory (DoIT; Rogers, 2003), and Unified Theory of Acceptance and Use (UTAUT; Venkatesh et al., 2003) – just to name a few (see also Sorgenfrei et al., 2014). Though differing in detail and the conceptual models of what drives technology acceptance or rejection, on a *meta*-level they do share some substantive overarching elements.

One of these common elements is seeing the adoption or acceptance of technology to be happening in sequential stages. Although the numbers and names of these vary in different theories, they can be divided into pre-acceptance, acceptance, and post-acceptance stages (Hameed et al., 2012; Rogers, 2003; Sorgenfrei et al., 2014; Venkatesh et al., 2003; Venkatesh et al., 2011). Pre-acceptance usually entails a mechanism of how actors come to an understanding about the need to innovate and change the work process (Sorgenfrei et al., 2014), often driven by simple task overload (Ahuja and Thatcher, 2005). The perceived need drives information seeking, followed by an evaluation of the potential benefits of the technology. The task related needs, technology characteristics and personal characteristics conducive to technology acceptance all combine into creating a positive or negative environment leading to the acceptance stage.

During the acceptance stage the technology is actually put to use or a decision to reject it is made. Studies of this stage usually focus on beliefs related to the given technology, motivations driving usage and actual initial user experience (Sorgenfrei et al., 2014). The acceptance stage is followed by post-acceptance, which entails more in-depth use of the technology and seeking to attain the desired goals of the technological conversion (Sorgenfrei et al., 2014). It also involves the transformation of beliefs and motivations in light of actual user experience. The pre-acceptance stage studies, however, use complicated conceptual models containing a large number of indicators requiring specifically designed survey items and targeted data gathering on that phase (Hameed et al., 2012; Sorgenfrei et al., 2014; Venkatesh et al., 2011). Such studies might suffer from endogeneity problems, as user experience clearly influences reported intentions or expected benefits of the technology. In the current study, we cannot investigate the pre-acceptance stage as we operate with process generated data in the form of usage logs.

For us the key lies in the acceptance and post-acceptance stage and what happens to usage patterns between these stages. The acceptance phase means the technology is taken up and used for the first time. The post-acceptance phase entails either more intensive, in depth usage or a rejection of the technology due to a non-fulfillment of initial motivations for usage (Burton-Jones and Straub Jr, 2006; Li et al., 2013; Po-An Hsieh and Wang, 2017; Sorgenfrei et al., 2014), e.g. some function the technology was supposed to serve (Lin et al., 2007) or simple belief or subjective norm about goodness of new technology (Eckhardt et al., 2009; Wixom and Todd, 2005). If the technology is properly adopted, then the post-acceptance stage is frequently characterized by more in depth and innovative usage (Bhattacharjee, 2001; Jasperson et al., 2005; Po-An Hsieh and Wang, 2017).

There is, however, also a contrary scenario. The nature of continued usage might change over time, but usage practices stay the same. This has been observed when the original motivation is substituted by pure habit as the behavioral driver (Limayem and Cheung, 2007), in which case future usage becomes automated and does not really differ over time. It might, therefore, simply be that distinct groups use technology consistently over time and the usage practices shown by frequency, duration and intensity all stay the same.

The second common element of the theories is assigning different user motivations, norms, beliefs, profiles and usage practices to the aforementioned stages (Burton-Jones and Straub Jr, 2006; Li et al., 2013; Po-An Hsieh and Wang, 2017; Sorgenfrei et al., 2014). Once the expectations meet actual user experience the goals for technology adoption might change leading to a re-evaluation of the cost-benefit analysis of the adopted innovation. The same applies to usage practices, where initial use cases will be replaced by more advanced practices as the adopted technology will change the work process and usually also entail some unexpected consequences on top of the expected ones.

4. Results

4.1. The X-Road traffic

Figs. 1 and 2 give a brief overview of the nature and volume of traffic on the X-Road. Fig. 1 shows the growth of data repositories connected to the X-Road. The largest part of these repositories are state-administered registers. It can also be seen how the number of institutions that provide e-services and the actual number of unique e-services have grown over time. We see that the number of unique e-services by the latest period (2015) stands above 2000, these include both human-usable services (such as the e-prescription) and machine-to-machine services (such as automated document exchange and registry update services).

The yearly volume of traffic on the X-Road is shown on Fig. 2 which depicts the number of service call queries. The yearly traffic in 2015 was between 400 and 500 million transactions, these include again both human- and machine-initiated service calls.



Fig. 1. Development of data repositories and members of X-Road and e-services rendered over X-Road.

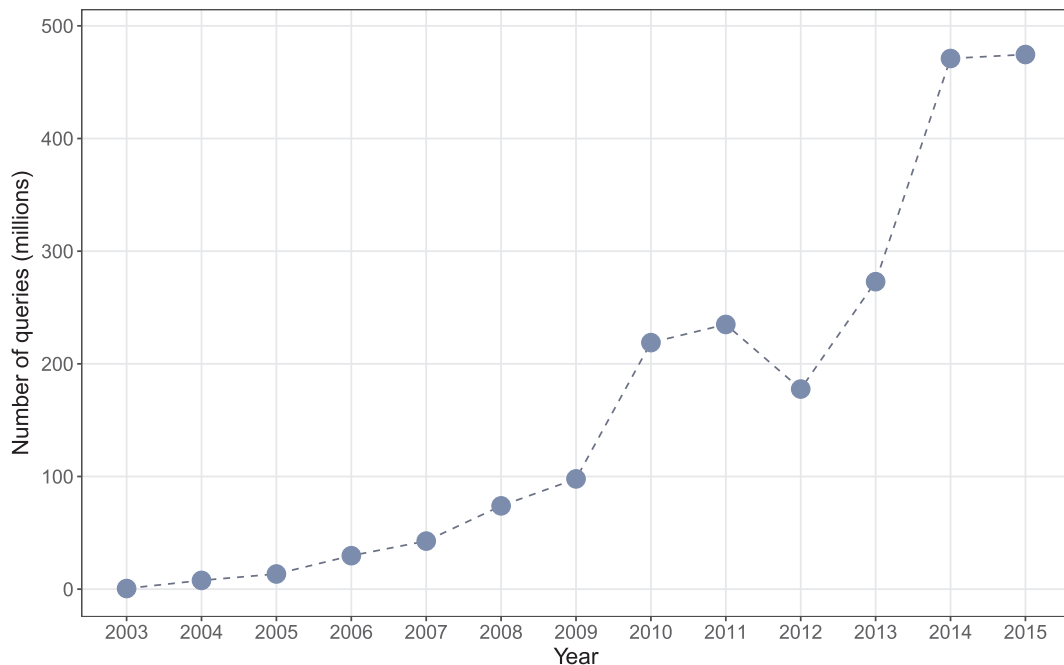


Fig. 2. Development of e-service call queries on the X-Road.

