



## The Effect of Information Communication Technology (ICT) on Health Outcomes: Evidence from BRICS-T Countries

### Bilgi İletişim Teknoloji (BİT) Kullanımının Sağlık Çıktıları Üzerine Etkisi: BRICS-T Ülkeleri Örneği

Munise ILIKKAN ÖZGÜR\*  
Cuma DEMİRTAŞ\*\*  
Zekiye ÖRTLEK\*\*\*

DOI: <https://doi.org/10.25204/iktisad.1023768>

#### Abstract

#### Article Info

**Paper Type:**  
Research Paper

**Received:**  
15.11.2021

**Accepted:**  
11.10.2022

© 2022 JEBUPOR  
All rights reserved.



This study analyzes the effects information and communications technology (ICTs) have had on health outcomes on Brazil, Russia, India, China, South Africa (BRICS countries), and Turkey both on a panel and country basis using data from the period 1990 to 2018. The study has created three models. According to the general findings obtained for the panel, the error correction coefficients of the models other than Model II are negative and statistically significant. Based on the variables of income level, number of physicians, education level, and CO2 emissions used in Model I, the number of physicians and education level are seen to negatively affect life expectancy both in the short and long terms, contrary to theoretical expectations, while income level positively and CO2 emissions negatively affect life expectancy. The number of mobile users represents ICTs and negatively affects life expectancy both in the long and short term. Model III includes number of Internet subscribers, and all variables in this model except number of physicians support theoretical expectations. Accordingly, education and income levels have positive effects, and CO2 emissions have a negative effect. The number of Internet subscribers has both long- and short-term negative effects. When evaluating the findings according to country groups, the variable of income level positively and CO2 emissions negatively affect life expectancy in all countries. The variable of number of physicians has a negative value in all models and countries except for China in Model II. Similarly, the variable of education level generally has a negative impact in all models except Model III. All the ICT variables have negative values and negatively affect life expectancy.

**Keywords:** Information communication and technology, health, Turkey, BRICS countries.

#### Öz

#### Makale Bilgileri

**Makale Türü:**  
Araştırma  
Makalesi

**Geliş Tarihi:**  
15.11.2021

**Kabul Tarihi:**  
11.10.2022

© 2022 İKTİSAD  
Tüm hakları saklıdır.



Bu çalışmada BRICS ülkelerinde ve Türkiye’de BİT’lerin sağlık çıktısı üzerine etkisi 1990-2018 dönemine ait veriler kullanılarak hem panel geneli hem de ülke bazlı olarak analiz edilmiştir. Çalışmada üç model oluşturulmuştur. Panel geneli için elde edilen bulgulara göre Model II dışında diğer modellere ait hata düzelme katsayıları negatif ve istatistikî açıdan anlamlıdır. Model I’de kontrol değişkenleri olarak kullanılan gelir düzeyi, doktor sayısı, eğitim düzeyi ve CO2 düzeyi değişkenlerinden doktor sayısı ve eğitim düzeyi teorik beklentinin tersi yönünde hem kısa dönemde hem de uzun dönemde negatif etkilerken; gelir düzeyi pozitif ve CO2 düzeyi ise negatif etkilemektedir. BİT’leri temsil eden değişkenlerden cep telefon kullanımı hem uzun hem de kısa dönemde negatif etkilemektedir. İnternet kullanımının yer aldığı Model III’te doktor sayısı dışında tüm değişkenler teorik beklentiyi desteklemektedir. Buna göre eğitim ve gelir düzeyi pozitif, CO2 düzeyi negatif etkilemektedir. İnternet kullanımı ise hem uzun hem de kısa dönemde negatif etkiye sahiptir. Gruplara göre bulgular değerlendirildiğinde ise tüm ülkelerde gelir düzeyi değişkeni pozitif, CO2 emisyonu ise negatif etkilemektedir. Doktor sayısı değişkeni Model II’de Çin dışında tüm model ve ülkelerde negatif işarete sahiptir. Benzer şekilde eğitim düzeyi değişkeni de Model III hariç diğer modellerde genel olarak negatif işarettedir. Çalışmanın konusunu oluşturan BİT’e ait değişkenlerin hepsi negatif değere sahip olup yaşam beklentisini olumsuz etkilemektedir.

