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RESEARCH ARTICLE

Diffusion of the Internet and Digital Divide in Post-Soviet Countries

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This study explores the diffusion process of the internet in countries that were previously known as the U.S.S.R. and are currently divided into 15 countries. Utilizing the S-shaped logistic curves, this paper forecasts future trends in internet diffusion in these economies. Data varied in range, with each country having different time frames for similar variables. The logistic curves for each country determined the length of time of internet diffusion, maximum carrying capacity, and different stages of the diffusion process, namely, emerging, growth, maturity, and saturation. The results show that all countries have exceeded the emerging and growth phases, with 13 countries having reached the saturation point. It was also revealed that more years were utilized in the emerging phase relative to the growth and maturity phase, confirming Rogers' thought that, even with obvious advantage, the adoption process is complex at the beginning. Further, income levels proved important to the internet diffusion trajectory of countries because high-income countries outperformed middle-income countries. Estonia emerged as the pinnacle of internet diffusion among the 15 countries for reasons related to futuristic policies and approaches to policy implementation. Telecommunication infrastructure emerged as the most important determinant of internet diffusion in a country, across all income groups, which has further important implications for policymakers.

Keywords: high-tech innovation, internet diffusion, growth, post-Soviet countries

The internet is believed to have evolved in the 1960s as a means for government researchers to share information. During the initial stages, computers were bulky and stationary, so to share information between computers, users had to move from one computer to another or use magnetic computer tapes through the traditional postal system. The Internet Society (1997 claimed that the initial documented account of networking-enabled social interactions was J.C.R. Licklider's 1962 memos from MIT, which outlined his "Galactic Network" concept, where he envisioned a globally connected computer network allowing universal access to data and programs, a concept akin to today's internet.

Today, more important than ever, the internet has grown to encompass the entire socioeconomic space, becoming part of daily life and allowing for interactions of various forms among individuals, businesses, and nations (Hoffman et al., 2004; Na et al., 2020). The 2023 Sustainable Development Goals (SDG) report acknowledges the need to increase access to digital technologies and investment in digital infrastructure to promote the achievement of SDG 9. However, the internet can be both a boon and a bane. On the upside, the internet supports development through inclusion, efficiency, and innovation (World Bank Group, 2016), enhances productivity at the workplace (Najarzadeh et al., 2014; Nguyen et al., 2023), increases opportunities for job seekers (Denzer et al., 2021), and even improves life expectancy (Byaro et al., 2023). According to the World Bank Group (2024), when a job seeker has access to high-speed internet, the chances of being employed increase by as much as 13.2% and a company's overall recruitment rate rises by 22%. In education, internet use has been argued to have made students' lives easier through the use of software and learning tools and has contributed to the advancement of quality education (Haleem et al., 2022). The internet has also spurred innovation in digital technologies such as artificial intelligence, robotics, Internet of Things, quantum computing, and blockchain technology.

On the downside, Gu et al. (2024) asserted that internet addiction can negatively affect the physical and mental wellness of students if not properly managed. Shrivastava et al. (2018)to see its consequence and effect on lifestyle and functioning. Methods and materials 250 employees of various Government/ Private sector organizations(using internet for more than a year and education level of graduation and above pointed out how internet addiction at the workplace can adversely affect lifestyle—workers may forfeit sleep, meals, personal hygiene, and family time. From a cost-and-efficiency-at-workplace standpoint, Vitak et al. (2011) claimed that at least one hour of internet use at the workplace is non-work related. Restubog et al. (2011) discovered that 30%-50% of internet use at the workplace is for personal or non-work-related reasons. For obvious reasons, one would expect that with the evolution of the internet and its growing use, the buzzing story should be that workers are able to accelerate their work output and connect faster to deliver quality services, and rightly so has been the case in most instances. Yet, an argument presented by Hsieh and Goel (2019) suggested a different story—that in some instances, and for almost the same reasons giving earlier, some workplaces record less than expected productivity.

Between 2018 and 2022, the global internet user base expanded by 1.5 billion individuals, culminating in a total of 5.3 billion users by 2022, which constitutes approximately two-thirds of the world's population (World Bank Group, 2024). The COVID-19 pandemic significantly sped up the propagation of internet users, particularly in middle-income countries. In 2020, the proportion of the global population utilizing the internet surged by 6%, equating to an additional 500 million users, primarily driven by mobility restrictions that necessitated a shift of activities to online platforms. Under the latent aegis of the COVID-19 pandemic and the ever-increasing adoption of the internet, the traditional work environment has undergone a deep shift, with remote work or a hybrid working style burgeoning at some workplaces. NWA Workplaces (2023) highlights a Forbes report indicating that, as of 2023, 12.7% of fulltime employees work remotely, while 28.2% engage in a hybrid work arrangement.