Finally, Fig. 3 shows the increase in the number of unique daily users on the X-Road, separating workdays and the weekend. We see that at the end of 2015 this number has reached roughly 25 000 unique daily users during the working week and 10 000 during the weekend. Given that Estonia has a population of only 1.3 million, the 25 000 amounts to roughly 2% of the population using some e-service on the X-Road on any given day as of 2015.

We present the findings using the calendar year as the aggregation unit, Table 1 lists the mean age with the standard deviation, gender distribution and number of individuals using the X-Road for any e-service according to years.

The mean age, its standard deviation and the overall user numbers increase over the years, possibly indicating that the user groups seem to have become more diverse. The gender balance fluctuates slightly, but is quite close to the general population

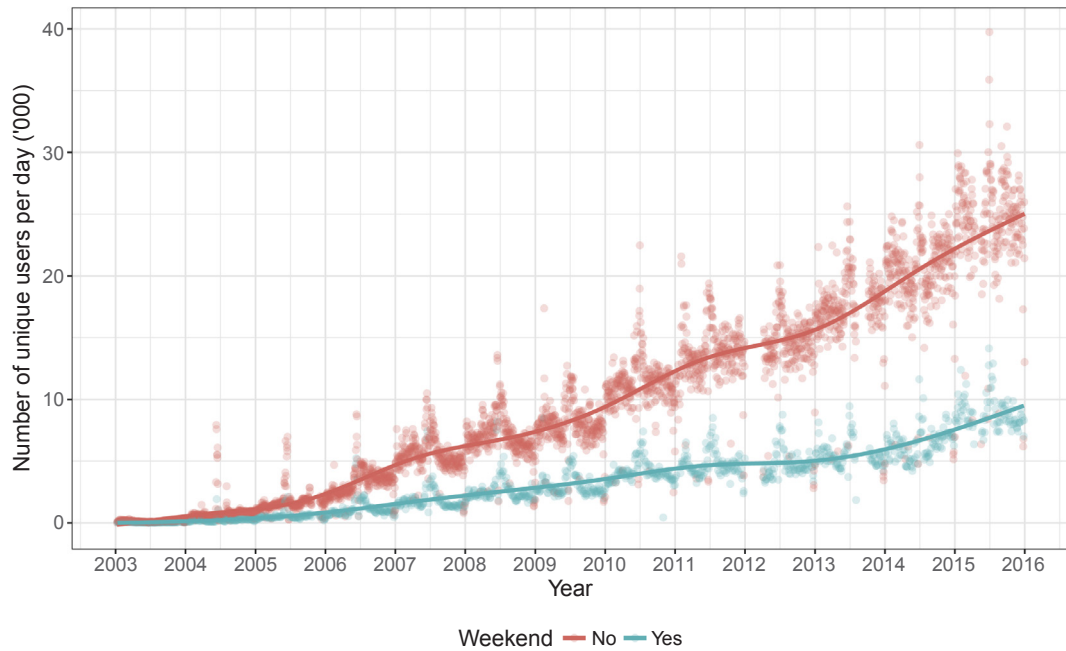


Fig. 3. Development in daily unique user numbers on X-road over years.

Table 1

Mean age and gender distribution of X-Road users over time.

Year	Age M (SD)	Male %	Female %	N
2003	33.5 (10.6)	53.1	46.9	19,317
2004	31.8 (12.1)	46.1	53.9	76,252
2005	32.7 (12.5)	45.0	55.0	113,608
2006	33.5 (12.5)	41.4	58.6	187,950
2007	34.7 (12.9)	43.4	56.6	249,789
2008	35.2 (13.3)	44.2	55.8	308,650
2009	36.3 (13.9)	45.0	55.0	360,027
2010	37.9 (14.7)	46.5	53.5	377,665
2011	40.2 (15.9)	46.1	53.9	454,766
2012	39.4 (15.6)	46.6	53.4	398,130
2013	41.1 (15.9)	47.5	52.5	510,714
2014	42.8 (17.7)	47.0	53.0	665,365
2015	41.9 (16.6)	49.4	50.6	657,958
Total				4,380,191

balance, where the male share over all age groups is around 46% for all those years.

4.2. Adoption rates

The cumulative adoption rate of e-governance by the population according to gender is shown in Fig. 4.

Two things stand out. First of all, there is hardly a gender difference: males and females seem to have adopted e-government solutions at the same rate. Secondly, no sigmoid shape could be observed, the adoption rate grows linearly over the years and has surpassed 50% as of 2015. There does not seem to be a latency period nor a clear change in adoption rate growth speed over the 13-year-period we analyzed.

The overall linear growth of adoption can mask non-linear patterns when subgroups are examined. This is done in Figs. 5 and 6. The former graph shows the cumulative adoption rate for age groups and the latter displays the peak adoption rate for all age levels in each of the observed years separately.

We can observe from Fig. 5 that the cumulative adoption rate grows fastest and reaches the highest peak adoption rate in the 20–29 and 30–44 year old groups. Cumulative adoption is, hence, clearly age-related, but with a distinct pattern. This pattern is shown more clearly when one looks at the peak adoption rates in Fig. 6. What stands out is a relatively small age group of roughly 18- to 20-year-old people who have adopted e-services at a very high pace. All other age groups follow, but more slowly as shown by the gradual lift in the right tail of the peak adoption rate age distributions over the years.

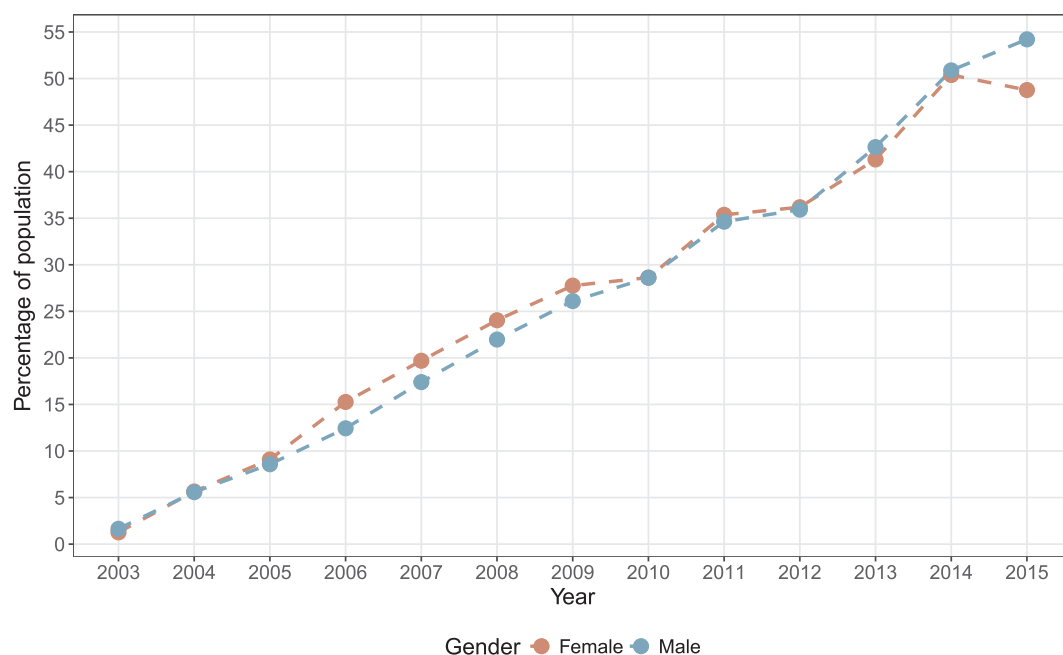


Fig. 4. Adoption rate of e-services by gender (as % of the population of males or females).

