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Usage of Electronic Education Services in Bulgaria

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Abstract: In the past twenty years, the range of electronic services offered by educational institutions in Bulgaria has increased substantially, allowing schools, universities, and vocational training centers to offer flexible learning options. These capabilities proved essential during the COVID-19 pandemic when most educational institutions switched to online teaching. The share of electronic service users among the population between 16 and 74 years of age almost tripled between 2019 (2.3%) and 2020 (6.9%). This paper explores the variation in usage rates of four types of electronic education-related services: online courses and examinations provided by schools and universities, private educational services, and administrative services like issuing electronic diplomas and certificates. The propensity to use these services is modeled within a multilevel logistic regression model using a sample of internet users conducted in July-August 2021. The results reveal a gender difference in the usage of electronic services, with women being more likely to access school and university services than men. Respondents living in rural areas were less likely to use private e-services. However, there were no significant differences between urban and rural dwellers regarding the rest of the service types. Individuals using one service type were more likely to use all the others. The regional variation of usage patterns indicates a positive association between the use of university and privately supplied electronic services.

Keywords: Digitalization, Education, Electronic services

1. Introduction

In late winter of 2020, the world began bracing for the shock of COVID-19. In the following two years, societies needed to adapt to a way of living under lockdowns, social distancing, and disrupted educational systems. During the lockdowns, schools, universities, and other private educational institutions moved to ensure the continuity of education by switching to online learning methods that are not tied to a specific place. The online delivery of government services, including education-related services, helped to reduce the need for dangerous face-to-face contact.

The abrupt shift to online learning and digital delivery of administrative services raised concerns that parts of the population may suffer disadvantages because they lack the equipment or the necessary skills to use these online services. Despite rapid expansion over the last ten years in Bulgaria, the country still had one of the lowest shares of households with internet access (84%) among European Union countries: (92% on average) in 2021 (Eurostat 2021). This access gap is less relevant for education-related e-services oriented toward younger people: 96% of households with children had internet access in 2021 (National Statistical Institute 2021). However, physical access to computer equipment and the internet is only part of the digital divide: effectively using these services requires a degree of digital literacy and skill, which are distributed unequally in society (Coleman 2021; van Deursen and van Dijk 2014; Helsper and Galácz 2009).

This paper contributes to research on e-government adoption by exploring the association between digital skills, socio-demographic factors, and the adoption of education-related electronic services in a sample of Bulgarian internet users. We distinguish the services of four provider types: primary and secondary education (schools), higher education (universities), private providers, and government agencies related to education. A multilevel logistic regression model showed a positive association between educational attainment, digital skills, prior experience with e-commerce, and the use of all four service types among economically active people (employed and unemployed). A separate analysis of the student's adoption of these services showed a positive association between their prior experience with e-commerce but no evidence of education or digital skill level differences.

2. Background

Ever since their spread in the 1990s, the adoption of electronic services by the general population has drawn considerable research interest. The technology acceptance model (Davis 1989) and its extensions have been among the primary tools employed in technology adoption studies. The model explains the behavioral intent of persons to use new technology in terms of two major factors: its usefulness and its ease of use perceived by their intended users. Although their findings differ depending on the context, numerous e-government and e-learning adoption studies report links between perceived usefulness and ease of use, behavioral intent, and actual usage (Chen and Aklikokou 2020; Saleh, Nat and Aqel 2022). Furthermore, the relationships between perceived usefulness and ease of use and the behavioral intention to use e-government services and e-learning have been found to vary with socio-demographic characteristics and between different cultures (Carter and Weerakkody 2008; Zhao, Wang and Li et al. 2021).

Venkatesh and Davis (2000), Venkatesh, Morris and Davis et al. (2003), Venkatesh and Morris (2000), and He and Freeman (2010) identify age and gender as important factors associated with attitudes towards adopting electronic services. However, these results vary between contexts. Regarding e-government adoption, studies from different countries produce inconsistent results: while Bélanger and Carter (2009) reported no gender effects (USA), Sarabdeen and Rodrigues (2010) (Dubai) found men significantly more likely to be e-government users than women. Regarding the adoption of e-learning during the COVID-19 outbreak, Jamalova and Bálint (2022) found that gender was a significant moderator variable of perceived usefulness and behavioral intent but did not find a significant gender difference in perceived ease of use in a study of Hungarian universities. Their finding contradicts the pre-COVID results of Tarhini, Hone and Liu (2014), and the authors explain the absence of a gender effect with the mandatory nature of e-learning during the lockdown. Studies on e-learning report a moderating effect of age (Acharjya and Das 2022; Wang, Wu and Wang 2009; Jamalova and Bálint 2022), and that older persons tend to be more reluctant to adopt e-learning. E-government adoption research largely agrees that age is a significant predictor of use (Dwivedi and Williams 2008; Mensah and Mi 2018; Mensah, Zeng and Luo 2020).