**Anahtar Kelimeler:** Bilgi, iletişim ve teknoloji, sağlık, Türkiye, BRICS ülkeleri.

**Atıf/ to Cite (APA):** İlikkan-Özgür, M., Demirtaş, C. and Örtlek, Z. (2022). The effect of information communication technology (ICT) on health outcomes: Evidence from BRICS-T countries. *İktisadi İdari ve Siyasal Araştırmalar Dergisi*, 7(19), 678-697

\* ORCID Prof. Dr., Aksaray Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İktisat Bölümü, mozgur@aksaray.edu.tr

\*\* ORCID Dr. Öğr. Üyesi, Aksaray Üniversitesi, Sosyal Bilimler Meslek Yüksekokulu, Dış Ticaret Bölümü, cumademirtas@aksaray.edu.tr

\*\*\* ORCID Öğr. Gör., Aksaray Üniversitesi Eski Meslek Yüksekokulu, Yönetim ve Organizasyon Bölümü, zekiyeortlek@aksaray.edu.tr

## 1. Introduction

Post-Industrial Revolution society has been based on an information/knowledge-based economy. The developments in information and telecommunication technologies are what have played the main role in the transition from industrial society to post-industrial society (Yankın, 2019). One example of this involves the number of transistors on a chip having increased from 2,300 to 100 million in the 50 years between 1971-2020 (Khan et al., 2021): transistors are almost 100,000 times faster and 1,000 times cheaper than they were in the 1950s (Patterson, 2020). These technological advances have helped personal computer manufacturers and those who use computer chips in their products to create much more powerful systems at lower costs (Chandrasekhar and Ghosh, 2001). A series of developments associated with changes in ICT has brought about improvements in models regarding production and distribution of goods, as well as in service. Thanks to ICT, end consumers have the opportunities to access service providers without the constraints of time and space and to access the goods and services they want easily and cheaply. Thus, access to vital needs such as health care has accelerated (Chandrasekhar and Ghosh, 2001). This has resulted in improvements in health care delivery and public health (Dutta et al., 2019; Adeola and Evans, 2018). For example, while life expectancy at birth increased globally from 52.5 years in 1960 to 67.5 years in 2000 and 72.7 years in 2019, the infant mortality rate per 1000 live births decreased from 171.5 in 1960 to 31.4 in 2000 and 8.6 in 2019 (World Bank, 2020).

Developments in health services and indicators have triggered various innovations that integrate mobile phones and the Internet into health services at the local, regional, and national levels. These innovations can be listed as things such as web-based analyses, microprocessors and integrated circuits, mobile phones and applications, telemedicine, and wearable robotic devices, and these developments have encouraged countries to increase their investments in information technology and communication to further improve health services and health outcomes (Adeola and Evans, 2018). For example, the respective numbers for fixed telephone subscribers, mobile phone subscribers, and Internet subscribers per 100 capita were 0.9, 0.00, and 0.00 in 1960; 17.7, 12.0, and 6.7 in 2000; and 15.9, 109.4, 48.9 in 2019 worldwide, while these numbers in Turkey were 0.7, 0.0, and 0.0 in 1960; 29.1, 25.5, and 3.8 in 2000, and 13.8, 96.8, and 73.9 in 2019 (World Bank, 2020). ICT are seen to have increased gradually from 1960 to 2019 both in Turkey and the world.

The gradual increased investments in and use of ICT has been accompanied by positive and negative effects on human health. Positive effects can be listed such as providing health information services by assisting the transfer, storage, and retrieval of data for clinical purposes (Adeola and Evans, 2018; Chandrasekhar and Ghosh 2001); helping reduce the information gap between patient and healthcare provider through effective disease prevention, management, and communication; facilitating medical consultations by removing geographical restrictions; reducing public health risks by providing effective supervision; and increasing the performance and management of the health system (Rana et al., 2018; Zonneveld et al., 2020; Dutta et al., 2019). For example, Uganda has achieved great success in reducing maternal mortality with a radio technology-based project for providing healthcare to pregnant women. By sending text messages to support different vaccination campaigns via mobile phones, mothers and children are less likely to come down with serious illnesses (Rana et al., 2018; Zonneveld et al., 2020; Dutta et al., 2019). Also, the *Hayat Eve Sığar* (HES; “Life fits in at home”) code application was downloaded to mobile phones in Turkey during the recent COVID-19 pandemic and provides important contributions in the fight against COVID within the scope of controlled social life by providing information on whether citizens carry a virus risk in their intercity journeys, institution visits, or in public spaces that require face-to-face communication. Similar practices can be found in many countries. Some studies also support that ICTs contribute positively to health outcomes. Majeed and Khan, (2019) showed ICT to have a significantly positive impact on population health. Adeola and Evans’ (2018) study concluded ICT to have a positive relationship with health and regions with higher ICT levels to have higher health levels. Dutta et al. (2019) found increases in investments in ICT infrastructure in selected Asian

countries to improve health outcomes by creating positive effects on maternal health and child mortality. Meanwhile, Kiberu et al. (2017) reported that applying developments in ICT to health services has made positive contributions to controlling and preventing disease in Uganda.