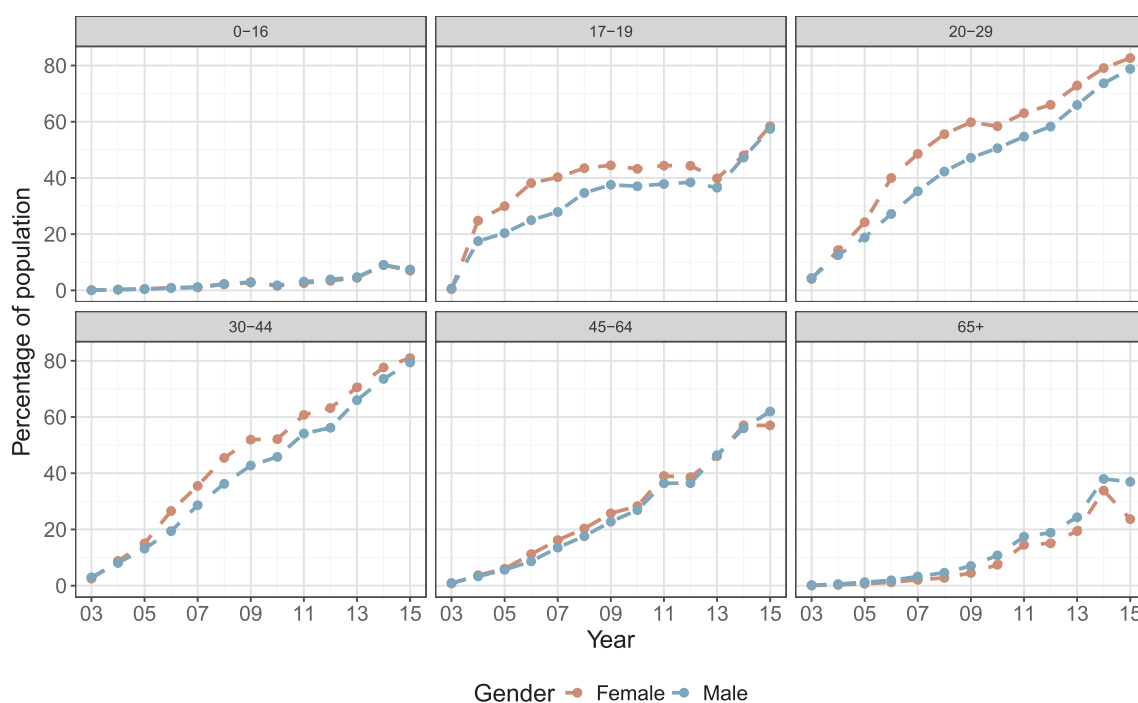


Fig. 5. Adoption rate of e-services by age groups and gender (as % of the population of given aged males or females).

What also stands out is the association with gender. Women use e-services at a higher rate than men, but the usage is dependent on specific age and time. In younger age groups, females have always used services at a higher rate as shown by Fig. 6; however, over the years this changes, as in the oldest age group males have a higher peak adoption rate.

Finally, as stated above, the technology acceptance stage can result in adoption or rejection of the technology, so let us also examine at what rate do adopters keep on using e-services over the years. This retention rate is shown in Fig. 7.

We can see that a majority who has used a service once stays on using services at an increasing rate as time passes. Again, a

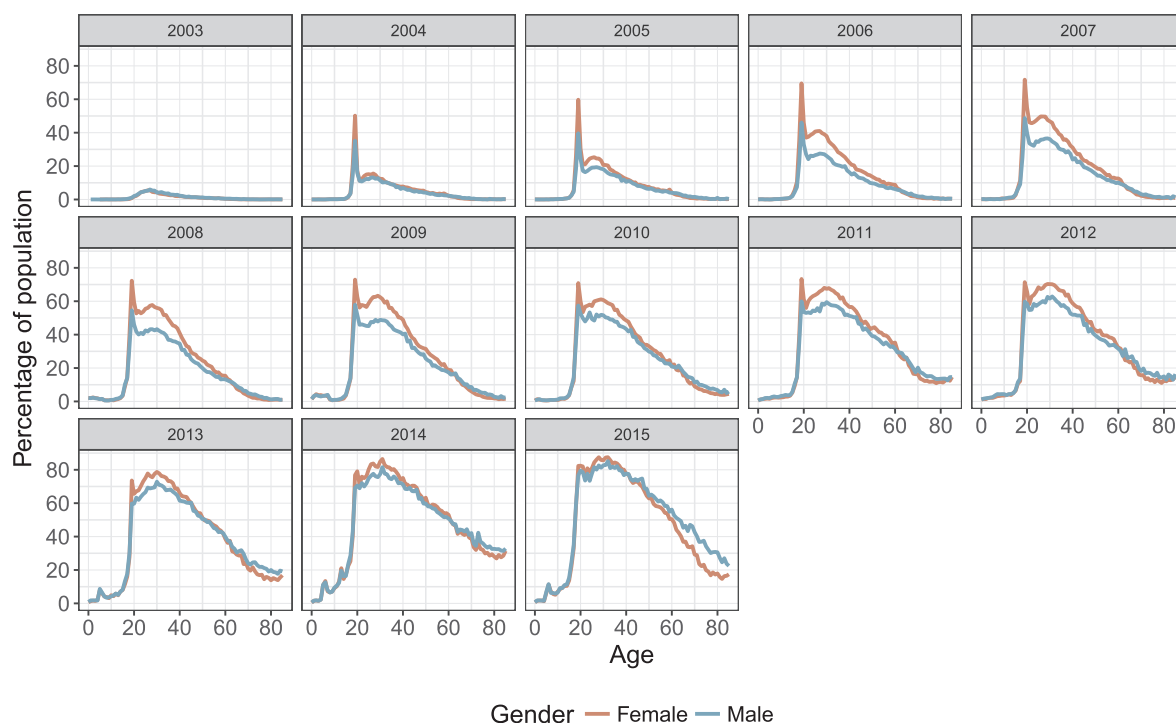


Fig. 6. Age specific peak adoption rate over time (as % of given age group in population in given year).