Despite extant studies on the determinants of internet use and access, very few can be found to have examined the diffusion pattern of the internet in various territories. Estimation of the diffusion trajectory of the internet is pertinent for expediting momentum through policy and infrastructural development. Keeping in mind the dearth of literature and motivated by the situational report that over 2 billion people globally have no or limited access (World Bank Group, 2024), we examined the internet diffusion in the post-Soviet countries. Secondary data sources revealed that there were extreme differences in internet penetration rates in the post-Soviet region as of 2021, ranging from a low of 29.4% in Tajikistan to 91% in Kazakhstan, Estonia, and Latvia (World Bank, 2021). The GSMA 2022 mobile connectivity index also showed significant disparities in various dimensions and indicators, with the overall index score ranging from 35.25 for Tajikistan to 84.38 for Estonia. For those reasons and many highlighted later in this study, the post-Soviet countries make a good touchpoint for this study.

The present study employed the logistic S-curve, which has been widely used for technological forecasting. The research aims to determine the highest carrying capacity, stage of internet diffusion, and length of period for each diffusion stage, for each country. We agree with Kucharavy and De Guio (2015) but reliable forecasts of coming and distant changes. Decision making about investments into emerging technologies and strategic planning activities also rely upon consistent forecasts of technological substitution. There is a long record of applying different extrapolation techniques and, in particular, the logistic growth curves (S-curves that in designing systems and processes, forecasting becomes indispensable to the extent that a decision to invest in new technologies relies on consistent forecasting, and S-curves are reliable models to do so.

This research also makes a significant contribution by showing the co-movement among the three phases of diffusion, which has not been demonstrated in any existing studies. To organize the paper, the next sections are structured as follows. Section 2 presents the literature review, and Section 3 details the research methodology. The results and discussions are in Section 4, while Section 5 concludes the paper with policy implications.

Literature Review

Theoretical Background

Several theories exist to underpin technology diffusion and adoption research: theory of planned behavior (Ajzen, 1991), technology acceptance model (Davis, 1989), theory of information behavior (Chatman, 1996), unified theory of acceptance and use of technology (Venkatesh et al., 2003), and many more. The present study focuses on the diffusion of innovation (DOI) theory (Rogers, 1995). Rogers (1995, p. 5) defined diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system." By this definition, four elements are identified: the innovation itself; the communication channels; the time needed to communicate, adopt, reject, or grow the innovation; and a social system. Rogers noted that the extent to which an innovation is diffused rapidly or not rests on its embedded characteristics, such as its relative advantage, how complex it is to realize and use, how visible the innovation results are to individuals, how easy it is to experiment with, and the compatibility of the innovation with norms of the social system. Relatedly, Rogers also argued that "more effective communication occurs when two or more individuals are homophilous" (1995, p. 19).

The essence of time in the diffusion process carries a heavy weight (Rogers, 1995) because it represents the rate of adoption and aids in categorizing adopters as innovators, early adopters, early majority, late majority, or laggards. According to Rogers, the rate of adoption of most innovations follows an S-shape, which is based on the information flow and reduction in uncertainty during the diffusion process. Wisdom et al. (2014) pointed out that the adoption process is complex and typically begins with the acknowledgment of an existing need, followed by the search for potential solutions. This leads to a preliminary decision to pursue the adoption of a particular solution, culminating in the final decision to proceed with its implementation. For this reason, Wani and Ali (2015) considered the DOI theory as one that considers an individual's perspective of need, central to the changes that bring about reinvention and new behavior.

Empirical Review

Literature on the diffusion of the internet continues to evolve, and scrolling back, relevant prior empirical works have been identified. For instance, using data from 1997 to 2007 for the United States and fitting through a logistic model, Kim (2011) predicted that in the United States, the maximum adoption would not go beyond 70% if the prevailing patterns remained unchanged, and he determined the take-off period to be between 1995 and 1997 corresponding to an adoption rate of 10% and 20%. This period marked the early introductory phase of the graphical user interface, corroborating Rogers' (1995) finding that innovation diffusion would normally begin with a 10%-20% adoption rate. Bacha et al. (2024) applied multiple approaches, including Logistics, Gompertz, and the Bass models, to study the adoption of broadband in Algeria. A key observation was that the adoption of broadband had suffered a delay due to macroeconomic factors such as institutional quality and enrollment in higher education, resulting in a U-shaped growth of broadband adoption.

Unlike the U-shaped broadband adoption in Algeria, internet diffusion followed an S-curve in the ASEAN bloc, with most countries already at the peak of their diffusion, while others were at saturation point (Quiban, 2021). Another study focused on internet diffusion in India. With its soaring economic potential, India's diffusion dynamics ought to be studied, and doing so, Singh and Singh (2023) used data from 1999 to 2020 and employed the S-curve models (Logistic and Gompertz) as the analytical approach. Their findings revealed that India's potential to attain universal internet access could be realized in 2028/2029. This finding aligns with numerous econometric predictions of the upside evolution of the Indian economy. Within China, richer provinces in the Eastern region had a better diffusion rate compared to the less rich provinces clustered in the Western and Central regions (Li & Shiu, 2012). Advisably, the income gap, which often leads to an access gap, plays a role.