Studying e-government adoption in the U.K., Dwivedi and Williams (2008) found that people with low educational attainment were less likely to use electronic services. The authors explained this finding as due to their lesser experience with computer technologies (Venkatesh and Davis 2000) and the government's more intensive promotion of these services to the country's elites. Subsequent research has reached inconsistent conclusions. In studies of electronic and mobile government services adoption in China, Mensah and Mi (2018) found that education was not a significant predictor of the willingness to use these services, in contrast to the findings of Taipale (2013), Mensah, Zeng and Luo (2020), and Rodriguez-Hevía, Navío-Marco and Ruiz-Gómez (2020).

Apart from educational attainment, the ability to handle the necessary computer equipment and interact with online resources is essential for users of electronic services, and people with poor digital skills are less likely to engage with e-government services (Rodriguez-Hevía, Navío-Marco and Ruiz-Gómez 2020). Similarly, Saleh, Nat and Aqel (2022) conclude that computer anxiety negatively affects the attitude toward e-learning. Income differences may also relate to adopting e-government and e-learning technologies, though the results vary between studies (Reddick 2005; Taipale 2013). Zhang and Zhu (2021) recently investigated a possible urban/rural divide in China and reported differences in the association between perceived usefulness, perceived security, and the intention to use e-government services between rural and urban residents. Concerning online learning, Zhao, Cao and Li et al. (2022) point to the existence of an urban/rural divide in computer self-efficacy and motivation.

3. Research Methodology

The data consists of a sample of 1039 internet users who have used electronic e-government services in the previous 12 months (users) and another sample of 385 persons who had not used any e-government service during the same period. Both samples were collected using an identical sampling design, except that residents of big cities were oversampled in the non-users survey. The participants (15 years or older) in both groups were interviewed face-to-face in the period between June and August 2021. The respondents provided information on whether they had accessed electronic services provided by governmental agencies, public and private educational, and healthcare institutions in the twelve months before the interview.

In the field of educational e-services, the questionnaire included questions about the use of schools (primary and secondary education providers), universities (higher education providers), non-governmental institutions, private educational institutions, and administrative services related to the issue of apostilles, and electronic copies of diplomas and other certificates. The e-services provided by the three providers included online e-learning courses, online examinations and consultation, online access to grades and electronic diaries, online enrollment in schools and universities, as well as the electronic payment of fees.

The questionnaire also included background questions about the type of place of residence (city, small town, or rural), gender, occupational status (retired, employed, self-employed, unemployed, and student), the level of educational attainment (primary, secondary, and higher), self-reported digital skills, measured in five categories between "low" and "high," and their usual frequency of online shopping: never, rarely (a couple of times a year), and often (more than once a month). In the subsequent analysis we merged the levels of the digital skills variable to three categories: low, middle, and high. The employed and unemployed respondents also gave information about their monthly income (6 categories). In the sample of users, the shares of persons who had accessed education-related services were: school services: 30%, university services: 18.7%, administrative services 18.6%, and private online services: 16.5%.

We expected students, economically active, and retired people to use electronic educational services differently: especially during the COVID-19-related school- and university closures, students were left with no option but to switch to online learning. As the respondents' age is not contained in the data, the occupational status of the respondents serves in part as a proxy measure of age. Therefore, we expected that employed and unemployed respondents would have less need for school e-services but would access these when assisting their children with online education. Furthermore, we excluded retired persons from the analysis, as all e-service types considered here are oriented toward younger people. Only 3 out of 114 retirees in the sample had accessed school-related services, and none had used any other services. These arguments motivated us to estimate two models for adopting educational services: one for the students subsample (n = 159) and another for the economically active (n = 1091). The two models also differ in terms of the explanatory variables, as the information about income was not collected from students.

We model the variation of the adoption probability for each type of e-service using a logistic regression model that includes the main effects of the explanatory variables: gender, educational attainment, type of residence, income group, digital skills, and online shopping experience. The linear predictors also include random effects for each of the 28 administrative regions of Bulgaria that account for unmeasured differences between these regions, such as varying internet access quality and ethnic composition. The random effects follow a multivariate normal distribution with zero mean and covariance matrix that is estimated within the model in order to capture dependencies between the random effects induced by an uneven distribution of educational institutions between the regions.