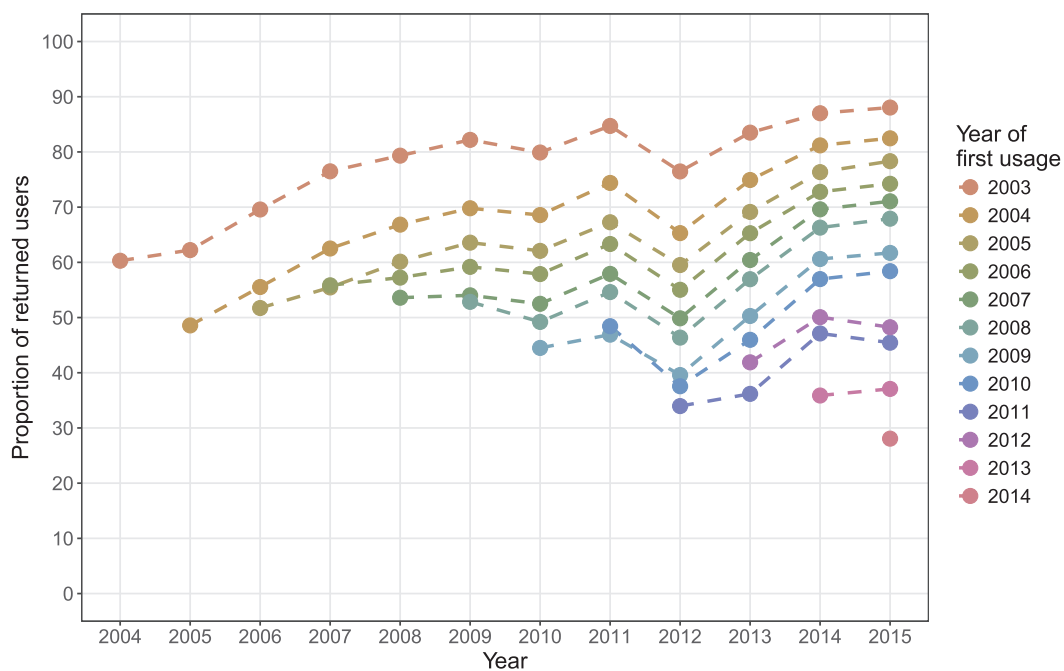


Fig. 7. Share of users who have kept on using e-services after first user experience depending on year first used.

surprising pattern emerges: the retention rate is persistently highest the earlier the person adopted a service.

4.3. E-service usage patterns

Turning to service usage patterns, let us first examine changes in the descriptive statistics of service usage depth and duration over

Table 2

Statistics of service usage by individuals and days of usage over the years.

Year	Services			Days			N
	Mdn	Min	Max	Mdn	Min	Max	
2003	6	1	63	1	1	200	19,137
2004	7	1	183	1	1	333	76,252
2005	7	1	209	1	1	325	113,608
2006	1	1	185	2	1	365	187,950
2007	6	1	220	2	1	365	249,789
2008	6	1	219	2	1	366	308,650
2009	5	1	259	2	1	364	360,027
2010	5	1	261	2	1	357	377,665
2011	5	1	224	2	1	350	454,766
2012	4	1	172	2	1	271	398,130
2013	5	1	201	2	1	301	510,714
2014	6	1	279	2	1	365	665,365
2015	8	1	261	3	1	334	657,958

the years [Table 2](#).

The distributions of both variables have a heavy positive skew, so we use the median rather than mean values for comparison. The table shows that the median number of services used is between 1 and 8. The pattern over the years is noteworthy: the initial high service usage is followed by lower usage values that then starts to gradually increase again. Furthermore, the maximum usage number in a year has clearly increased over time and there are individuals who use more than 200 separate e-services a year. In any case, it seems that the typical individual uses only a handful of unique services in any given year.

The number of days on which e-services were used by individuals seems to be quite stable. The medians show that, typically, e-services were used on one to three days during a full year, suggesting that some services were used only on a daily basis. [Fig. 8](#) shows

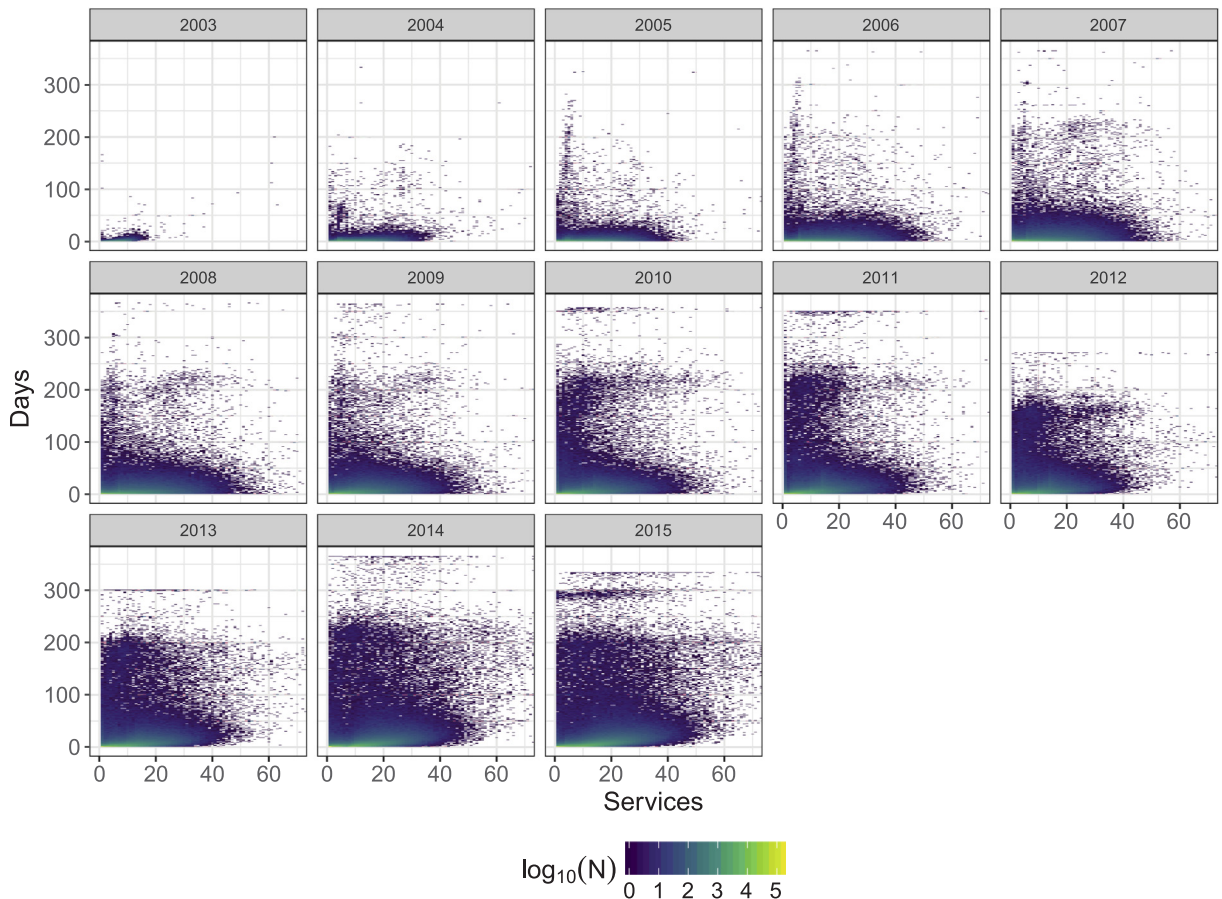


Fig. 8. Densities of number of services used and days of e-service usage over time.