ICT has both positive and negative effects on health. These negative effects can be expressed as follows: The development and widespread use of ICTs can facilitate information search processes that may result in people becoming overly concerned about their health, thus creating negative effects on health system sustainability (Benvenuto et al., 2019; Iverson et al., 2008). In addition, the widespread use of the Internet and smartphones often leads to negative effects such as headaches, neckaches, backaches, wrist pain, obesity, anxiety, depression, attention deficits, decreased social interactions, decreased academic achievement, and problems emerging in business life (Reinecke et al., 2017; Booth et al., 2001; Rosell et al., 2007; Kim et al., 2010; Rana et al., 2018). Reinecke et al. (2017) showed multitasking on the Internet as well as the communication burden from e-mail and social media messages to be associated with stress, burnout, depression, and anxiety. Rosell et al. (2007) found a relationship to exist between mental problems and ICT use. Booth et al. (2001) concluded the increased use of ICT to decrease physical activities. Kim et al. (2010) revealed increased Internet use to be associated with irregular food intake.

In addition to ICT's positive and negative effects, some studies have found both positive and negative effects. For example, Damant et al. (2017) found elderly people's ICT use to have both positive and negative effects on various aspects of their quality of life. Rana et al. (2018) concluded that developments in ICT access and use in OECD countries to have had negative health outcomes, while improved ICT skill levels have a positive effect. In light of the above discussion, the impact developments in ICT have on health outcomes still needs to be examined. This study aims to examine the effect ICT use has on health outcomes in Brazil, Russia, India, China, South Africa, and Turkey (BRICS-T countries). The current study is one of the first studies to examine ICT's impact on health outcomes in Turkey. In addition, the study examines the BRICS countries in the developing country group such as Turkey; It will also allow for whether the impact of ICTs on health output differs in these countries.

The study consists of four parts. The second part provides information about studies conducted on ICT in Turkey and the foreign literature. The third part presents the data set and method used in the study, and the last section presents the research findings and conclusions.

## 2. Literature Review

Expanding ICT use is important these days for improving individuals' life quality and longevity. Therefore, efforts encouraging the use of ICTs need to be accelerated so that health care providers can produce effective solutions to health outcomes by increasing service and quality (May et al., 2011).

Health systems are becoming more and more versatile at providing high-quality, cost-effective health care services, and are turning to technology-oriented processes as a requirement of the age (Arhete and Erasmus, 2016: 501). As a result, the information and technology aspects of health outcomes have a significant impact on individuals and play a vital role in providing effective quality health care. This has encouraged studies to examine the impact ICT has on health outcomes. Table 1 includes studies in the literature that have examined the effect ICT use has had on health outcomes.

**Table 1.** Literature Review

<i>Author(s)</i>	<i>Aim</i>	<i>Variables</i>	<i>Method</i>	<i>Country/ Year</i>	<i>Result</i>
Chandrasekhar and Ghosh (2001)	Summarizes the potential of technological progress in the ICT sector from a healthcare perspective.		Theoretical Study	India	ICTs have been found to affect health conditions in poor countries both directly and indirectly.
Booth et al. (2001)	Aims to contribute to a rational planning process for developing strategies to improve diet and physical activity habits.	Physical activity, nutrition, population development	Empirical Study (Database)	USA	Concluded that efforts to improve environmental support for healthy nutrition and physical activity should be accelerated.
Yücel and Erkut (2003)	Explores the impact of information technologies on quality of life and quality of management.	Quality of working in IT, institutional parameters.	SPSS Statistical Analysis	Turkey/2000	Banks were found to have safe and healthy working conditions, these being dimensions of quality of work-life influenced by information technology.
Ömürbek and Altın (2009)	Explores the level of information technology concerning the use of health information systems.	Health information systems and information technologies usage levels in hospitals,	Survey Study	Turkey (İzmir Province)/2008	Concluded Turkey to be unable to reach the desired level in terms of health services.
Kim et al. (2010)	Studies the lifestyle and dietary habits of Korean adolescents regarding Internet addiction levels.	Monthly household income, level of internet dependence.	Survey	Korea/ 2008 – 2018	Concluded excessive Internet use to be associated with irregular food intake.
Top and Dilek (2013)	Explains the relationship between health care workers and factors affecting institutional technical information exchange.	Demographic and occupational outcomes	Survey Study	Turkey (İstanbul)/ 1993	Concluded that information cannot be considered a sufficient strategic resource for workers' perceptions compared to other factors.
Mahmud et al. (2013)	Aims to achieve better understanding of health communication for health promotion and developing the ICT-based interactive health channel.	Health communication, population, individual	Qualitative content analysis	Hälsotorg/ 2008 - 2009	Concluded health communication to contribute to the development of health care when individualized, reactive, and preventive.
Štaras et al. (2013)	Explores the impact of ICT on health service delivery.	ICT, healthcare workers	Survey	Lithuania/ 2010 - 2012	The introduction of e-health systems has a direct impact on the efficiency of healthcare institutions, the quality of medical services provided, and patient safety.
Reinecke et al. (2017)	Explains the impact of digital stress on mental health.	Private email, social media messages, internet multitasking, perceived stress, burnout, depression and anxiety, fear of missing out on information and social interaction, communication burden.	Survey	Germany	Concluded that digital stress should be approached from a lifelong perspective.