The posterior distribution of the model is explored using four MCMC chains with 6000 iterations of each chain (NUTS sampling). The model includes broad prior distributions N(0, 2) for the fixed effects and unit mean exponential prior distributions for the variance parameters of the regional effects. The prior for the correlation coefficients is LKJ(1). We experimented with different specifications of the prior distributions but did not observe substantial changes in the main conclusions of the analysis.

4. Results

Table 1 summarizes the posterior distribution of the fixed effects of the logistic regression models for the economically active population. The posterior distribution of the gender effects shows no evidence of different behavior between men and women regarding the usage of three of the four types of services. The exception is a higher propensity for women to access school e-services compared to men. In our opinion, this finding does not suggest a lack of ability for men to use these services. Instead, it reflects a traditional division of labor in Bulgarian families, where women tend to be more involved in their children's education than men.

The model shows no substantial variation in the service adoption probability between income groups, except for university e-services, where high income is associated with a low usage probability. As the questionnaire did not distinguish between part-time and full-time employment, and age is not present in the model, we argue that this effect captures an age difference between the respondents. Younger people still studying at a university tend to receive lower wages and are more likely to work part-time than other workers. The usage propensity for administrative and private educational e-services does not appear to vary substantially between income groups. The model shows no evidence of an association between employment status and the propensity to use any of the e-service types. The model indicates that low levels of educational attainment were associated with a lower propensity to use all types of e-services. The 95% credible intervals for the coefficients of the primary education indicator include zero for every service type, but this is related to the low number of respondents (14) in that category, resulting in high posterior standard errors. Apart from the effect of education, the model predicts a lower usage probability across all four service types for persons with poor self-assessed digital skills. In the case of private educational e-services, the 95% central credible interval includes zero, but the posterior probability that it is less than zero is still 97%. The frequency of online shopping, used as a measure of the respondents' online experience, is positively associated with usage propensity for all service types except those delivered by private providers.

For private e-services, the model only shows evidence of a rural/urban divide, with rural and small-town residents having a lower predicted usage probability. This finding is significant because of the oversampling of big-city residents in the non-users sample. A possible explanation is that private education providers tend to be concentrated in the large cities in Bulgaria. The lack of evidence of an urban/rural divide for the rest of the e-service types should be regarded with caution, as the effects reflect the survey's sampling design that may mask an urban/rural difference in usage probabilities.

Table 1: Logistic regression results for the economically active sample. Posterior means and standard deviations. Coefficients with 95% credible intervals not including zero are set in boldface.

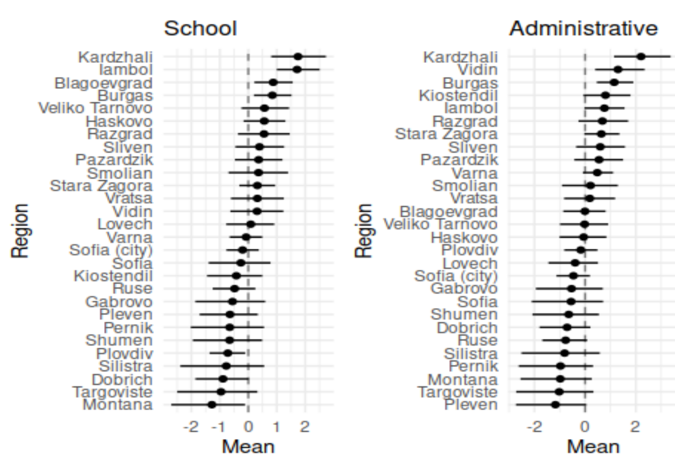
		Schools		Universities		Administration		Private/NGO	
Variable	Level	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Gender (ref: male)	Female	**0.80**	0.20	0.16	0.25	0.23	0.23	0.38	0.24
Residence type	Rural	-0.01	0.26	-0.15	0.35	-0.16	0.34	**-1.24**	0.41
(ref: city)	Small town	0.11	0.24	-0.03	0.33	-0.57	0.34	**-1.41**	0.42
Income	650-1250	0.25	0.39	-0.52	0.47	-0.38	0.44	-0.13	0.46
(ref <650)	1251-1850	0.16	0.41	-0.95	0.50	-0.76	0.48	-0.65	0.49
	1850-2450	-0.06	0.46	**-1.92**	0.64	-0.48	0.53	-0.80	0.57
	2451-3000	-0.02	0.49	**-1.36**	0.61	-0.05	0.53	-0.08	0.55
	>3000	-1.25	0.69	**-1.50**	0.73	-0.91	0.68	-1.08	0.74
	Missing	0.06	0.45	**-1.29**	0.57	**-1.50**	0.58	-0.99	0.56
Labor status (ref: employed)	Unemployed	0.30	0.44	-0.31	0.57	-0.57	0.58	0.04	0.54
Education (ref: higher)	Primary	-2.10	1.28	-1.56	1.39	-0.21	1.06	-0.15	1.09
	Secondary	**-0.56**	0.19	**-0.80**	0.27	**-0.56**	0.24	-0.99	0.56
ICT skills (ref: high)	Middle	**-0.50**	0.20	**-0.55**	0.28	**-0.58**	0.25	-0.47	0.26
	Low	**-1.36**	0.48	**-2.03**	0.86	**-1.35**	0.62	**-3.10**	1.12
Online shopping	Rarely	**0.65**	0.26	**0.92**	0.42	**0.70**	0.35	0.53	0.35
(ref: never)	Often	**0.76**	0.30	**1.47**	0.45	**1.07**	0.39	0.69	0.39