In Europe, Zatonatska et al. (2019) analyzed the diffusion process of the internet and e-commerce across Austria, Poland, and Ukraine. Using the Bass model, Austria emerged as the country with the greatest internet diffusion capacity, with the potential to attain 87% usage by 2025. Ukraine recorded the highest growth rate of 14% against 3% for Poland and 4% for Austria. A study under the World Bank's Policy Research Initiative by Andres et al. (2007) produced one of the early multi-country studies on internet diffusion covering 199 countries with data spanning 1990 to 2004. Applying the S-Curve, they clustered the sample into low-income and high-income countries to show that the diffusion curve for low-income countries was steeper than for high-income countries. So, to stretch policies aimed at driving diffusion across both clusters of economic categories, competition in the supply side of internet services has to be carefully monitored. Earlier, Chong and Micco (2003) identified that the disparity in internet diffusion between high-income economies and low-income countries could be traced to their digital infrastructure base. Another interesting study by Lin and Wu (2013) found that the diffusion of broadband is stage-distinctive for OECD countries, with innovators and early adopters mostly influenced by income and education level, whereas laggards and late majority countries were affected by broadband prices.

Methods

Internet use was measured by the number of users per 100, obtained from the International Telecommunication Union (ITU) database. To provide a true representation of the findings, the data span differed by country. Diffusion trends for the internet across the 15 post-Soviet countries were estimated by employing the logistic S-curve. Following Meyer et al. (1999), the internet users over time, p(t), is proportional to the population, such that the growth rate at time "t" is defined as the derivative dP(t)/dt.

Mathematically, we can represent the logistic curve as

$$P(t) = \frac{k}{1+e^{-\alpha-\beta t}} \tag{1}$$

where

$P(t)$ depicts the number of internet users over time "t";
α signifies growth rate parameter and indicates steepness of the sigmoidal (S) curve;
k is the maximum value of the limit known as the carrying capacity or the saturation level of growth, showing how large the number of users will be at time "t";
β signifies the time the curve reaches $k/2$ or the growth midpoint, which is also the inflection point in the growth path.

Variable α can be replaced with a variable that specifies the time required for the trajectory to grow from 10% to 90% of the limit k. This new variable, "*dt,*" would represent the curve's typical time duration. Similarly, β can be replaced with a variable to represent the point on the curve where 50% of k is attained such that $P(t_m) = k/2$. Then, algebraically, we can derive *dt* as

$$dt = \frac{\ln(81)}{\alpha} \tag{2}$$

As described in Chen et al. (2011), the logistic Equation (1) can then be denoted as

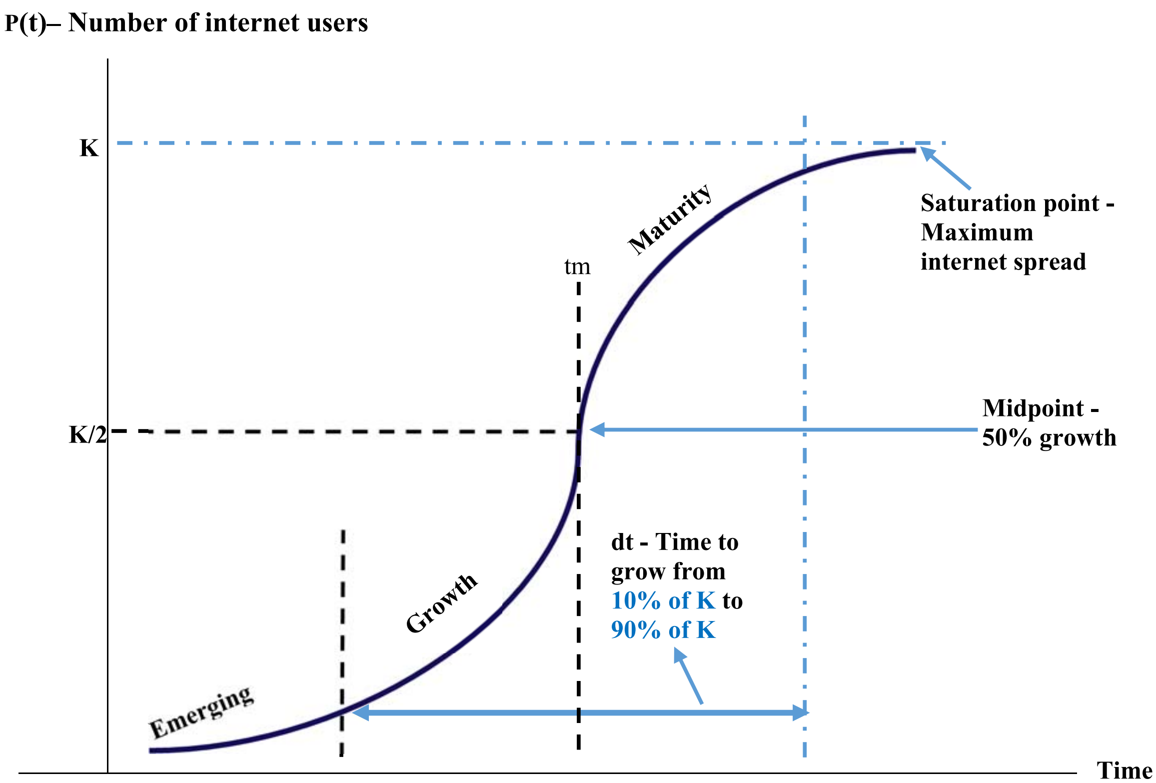
$$P(t) = \frac{k}{1+e^{-\frac{\ln(81)}{dt}(t-t_m}} \tag{3}$$