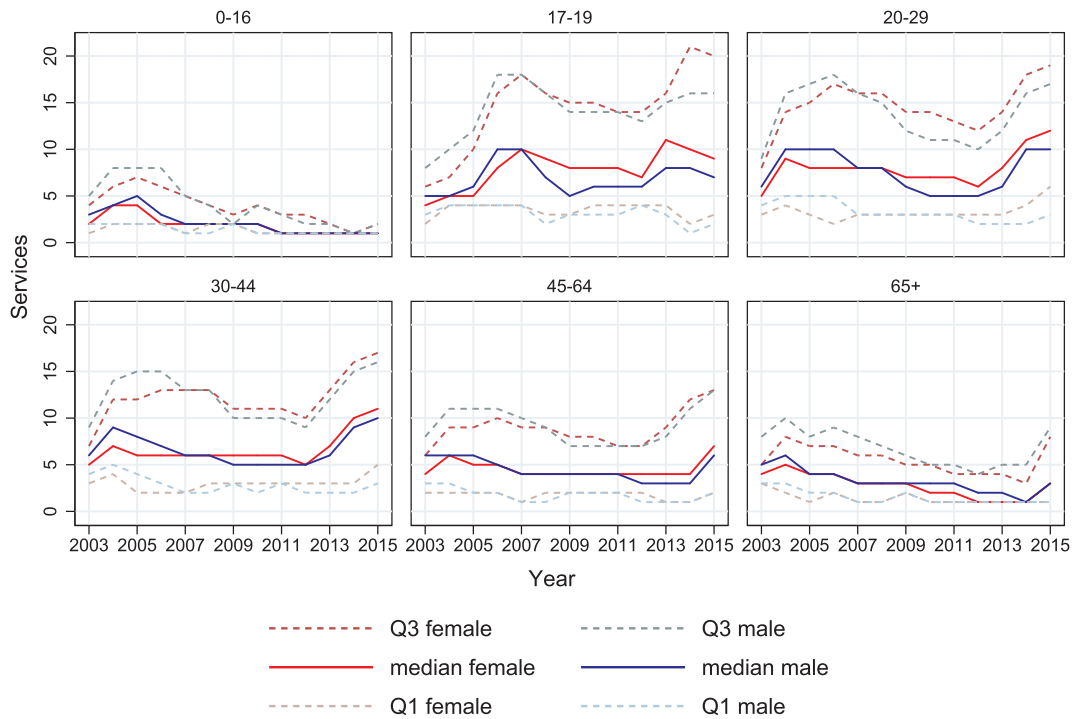


Fig. 9. Service usage depth over the years for age and gender.

the distributions of depth against duration over the years in more detail.

It is clearly observable how the high density area extends along the x-axis of service usage depth before increasing along the y-axis of service usage duration.

Even though the medians in Table 2 do not seem to suggest that both usage duration and depth increase in time, the distributions in Fig. 8 do show it with the centre of the high intensity area gradually extending towards the left and upwards as the years pass. Also, the upper areas of the graph become more and more populated as time passes, meaning that people use e-services on more days of the year than they did in the first years of the X-Road.

Service usage patterns for user groups are shown in Fig. 9. It displays the medians and upper and lower quartiles for the numbers of services used according to age groups and gender over the years.

First, we see that three groups (17–19; 20–29; 30–44) have a higher median service usage over the years. As discussed earlier in the paper, two of those groups (20–29; 30–44) were also found that to have the highest service adoption rates. These two groups also display a marked increase in services used in the last three years we have data on. We also see that the groups with the highest usage have upper quartile limits at relatively higher values compared to the median, so the high usage groups have also a larger share of very heavy service users.

As for gender differences, some noteworthy observations could be made. Women used to use fewer e-services than men during the first years, but this has turned around in almost all age groups except for the oldest. Comparable information on service usage duration is shown in Fig. 10.

Here also the already highlighted age groups stand out as using services longer than other groups. It could be seen that the upper quartile limit is further away from the median for age groups 17–19, 20–29 and 30–44, and it is especially well evident in the first group. This means there are comparatively more high duration e-service users than in other groups and this is again more pronounced for women.

5. Discussion

There were two major aims that this study sought to achieve. Firstly, to see what are the adoption patterns and at what rate and speed does the uptake of e-governance happen on a population level. Secondly, how has e-service usage depth and duration evolved over time. Estonia provides a unique testing ground for these research questions, given the high level of e-governance infrastructure, a large number of usable e-services and sufficient time period to be able to see diffusion patterns. We examined this using a unique dataset of service call logs on all individual level e-service usage instances over a 13 year period from 2003 to 2015, including around 2.1 billion rows of data.