Table 2: Logistic regression results for the students sample: fixed effects posterior means and standard deviations. Coefficients with 95% credible intervals not including zero are set in boldface.

		Schools		Universities		Private/NGO		Administration	
Variable	Level	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Gender (ref: male)	Female	-0.29	0.38	0.16	0.48	0.01	0.40	-0.38	0.43
Residence type(ref: city)	Rural	-0.34	0.52	0.12	0.72	**-1.33**	0.70	-0.63	0.64
	Small town	0.06	0.49	0.21	0.62	0.75	0.49	-0.31	0.53
ICT skills (ref: middle)	High	-0.66	0.65	**-2.09**	0.89	-1.17	0.68	-1.30	0.73
Online shopping (ref: never)	Rarely	**1.22**	0.51	**1.55**	0.61	0.96	0.57	0.67	0.57
	Often	**1.94**	0.57	**1.88**	0.65	**1.51**	0.58	**2.54**	0.61

For all four types of e-services, the random effects indicate the presence of between-region variation in adoption rates (Figure 1) after accounting for the fixed effects part of the model. The posterior average standard deviations range from 0.86 (school services) to 1.01 (administrative services), and all standard deviations have 95% credible intervals with a lower limit greater than 0.54. The uneven distribution of educational institutions between the regions may partially explain this variation, as most universities and private institutions are located in larger cities. The oversampling of non-users of e-government services in large cities may be another factor. The only correlation with a 95% credible interval covering zero is between the regional effects of school and administrative services. All other correlations are positive and range from moderate (university and administrative services: 0.47) to strong (administrative and private services: 0.76). The regional estimates of the regional effects may provide the basis for further analysis of the differences between the regions and help identify local success factors. An example may be the region of Burgas, which contains the fourth largest city in the country and exhibits one of the larger propensities of educational e-services adoption despite the survey's sampling design.

Figure 1: Posterior means and 95% credible intervals of region-level intercepts for school- and administrative e-services. University and private services are omitted for brevity.



In contrast to the economically active model's findings, the model for the students sub-sample (Table 2) does not reveal evidence of gender, education, or digital skills effects on the predicted adoption probabilities. However, there were no students in the sample with low self-reported digital skills. The large coefficients for the education attainment levels reflect that students with primary education were interested in services provided by schools. In contrast, students with a secondary school degree were interested in accessing university e-services. A robustness analysis showed that this results from a low number of students with higher educational attainment in the sample (8 respondents), all of whom reported a high level of digital skills. Similar to the results for the economically active persons, students in rural areas had a lower propensity to access private e-services. Students who lacked a prior experience with e-shopping were less likely to engage with all types of e-services considered in the model.

5. Conclusion

This study analyzed the adoption of education-related electronic services using a sample of Bulgarian internet users. For the economically active population, the results showed evidence of a persisting skills-based divide in Bulgaria: lower levels of education, digital skills, and e-commerce experience were associated with a lower adoption rate of publicly and privately provided e-services. For a sample of students, the model showed evidence only of an association between prior e-commerce experience and the adoption rate of the services. A limitation due to the sampling design of this study prevents the exploration of rural/urban differences. However, the model points to an urban/rural divide in the access to privately supplied electronic education services.

The lower propensity to access education-related services by persons with lower levels of digital skills may be a call to examine the existing e-government services related to education. Simpler user-facing interfaces and better organization of information on school, university, and government agencies' online sites may lower the effort required to use them and extend the benefit of these e-services to users with lower digital abilities.

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