The logistic sigmoidal curve and its parameters can be represented as shown in Figure 1.

Based on the years of the life cycle of internet diffusion, the stage of each country was determined as

Emerging	before 10%
Growth	10% to 50%
Maturity	50% to 90%
Saturation	after 90%

The logistic S-curves were fitted for each country, and predictions were made within a boundary of 95% confidence levels. The software is Loglet Lab 4.0. The results of the logistic curve helped to classify each country according to their level of internet diffusion and the timescale of the growth of internet in the respective countries. These classifications were assigned numerical values such that "1" would signify



Source: Rezaeian et al. (2017)

Figure 1
Logistic Curve and Parameters

a country that is below the emerging period of internet diffusion, whereas "5" signified a country that has achieved its saturation, and the years beyond the saturation period were then assigned ascending numbers. In this manner, the categorical data were assigned numerical values and were transformed into ordinal data. This formed the basis of a categorical regression model (Meulman, 2003), where the nonlinearity was based on the modification of the dependent variables such that the model permitted ranking the dependent variable into ordinal categories (Majumdar & Pujari, 2022).

We then used the general functional form for the regression analysis.

$$\textit{Internet Diffusion}_i = f\,(\textit{constant, predictor variables}_j,\ \textit{factor variables}_k,\ \textit{error}) \tag{4}$$

where

'i' =1, 2, 3… according to the level of internet diffusion level specified for each country
'j' = country specific characteristics like per capita income
'k' = factors that are related to internet diffusion like telecommunication infrastructure and human capital

Results and Discussion

Logistic S-Curve

The present study has been carried out across 15 post-Soviet countries. The World Bank classification of these countries by income has been shown in Table 1 for the 2024 fiscal year.

The logistic S-curves were fitted for each country, within the 95% confidence levels. Each country showed a different pattern of its S-curves, pointing to differences in the time and the growth rates for each country. Midpoint, in Table 2, shows that at the time of analysis (2024), all countries except the Kyrgyz Republic (referred to as "Kyrgyz") had reached 50% of their internet diffusion. The fastest country to reach the inflection point was Estonia in 2003, and by 2010, five more countries had reached 50% growth: Latvia in 2005, Lithuania in 2006, Russia in 2009, and Tajikistan and Azerbaijan in 2010. Aside from Kyrgyz, which outliers the sample growth pattern, Uzbekistan emerged as the latecomer. On average, most countries had obtained 50% internet adoption by 2011-2012.

Further, Table 2 reveals that countries have taken varying number of years to grow the internet from 10% coverage to 90%. Kyrgyz, once again, emerged as the outlier country in the sample, with a growth period of 25.3 years, whereas Azerbaijan and Kazakhstan showed the lowest growth time at 7.3 years and 8.8 years, respectively. With the exception of Kyrgyz, the remaining countries had an average of 12.8 years to reach the 90% mark. The saturation point determined the maximum carrying capacity. Uzbekistan (104), Moldova (106), and Kyrgyz (260) showed the potential of achieving the largest internet users per 100 people, whereby the individuals are likely to use more than one internet account or hold service from multiple service providers. This implies that infrastructure policies need to be prepared to sufficiently accommodate the likely oversubscription in these countries.

Table 1. *Income Level of Countries, based on World Bank (2022) Classification*

Classification	GNI per capita	Countries in Post-Soviet era
Low-income economies	Less than $1,135	
Lower middle-income	$1,136 and $4,465	Kyrgyz Republic Tajikistan Ukraine Uzbekistan
Upper middle-income	$4,466 and $13,845	Armenia Azerbaijan Belarus Georgia Kazakhstan Moldova Turkmenistan
High-income economies	$13,846 or more	Estonia Latvia Lithuania Russia