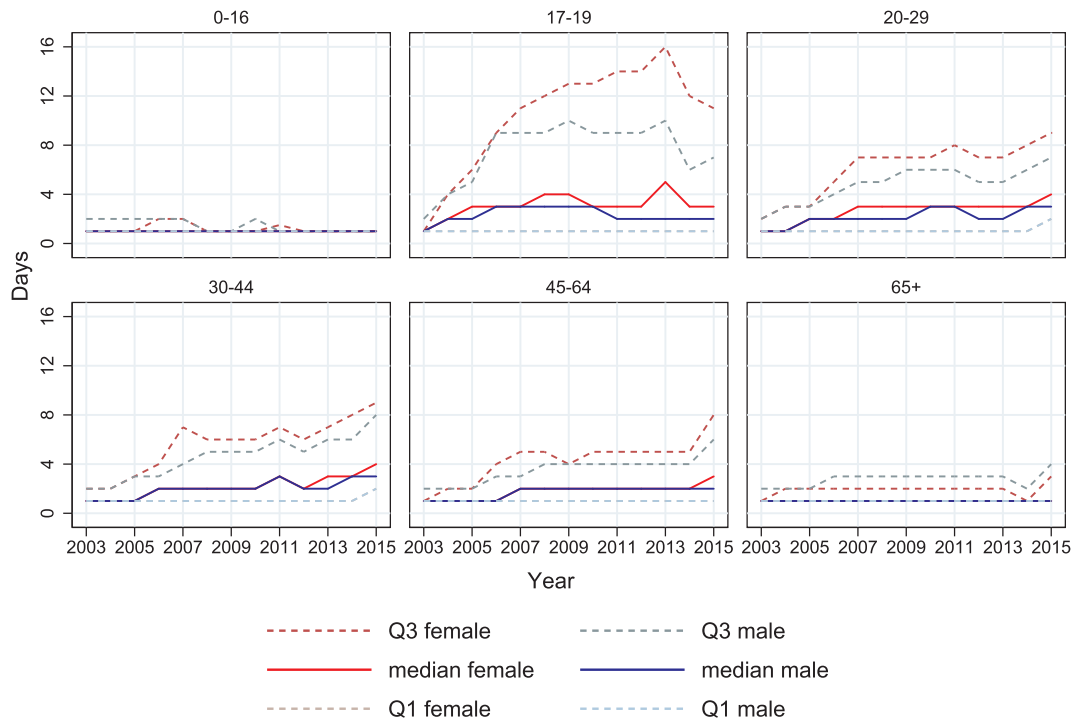


Fig. 10. Service usage duration over the years for age and gender.

5.1. Main findings

We posed several hypotheses to address the aims for the paper. According to our first hypothesis (H1), we expected that the cumulative adoption rate of e-services has a sigmoid shape with slow initial growth and increasing growth rate as time passes. The results of our study do not support this hypothesis, as no sigmoid shape could be observed. The adoption rate of e-services grows linearly and has surpassed 50% as of 2015. It seems that no latency period nor a clear change in adoption rate growth speed over the 13-year-period could be observed. This is certainly surprising and unusual; if anything, linear models in scientific literature are seen as poorly performing naive models given the nature of the diffusion process (Meade and Islam, 2006). Therefore, it could be that we are still observing the almost linear growth period of a process that has to, by definition, be non-linear (i.e. be best described by some exponential growth model), where the growth speed is bound to decrease as the possible saturation point approaches. The first hypothesis is, therefore, clearly rejected with the currently observable data.

According to our second and third hypothesis, we expected that the cumulative adoption rate grows faster and peak adoption rate increases as user age decreases (H2), and is higher among men (H3). The cumulative adoption rate grows fastest and reaches the highest peak adoption rate in the 20–29 and 30–44 year old groups. Cumulative adoption is, clearly age-related, but with a distinct pattern. We can conclude that the age hypothesis holds with qualifications, cumulative adoption rate is highest among age groups that are most likely currently in higher education or active on the labour market and it starts to decrease for age groups closer to or over the retirement age.

With regards to third hypothesis, it is actually women who seem to adopt the technology faster – this finding, again, is contrary to what was expected in our hypothesis, and is certainly surprising. Though women use e-services at a higher rate than men, usage is dependent on specific age and time. In addition, it could be that men in Estonia die, on average, at a younger age than women; therefore, it could be an indication that a non-random subgroup of older men with a better socio-economic status might have a higher likelihood of using digital services due to living longer.

We also expected that e-services usage duration (measured as number of days services were used) and depth (measured as number of services used) increase over time (H4). The results indicate that there might be indeed a non-linear growing trend in both the median number of services used and the median number of days these services are used per year. The potential explanation for this finding could be that as the technology acceptance stage morphs into the post-acceptance stage service, usage goes up both in depth and duration. In addition, people use e-services on more days of the year than they did in the first years of the X-Road.

The vast majority of those who use an e-service once continue to use more services over time. Interestingly, the retention rate is persistently highest the earlier the person adopted a service. We can only speculate that this is due to early users being atypically tech-savvy and interested in new technology as demonstrated by technology diffusion studies (Czaja et al., 2006; Meyer, 2009; Morris and Venkatesh, 2000). It could be that as the acceptance stage morphs into the post-acceptance stage service, usage goes up along all dimensions, both in depth (measured as number of services used) and duration (measured as number of days services were used). The

results demonstrate that this could be indeed the case, and that technology rejection after initial usage is relatively rare.

According to the fifth hypothesis, we expected that e-service usage duration increases faster than usage depth (H5), as it is more likely that individuals use the few more familiar services more heavily before adopting new e-services. In the beginning, e-service usage is limited and characterized by minimal complexity, services can be used independently. As time passes and new functionalities and new services are added, complexity is increased and interdependent services usage patterns develop. It is then likely that we will first see an increase in usage duration before in usage depth. We expected this to manifest so that a limited number of services is simply being used more often, but no new services are being taken up. However, the results suggest that this expectation might be wrong, and that this hypothesis is not supported by the data.

In the sixth hypothesis we expected the usage depth and duration increase as user age decreases (H6). We found that service usage duration is highest between 17 and 44 years after which it decreases. Three youngest age group (from 17 to 44) have a higher median service usage over the years. It is interesting, as users aged 20–44 could also be described as the highest service adopters. We also see that the groups with the highest usage have upper quartile limits at relatively higher values compared to the median, so the high usage groups have also a larger share of very heavy service users. Though the pattern does not seem to be linear, it does provide some support for the hypothesis.

In our final hypothesis, we expected that the e-service usage depth and duration are lower in women (H7). Although literature has shown males to be more active and persistent users of e-services given that women have been shown to be more tech-averse (Ahuja and Thatcher, 2005), our results indicate to the contrary: women used to use fewer e-services than men during the first years, but this has turned around in almost all age groups except for the oldest. The seventh hypothesis can, however, be firmly rejected, as women are overwhelmingly more durable service users, especially when comparing groups with well above average service usage duration.

5.2. The adoption and diffusion of e-governance

The results showed that e-governance adoption rate grows in a linear manner for the whole population and peak adoption rate is very high. However, once adoption happens, growth in usage depth and duration is limited. Cumulative adoption, peak adoption rate and usage depth and duration all differ in age and gender.

These findings proved to be both expected and unexpected. The diffusion of e-service usage as service adoption showed an unexpectedly persistent linear growth with peak adoption rate standing now above 50% of the population. This is highly unusual as prior experience and widely confirmed diffusion models are almost all non-linear in nature. Though the cumulative adoption rate will have to slow in its growth rate as the 100% ceiling starts to appear, and some exponential decrease in growth is bound to occur, this still has not happened over a 13 year long period.

What to make of this? First of all, these findings indicate that the population in general does not face strong hurdles in uptake. Becoming an e-state has been a stated government goal for well over a decade and state institutions have been strongly incentivized to offer more and more of their services online. At the same time, both public institutions and private companies have encouraged the population to use e-services mainly to cut their own business costs. Especially the banking sector has been instrumental in making eID usage widespread through encouraging its clients to use more secure identifications systems than simple passwords or code cards. A large number of online services plus a positive image of an innovative e-state does, therefore, encourage persistent linear diffusion growth. Given the highly unusual and theoretically unexpected linear growth pattern, the generalizability of the findings to other contexts ought to be treated with caution.