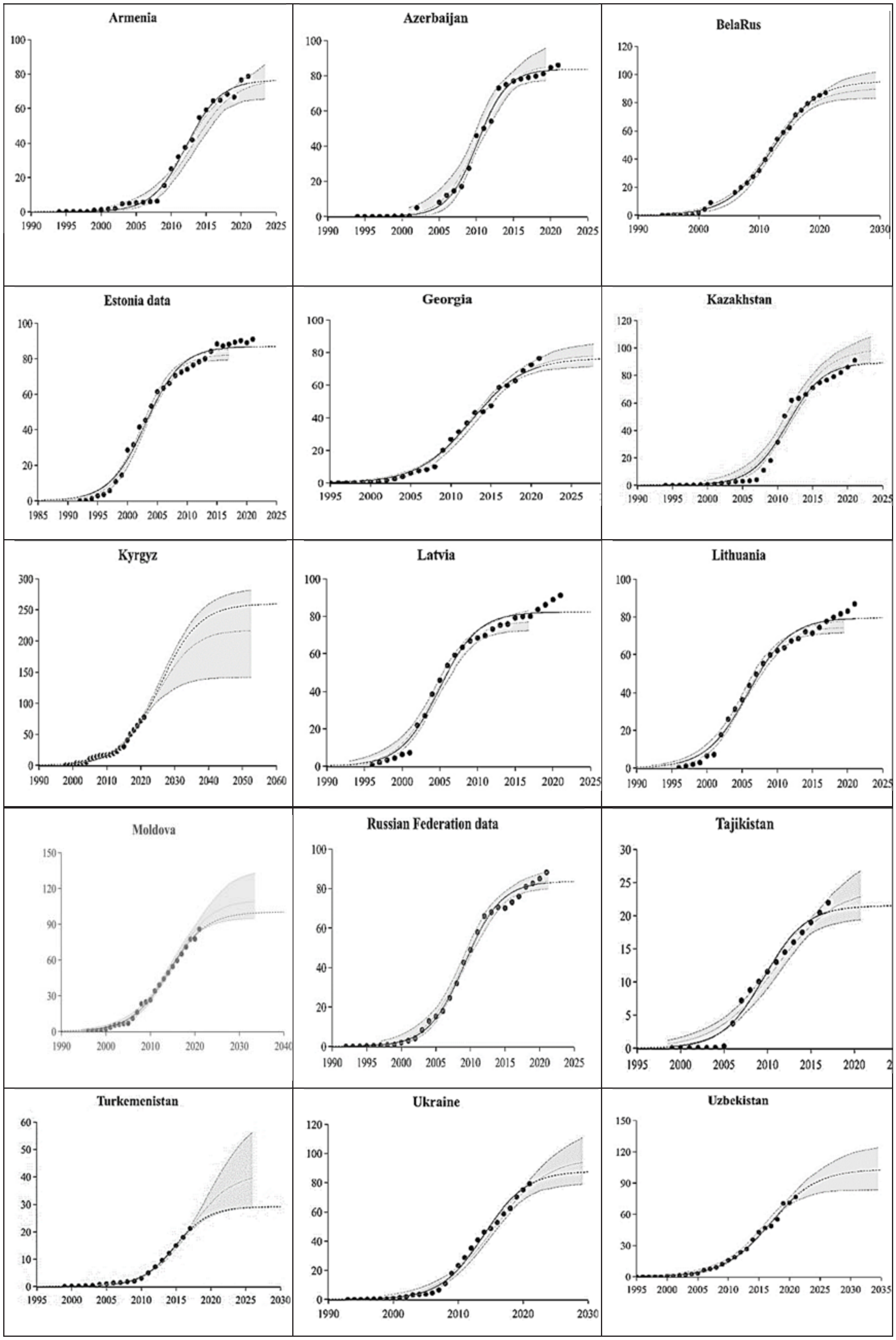


Figure 2
Logistic S-Curves of Internet Diffusion for 15 Post-Soviet Countries

Table 2. *Logistic Growth Parameters*

Country	Midpoint (t_m)[a]			Growth time (Δt)[b]			Saturation (*k*)[c]				*F*-test
	Value	Min.	Max	Value	Min	Max	Value	Min	Max	R^2	*p*-value
Armenia	2012	2011	2014	11.3	9.6	18	77.5	69	97	0.953	0.000
Azerbaijan	2010	2009	2012	8.8	6.3	15	83.7	77	106	0.955	0.000
Belarus	2012	2011	2013	16.2	13	18	95.3	83	103	0.914	0.000
Estonia	2003	2002	2003	13.3	10	14	87	80	86	0.920	0.000
Georgia	2013	2012	2014	14.5	12	17	76.6	72	88	0.949	0.000
Kazakhstan	2011	2009	2014	7.3	6.4	18	81.3	65	107	0.974	0.000
Kyrgyz	2026	2019	2026	25.3	19	26	260	142	285	0.942	0.000
Latvia	2005	2004	2005	11.3	9.2	15	82.3	73	86	0.966	0.000
Lithuania	2006	2005	2006	13	10	15	79.6	72	79	0.945	0.000
Moldova	2015	2012	2015	19.4	14	20	106	81	109	0.963	0.000
Russia	2009	2008	2010	11.5	10	16	83.7	80	91	0.984	0.000
Tajikistan	2010	2009	2014	10.6	11	20	21.5	20	31	0.931	0.000
Turkmenistan	2015	2015	2019	10.6	11	15	29.3	30	64	0.975	0.000
Ukraine	2014	2014	2018	14.6	14	23	87.9	80	123	0.988	0.000
Uzbekistan	2017	2015	2018	16.7	13	20	104	83	129	0.984	0.000