What clearly fits prior expectations is the differentiation in diffusion rates and patterns according to age. Individuals in age groups typical for higher education attainments or working people take e-services up quicker than other age groups and they are also more active users in terms of usage duration and depth. We point out, however, that even with the very large number of online services individuals still typically use a somewhat limited number of these.

It seems that making a large number of services available *per se* does not encourage more active usage. Instead, people choose a limited number of services that are probably the most convenient and critical, but do not use e-services solely because they are offered online. Then again, the usage is entrenched, rejection of the technology is rare and once a service is used, the individual is very likely to keep on using it, as the data implies to the increased share of repeated usage over time.

As for the well-accounted gender difference in technology usage, we saw this to be typical in the initial stages, with males scoring higher in e-service depth and duration, but the roles are changed after a certain period and women become clearly more active service users. There is a gender gap that is the opposite as prior literature on technology adoption has described (Ahuja and Thatcher, 2005) both in the acceptance and post-acceptance stage.

The current study demonstrates that wide diffusion of e-services usage is possible once critical infrastructure is in place that allows to efficiently scale service development and provision, and offering many services is an essential premise. This might seem like a truism, as it was written in the World Bank report cited in the introduction, making only select state's core business services digital in itself is not enough to encourage the very heterogeneous population to take up usage and bring larger benefits. Diverse service supply is key for diffusion among a diverse population with diverse service demand.

5.3. Contribution and limitations

This study contributes to the body of literature primarily by including objectively measured behavioral data in the domain of technology adoption. Research on technology adoption has previously mainly relied on survey data (Chen, 2010; Deng et al., 2018; Szopiński and Staniewski, 2017), and could be less valid reliable and valid than actual observed behavior. In addition, contemporary

digitalization paves the road for higher e-governance, and other states could benefit from these results while developing their own ecosystem. It could be reasonably assumed that the penetration of digital technologies across the world is still increasing, and the demand for governmental e-services will likely also rise. This study provides some insight how an e-ecosystem of a state could develop. It may be that the evolution of adoption and diffusion of e-governance might not necessarily follow theoretically well-established patterns. Group differences in e-service usage will likely occur. In addition to these notions, both the Estonian government but also other states' governments may find these group differences interesting and practical, as we provide strong empirical evidence that within some population groups there may be a higher need for promotional campaigns regarding e-service usage, if the goal is to increase e-service penetration. Of more theoretical contributions, the results of this study demonstrated that, on the example of Estonia, the diffusion of e-governance might not follow the sigmoid shape commonly associated with technology diffusion (Bass, 1969; Rogers, 2003), and that though age had an expected relationship with technology adoption, gender did not. As mentioned earlier, these findings carry potential practical implications, too. Finally, we demonstrated how seemingly non-meaningful log data could be used to study complex, macro-level systems, such as the adoption of technology on the example of Estonian e-governance.

There are also some limitations that ought to be acknowledged. Firstly, it could be that e-governance diffusion takes more time than we have data on, and the linear trend of e-services adoption could transform. This limitation could probably be overcome by only allowing to add more data that could be collected over time. Secondly, we only used the log data for our study aims. Though we found several patterns of technology adoption, we do not know the qualitative reasons for these behaviors. There is no clear indication to people's motivation for why they started using e-services. In addition, the profile of high e-services users would help to understand the diffusion more if there was information on in which contexts are these e-services used. Is it because the work of some particular individual entails using the e-environment more? Are some services 100% electronic and are, therefore, forced to be used? Though these questions are out of the scope of the current study, they should still be investigated in future research. One way would be to continue the use of traditional survey methods to address these limitations.

6. Conclusions

The aim of this study was to examine how the diffusion of e-services takes place on a population level in Estonia in the period of 2003–2015. We used the e-services usage logs from the whole population across that time period, including approximately 2.1 billion rows of data. We found that, contrary to several technology adoption theories, the diffusion of e-governance is rather linear, not sigmoid-shaped. In addition, we found that age is positively related to technology diffusion, and – once again, contradicting literature – women tend to be faster adopters of technology than men. These findings add to the body of literature on technology diffusion, and could be helpful in development of e-governance.

Acknowledgments

Declarations of interest: None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.tele.2018.11.005>.

References

- Abrahamson, E., 1991. Managerial fads and fashions: the diffusion and refection of innovations. *Acad. Manage. Rev.* 16, 586–612.
- Ahuja, M.K., Thatcher, J.B., 2005. Moving beyond intentions and toward the theory of trying: effects of work environment and gender on post-adoption information technology use. *MIS Q.* 29, 427–459.
- Ajzen, I., 1991. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* 50, 179–211.
- Bass, F.M., 1969. A New Product Growth for Model Consumer Durables. *Manage. Sci.* 15, 215–227.
- Bhattacharjee, A., 2001. Understanding information systems continuance: an expectation-confirmation model. *MIS Q.* 25.
- Bonus, H., 1973. Quasi-engel curves, diffusion, and the ownership of major consumer durables. *J. Polit. Economy.* 81, 655–677.
- Burton-Jones, A., Grange, C., 2012. From use to effective use: a representation theory perspective. *Inf. Syst. Res.* 24, 632–658.
- Burton-Jones, A., Straub Jr, D.W., 2006. Reconceptualizing system usage: an approach and empirical test. *Inf. Syst. Res.* 17, 228–246.
- Chadwick, A., 2016. Bringing e-democracy back in. *Soc. Sci. Comput. Rev.* 21, 443–455.
- Chen, Y.-C., 2010. Citizen-centric e-government services: understanding integrated citizen service information systems. *Soc. Sci. Comput. Rev.* 28, 427–442.
- Czaja, S.J., Charness, N., Fisk, A.D., Hertzog, C., Nair, S.N., Rogers, W.A., Sharit, J., 2006. Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychol. Aging.* 21, 333–352.
- Davis, F.D., 1985. A technology acceptance model for empirically testing new end-user information systems: theory and results. *Massachusetts Inst. Technol.*
- Deng, H., Karunasena, K., Xu, W., 2018. Evaluating the performance of e-government in developing countries. *Internet Res.* 28, 169–190.
- Duesenberry, J., 1949. *Income, Saving and the Theory of Consumer Behavior*. Harvard University Press, Cambridge, MA, USA.
- e-Estonia. e-tax. 2017. < <https://e-estonia.com/solutions/business-and-finance/e-tax/> > (accessed 11 November 2018).
- Eckhardt, A., Laumer, S., Weitzel, T., 2009. Who influences whom? Analyzing workplace referents' social influence on IT adoption and non-adoption. *J. Inf. Technol.* 24, 11–24.
- Estonian Health Insurance Fund. [Soodusravimite Statistika]. 2018. < <https://www.haigekassa.ee/haigekassa/aruanded-eelarve-ja-statistika/finantsnaitajad-soodusravimite-statistika> > (accessed 11 November 2018).
- Fishbein, M., 1979. A theory of reasoned action: Some applications and implications. *Nebr. Symp. Motiv.* 27, 65–116.
- Fliegel, F., 1993. *Diffusion Research in Rural Sociology: The Record for the Future*. Greenwood, Praeger, Westport, CT.
- Granovetter, M., 1978. Threshold models of collective behavior. *Amer. J. Sociol.* 83, 1420–1443.
- Greenhalgh, T., Robert, G., Macfarlane, F., Bate, P., Kyriakidou, O., 2004. Diffusion of innovations in service organizations: systematic review and recommendations.