Note:

[a]Midpoint (t_m) is the time the growth of the internet reaches 50%; [b]Growth time (Δt) indicates the time (number of years) internet grows from 10% to 90% of its capacity; [c]Saturation (k) shows the point where growth reaches its carrying capacity; Min and Max represent the 95% lower and upper bounds estimated by bootstrapping; R^2 is the coefficient of determination, and the p-value of the F-test shows the statistical significance of the model

Table 3 shows the years of the life cycle of internet diffusion, along with the stage of the life cycle for each country. Except for Kyrgyz, all countries have crossed their maturity stage, and 13 out of the 15 countries have attained their saturation points. Kyrgyz took 13 years from the growth stage to the maturity stage and another 14 years from the emerging stage to the growth stage.

In Table 4, we look into the number of years utilized by each country to go through the various stages of internet spread. On average, the 15 countries utilized 11 years to reach 10% growth from their distinct launch years. Estonia and Lithuania reached 10% within seven years, whereas Kyrgyz took the longest time. Consistent with the report by Kreitem et al. (2020), we find that countries like Armenia, Georgia, Azerbaijan, Ukraine, and Kazakhstan needed 10 years or more to cross the 10% threshold from their launch year. The years of growth from 10% to 50% and from 50% to 90% were the shortest for Kazakhstan.

Post-Soviet 1991, economic restructuring took the center stage of government efforts, which was focused on real sectors like agriculture, industry, and services (Benešová & Smutka, 2016). Given the heavy effort to build the primary economy, the digital economy remained underdeveloped as the transition from a socialist to a market-driven economy took time (Baimenov & Liebert, 2019). Moreover, the growth path faced numerous challenges, including high unemployment, inflation, and heavy dependence on commodity exports (Benešová & Smutka, 2016).

Estonia was among the fastest to spread the use of the internet among its citizens following the collapse of the Soviet Union. Historically, this is traced to the unveiling of the Principles on Estonian Information

Table 3. *Years of the Life Cycle of Internet Diffusion and the Type of Stage*

Country	Launch of Internet	Emerging (before 10%)	Growth (10%- 50%)	Maturity (50%-90%)	Saturation (After 90%)	Stage in 2024
Armenia	1994	2001	2007	2012	2018	Saturation
Azerbaijan	1994	2001	2006	2010	2015	Saturation
Belarus	1994	1996	2004	2012	2021	Saturation
Estonia	1989	1989	1996	2003	2010	Saturation
Georgia	1995	1998	2005	2013	2020	Saturation
Kazakhstan	1994	2003	2007	2011	2015	Saturation
Kyrgyz	1998	1999	2013	2026	2039	Late Growth
Latvia	1990	1992	1998	2005	2012	Saturation
Lithuania	1992	1992	1999	2006	2013	Saturation
Moldova	1992	1995	2004	2014	2023	Early Saturation
Russia	1992	1997	2003	2009	2015	Saturation
Tajikistan	1990	1999	2004	2010	2015	Saturation
Turkmenistan	1999	2003	2009	2015	2021	Saturation
Ukraine	1993	1998	2006	2014	2020	Saturation
Uzbekistan	1999	1999	2008	2017	2026	Maturity

Note:
A country is in the ***emerging stage*** *(early growth) if growth has not reached 10% in a year before the study year (2024)*
A country is in the ***growth stage*** *if the internet growth is between 10% and 50% in a year before the study year (2024)*
A country is in the ***maturity stage*** *if the internet growth is between 50% and 90% in a year before the study year (2024)*
A country is in the ***saturation stage*** *if the internet growth reaches 90% or more in a year before the study year (2024)*

Policy in 1998. The policy was adopted by the Government of Estonia soon after the launch of the 1997 Tiger Leap Programme, which was aimed at providing digital education infrastructure at schools through access to the internet and the development of digital technology (Runnel et al., 2009). By 2000, every Estonian school had computers, 75% of all schools had internet connections, and the others could use a dial-up option. Soon, public internet access points (PIAPs) were established throughout the country, followed by the launch of internet voting in nationwide elections by 2005 (Kreitem et al., 2020; Runnel et al., 2009).

In Lithuania, the internet was launched in 1992 with the establishment of the first intercity communication channel between Vilnius University, Kaunas University of Technology, and the Institute of Mathematics and Informatics. By 1993, six universities, 11 research institutes, and over 60 governmental organizations and NGOs began using internet services, especially for emails. Another significant push was the RAIN (rural area information network) project launched in 2004, which provided high-speed internet to all remote rural areas.

Tables 3 and 4, therefore, highlight that the adoption of internet in the post-Soviet countries reveals substantial progress enhanced by policies favoring digital infrastructure that has resulted in significant increases in the number of individuals using the internet, an increased adoption of technology by businesses and government, and widespread use of digital devices such as smartphones and tablets. Data from the World Bank database suggests that, on average, 75.5% of individuals were using the internet in the 15 countries, with seven countries exceeding 85% usage.