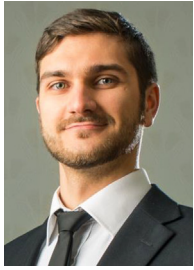
- Milbank Q. 82, 581–629.
- Hameed, M.A., Counsell, S., Swift, S., 2012. A conceptual model for the process of IT innovation adoption in organizations. *J. Eng. Technol. Manage.* 29, 358–390.
- Iivari, J., 2005. An empirical test of the DeLone-McLean model of information system success. *ACM SIGMIS Database.* 36, 8–27.
- Information System Authority, 2018. *Cyber Security Yearbook 2018 [Küberturvalisus 2018]* <https://www.ria.ee/sites/default/files/content-editors/kuberturve/ria-kuberturvalisus-2018.pdf> accessed on 11.11.2018.
- Jaspersion, J.S., Carter, P.E., Zmud, R.W., 2005. A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Q.* 29, 525–557.
- Layne, K., Lee, J., 2001. Developing fully functional E-government: a four stage model. *Gov. Inf. Q.* 18, 122–136.
- Li, X., Hsieh, J.P.A., Rai, A., 2013. Motivational differences across post-acceptance information system usage behaviors: an investigation in the business intelligence systems context. *Inf. Syst. Res.* 24, 659–682.
- Liebermann, Y., Paroush, J., 1982. Economic aspects of diffusion models. *J. Econ. Bus.* 34, 95–100.
- Limayem, H., Hirt, C., Cheung, 2007. How habit limits the predictive power of intention: the case of information systems continuance. *Information Systems Continuance. MIS Q.* 31.
- Lin, C.-H., Shih, H.-Y., Sher, P.J., 2007. Integrating technology readiness into technology acceptance: the TRAM model. *Psychol. Mark.* 24, 641–657.
- MacVaugh, J., Schiavone, F., 2010. Limits to the diffusion of innovation. *E. J. Innovat. Manage.* 13, 197–221.
- Meade, N., Islam, T., 2006. Modelling and forecasting the diffusion of innovation – A 25-year review. *Int. J. Forecasting.* 22, 519–545.
- Meyer, J., 2009. Workforce age and technology adoption in small and medium-sized service firms. *Small Bus. Econ.* 37, 305–324.
- Morris, M.G., Venkatesh, V., 2000. Age differences in technology adoption decisions: implications for a changing work force. *Pers. Psychol.* 53, 375–403.
- Pardo, T.A., Nam, T., Burke, G.B., 2011. E-government interoperability. *Soc. Sci. Comput. Rev.* 30, 7–23.
- Po-An Hsieh, J.J., Wang, W., 2017. Explaining employees' extended Use of complex information systems. *Eur. J. Inf. Syst.* 16, 216–227.
- Riigi Teataja, 2008. *Personal Data Protection Act. Republic of Estonia*, <https://www.riigiteataja.ee/en/eli/512112013011/consolide>, accessed on 11.11.2018.
- Rogers, E.M., 2003. *Diffusion of Innovations*, 5th ed. Free Press, New York, USA.
- Saeed, K.A., Abdinnour, S., 2013. Understanding post-adoption IS usage stages: an empirical assessment of self-service information systems. *Inf. Syst. J.* 23, 219–244.
- Sheppard, B.H., Hartwick, J., Warshaw, P.R., 1988. The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research. *J. Cons. Res.* 15.
- Solvak, M., Vassil, K., 2016. E-voting in Estonia: Technological Diffusion and Other Developments Over Ten Years (2005–2015). Johan Skytte Institute of Political Studies, University of Tartu, Tartu, Estonia.
- Sorgenfrei, C., Ebner, K., Smolnik, S., Jennex, M., 2014. From acceptance to outcome: towards an integrative framework for information technology adoption. 22nd european conference on information systems. Tel Aviv, Israel.
- Szopiński, T., Staniewski, M.W., 2017. Manifestations of e-government usage in post-communist European countries. *Internet Res.* 27, 199–210.
- Unt, T., Solvak, M., Vassil, K., 2017. Does Internet voting make elections less social? Group voting patterns in Estonian e-voting log files (2013–2015). *PLoS One* 12, e0177864.
- Vassil, K., Solvak, M., Vinkel, P., Trechsel, A.H., Alvarez, R.M., 2016. The diffusion of internet voting. Usage patterns of internet voting in Estonia between 2005 and 2015. *Gov. Inf. Q.* 33, 453–459.
- Venkatesh, V., Davis, F.D., 2000. A theoretical extension of the technology acceptance model: four longitudinal field studies. *Manage. Sci.* 46, 186–204.
- Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. *MIS Q.* 27, 425–478.
- Venkatesh, V., Thong, J.Y.L., Chan, F.K.Y., Hu, P.J.-H., Brown, S.A., 2011. Extending the two-stage information systems continuance model: incorporating UTAUT predictors and the role of context. *Inf. Syst. J.* 21, 527–555.
- We Are Social Inc. Digital in 2018: World's internet users pass 4 billion mark. 2018. < <https://wearesocial.com/blog/2018/01/global-digital-report-2018> > (accessed 10 June 2018).
- Wixom, B.H., Todd, P.A., 2005. A theoretical integration of user satisfaction and technology acceptance. *Inf. Syst. Res.* 16, 85–102.
- World Bank Group, 2016. *World Development Report 2016: Digital Dividends*. World Bank Group, Washington DC, USA.



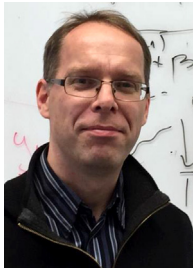
Mihkel Solvak is a Senior Researcher in Technology Studies at University of Tartu.



Taavi Unt is a Junior Research Fellow at the Center of IT Impact Studies at University of Tartu.



Dmitri Rozgonjuk is a Junior Research Fellow in Social Psychology and a Doctoral Student in Psychology at University of Tartu.



Andres Võrk is an Analyst and Lecturer in Econometrics at University of Tartu.



Märten Veskimäe is an Analyst and a Doctoral Student at University of Tartu.



Kristjan Vassil is a Senior Researcher in Technology Studies at University of Tartu.