Table 4. *Timescale of the Phases of Growth in Internet*

Country	Reaching 10% growth	No. of Years	Growth to Maturity	No. of Years	Maturity to Saturation	No. of Years	Total length
Armenia	1994-2007	13	2007-2012	5	2012-2018	6	24
Azerbaijan	1994-2006	12	2006-2010	4	2010-2015	5	21
Belarus	1994-2004	10	2004-2012	8	2012-2021	9	27
Estonia	1989-1996	7	1996-2003	7	2003-2010	7	21
Georgia	1995-2005	10	2005-2013	8	2013-2020	7	25
Kazakhstan	1994-2007	13	2007-2011	4	2011-2015	4	21
Kyrgyz Republic	1998-2013	15	2013-2026	13	2026-2039	13	41
Latvia	1990-1998	8	1998-2005	7	2005-2012	7	22
Lithuania	1992-1999	7	1999-2006	7	2006-2013	7	21
Moldova	1992-2004	12	2004-2014	10	2014-2023	9	31
Russia Federation	1992-2003	11	2003-2009	6	2009-2015	6	23
Tajikistan	1990-2004	14	2004-2010	6	2010-2015	5	25
Turkmenistan	1999-2009	10	2009-2015	6	2015-2021	6	22
Ukraine	1993-2006	13	2006-2014	8	2014-2020	6	27
Uzbekistan	1999-2008	9	2008-2017	9	2017-2026	9	27
Average		11		7		7	25

Regression Analysis

The functional form for the categorical panel regression was undertaken, following Equation (4):

$$\textit{Internet Diffusion}_i = f\,(\textit{constant, predictor variables}_j, \textit{factor variables}_k, \textit{error}) \tag{4}$$

where

Internet Diffusion	=	1 denoted the country did not reach the “emerging” stage
	=	2 denoted the country was between “emerging” and “growth”
	=	3 denoted the country was between “growth” and “maturity”
	=	4 denoted the country between “maturity” and “saturation”
	≥	5 denoted the country was beyond the “saturation” stage
Predictor Variable	=	per capita income
Factor Variables	=	e-Participation, Telecommunication infrastructure, Human capital Index, Mobile subscriptions

Data was calculated from Table 3, which estimated the lifecycle of internet diffusion for each country. Per capita income for each country was obtained from the World Bank, using the GDP per capita, PPP (constant 2021). E-government development index (EGDI) is calculated by the United Nations Division for Public Institutions and Digital Government, which incorporates digital access characteristics to reflect how a country uses information technologies to promote internet access and inclusion for its people. This database was used to take the components of EGDI, namely the e-participation index, the telecommunication infrastructure, and the human capital. The e-participation index is used to assess the degree of digitization of a country where citizens use the internet to interact with the government and participate in policy and decision-making. The World Bank database was also used to procure the country-wise data on mobile cellular subscriptions per 100 people.

Multicollinearity and heteroscedasticity amongst the variables were checked using the variance inflation factor and the Breusch Pagan test, respectively. The results (Table 5) show that there was no multicollinearity because the variance inflation factors are less than 10 for each variable. But robust regressions were used to tackle the presence of heteroscedasticity in the dataset, as the null hypothesis of constant variance was rejected by the diagnostic test.

Panel regression results are presented in Table 6. The full model included all 15 countries for the years 2003 to 2024. Thereafter, the countries were divided according to their income categories, based on Table 1.

Table 5. *Diagnostic Tests*

	Variables	**Variance Inflation Factor**
Multicollinearity	Telecom Infrastructure	5.64
	Per capita GDP	4.23
	E-Participation Index	3.59
	Mobile subscriptions	2.61
	Human Capital	2.02
Heteroscedasticity	Ho: Constant variance	chi2(1) = 120.7 Prob > chi2 = 0.0000

Table 6. *Regression Results*

	Coeff	**Robust Std. Err**	**Coeff**	**Robust Std. Error**	**Coeff.**	**Robust Std. Err**	**Coeff.**	**Robust Std. Err**
	Full Model (FE)		**High Income (FE)**		**Upper Middle Income (FE)**		**Lower Middle Income (FE)**	
Human Capital Index	-1.70418	3.2866	5.0986	5.532	.71993	1.9714	-5.0716	3.387
Telecom Infrastructure	**4.915****	2.1867	**7.7058*****	2.7072	**6.386*****	1.1306	**1.7508***	.71725
e-Participation	-.22715	.76922	-.087785	1.8337	-.67797	.70378	.717247	.411869
Per capita GDP	**.0004*****	.0000	**.0005*****	.000066	**.00016****	.000067	-.00001	.0003
Mobile Subscription	**-.0183*****	.00587	**-.0284****	5.7085	**-.01016****	.0047	.0077	.009587
constant	-1.2667	3.0898	**-13.686****	6.2147	-.54182	1.8538	**6.4825****	1.9601
Hausman Test Chi^2	138.25***		19.38***		402.75***		153.56***	
F Statistic	15.64***		73.90***		51.42***		19.05***	

Note: Dependent Variable is the Phase of Internet Diffusion; FE denotes Fixed Effects Model
*Significance level: ***denotes 99% level of significance, **denotes 95% level of significance, *denotes 90% level of significance*

The Hausman test chi^2 showed the fixed effects model would be appropriate in each scenario.

The regression result, shown in Table 6, helps to identify the significant factors that affect diffusion levels of the post-Soviet countries and the regression model added another layer of justification to the findings in this study.

For the full model with all the countries, the degree of telecommunication infrastructure ($\beta = 4.915$, $p < 0.05$) and per capita GDP ($\beta = 0.0004$, $p < 0.01$) significantly and positively contributed to the diffusion trajectory of post-Soviet countries, showing that increasing the level of these predictors augments the diffusion process. However, and surprisingly, mobile subscription ($\beta = -0.0183$, $p < 0.01$) was statistically and negatively significant as determinant of internet diffusion. Additionally, human capital index and e-participation were not significantly impactful on the internet diffusion processes, both in the full model and the income-level based models.

The panel regression was then applied for each income category separately, based on the segregation of Table 1. The impact of telecommunication infrastructure remained positive and significant across all income categories and emerged as an important factor for predicting the degree of internet diffusion in a country. Per capita GDP was also significant and positive across the countries, whereas mobile subscription was statistically significant and negative as determinants of internet diffusion for all the post-Soviet countries, except the lower middle income countries where these factors did not give any significant results. So, only telecommunication infrastructure emerged as a significant predicting variable explaining the internet diffusion among lower-middle income countries, which indicated that, regardless of existing indicators, it may be difficult to roll out internet diffusion appropriately without a robust infrastructure in these countries.

Discussion of Results

Internet diffusion among the post-Soviet countries revealed a progressively carved effort between the emerging and saturation stages. Given the full length of diffusion, the regression results revealed that per capita income was a positive predictor of internet diffusion. On top of that, income levels defined the pace and lifecycle of the diffusion path. On average, high-income countries recorded shorter diffusion lengths than those considered lower-income countries. It would be relevant for policymakers to note that telecommunication infrastructure emerged as the most dominant predictor of internet diffusion across all the models. The relevance of this observation recalls earlier assertions by Oyelaran-Oyeyinka and Lal (2005)the notions of digital inequality and digital divide have been employed to describe two levels of Information and Communications Technologies (ICTs, who highlighted a firm support for telecommunication growth as a pivot for scaling wide internet connectivity. Observing from the findings, countries that impressively pulled off the internet spread drive were guided by clear policy choices that favored telecommunication infrastructure.

Anchoring this policy choice is the sound layering of political and economic institutions, which bears a high notch in catalyzing government development efforts (Villanueva, 2022). In Estonia and Lithuania, academic and research institutions, as well as NGOs, heavily participated in the internet diffusion drive from a behavioral standpoint. As Valencia et al. (2021) argued, the shaping of attitude, perception, and intention to use innovations is further facilitated and accelerated. Doubling down on this proposition, Tugas and Tullao (2024) human construct (teamwork competence [TC] and technology readiness [TR] emphasized that the spread of new technologies hinges on a well-calibrated framework that channels access and use to institutions that enable both learning and comfort.

Consequently, the inequality in digital frameworks among countries explains the disparity in the rate of internet diffusion among countries. Lee and Leonard (2023) also highlighted that the infrastructure in support of internet connectivity is as important as physical infrastructure, such as roads. It is foundational to both access and use, and helps in bridging the internet gap among citizens.

Conclusion and Policy Implications

Since the launch of the internet and the diffusion of internet connectivity, economic activities of countries, along with businesses and personal lives, have relied heavily on it. In the era of technological innovations, the importance of the internet is non-negotiable. For the 15 countries in our sample, the results show varying diffusion capacities as measured by the total number of years to reach saturation or full maturity. Countries like Estonia and Lithuania recorded impressive results in their diffusion offtake, due to bold, quick, and timely aggressive approaches, which aided them to reach saturation levels faster relative to the other countries. Our results suggest that deliberate policy implementation is imperative to ensuring optimized internet diffusion.

The discussions highlighted the internet diffusion path across all 15 countries, and we were able to show the stage each has reached as of the reporting date. We have employed robust analytical techniques that fit the purpose of this study. Robust infrastructure emerged as the most important factor that defined the diffusion of internet services and explains the differences in the diffusion gaps amongst the post-Soviet countries as well. The findings of the present study confirm that the internet cannot be deployed without the requisite telecommunication infrastructure, regardless of factors like human capital, GDP, or the e-participation levels encouraged by the national government. With potential opportunities for growth, policymakers and regulatory regimes must support the development of the telecommunication industry by encouraging infrastructure enhancement and upgrading efforts needed to accelerate internet diffusion. For future study, testing the diffusion trajectory using different methods is recommended.

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