**Table 1 (Cont.). Literature Review**

Haluz and Jungwirth (2015)	Aims to promote and develop ICT-supported health services among stakeholders.	Professionals working in the health sector, standard of living, quality of health services, financing of health services.	Delphi Method	Austria/2010 - 2030	Concluded that problems must be identified to successfully implement ICT-based health solutions.
Damant et al. (2017)	Explores the elderly's use of ICT-based care, such as telecare and telehealth.	Email, Skype, ICT	ASCOT and WHOQOL models	2007 - 2014	Concluded some inconsistencies to exist regarding the impact of ICT use on the elderly's quality of life.
Majeed and Khan (2019)	Investigates the relationship between ICT and public health.	Health (life expectancy at birth and infant mortality rate). ICT (Internet users, mobile and fixed-line subscriptions).	Panel data	184 Countries/ 1990 -2014	ICT has a positive impact on population health.
Adeola and Evans (2018)	Explores the relationship between ICT and health.	ICT health outcomes	Generalized method of moments (GMM)	Africa/ 1995-2015	The use of ICT has a positive impact on health outcomes.
Tavares (2018)	Examines the relationship between ICT and health status.	ICT and e-health	Panel data	28 EU Countries/ 2014	A significant relationship exists between health outcomes and ICT indices.
Rana et al. (2018)	Aims to create a health outcome index that includes the variables mortality (life expectancy, infant mortality) and morbidity (perceived health status).	Income inequality, ethnic diversity, ICT	Panel data	30 OECD Countries / 2004 -2015	Developing ICT skills positively impacts health outcomes, while developing ICT access/use has negative impacts.
Kırılmaz et al. (2018)	Examines the impact of health care workers' use of information systems on organizational performance.	Organizational performance, IT	Survey Study	Turkey (İstanbul)/ 2017	Concluded IT to have a positive impact on organizational performance.
Dutta et al. (2019)	Examines the impact of ICT on health outcomes.	ICT, health outcome	Panel data	30 Asian Countries/ 2000-2016	Concluded ICT to be usable as a tool for achieving broader health and development goals.
Afroz et al. (2020)	Examines the relationship between ICT and economic growth and public health.	Income, education, health care costs, medical facilities, environment, and lifestyle.	Time series	Malaysia/ 1993-2017	Concluded that policymakers should develop policies that improve public health by increasing health literacy, disseminating health information, and facilitating medical care.
Ibeneme et al. (2020)	Studies the impact of ICT diffusion on various health outcomes in HIV and tuberculosis.	Mobile use, Internet access, fixed-line subscriptions, HIV and tuberculosis outcomes.	Panel data	African continent/2000-2016	Found the coefficients on ICT variables to be negative for tuberculosis health interventions and HIV prevalence (excluding fixed-line) and positive for access to antiretroviral treatment.

**Table 1 (Cont.). Literature Review**

Kouton et al. (2021)	Examines the role of freedom in ICT development.	Mortality rate, ICT development index	Panel data	35 African countries/ 2000-2016	Concluded economic freedom to play an important role in the relationship between ICT development and health outcomes.
Zhang et al. (2022)	Explores the impact of ICT on public health.	Mortality rate, Internet, mobiles	Panel data	China/ 2001-2016	The diffusion of ICT has been shown to reduce mortality rates.
Viorela and Achim (2022)	Explores the impact of ICT on physical health.	Life expectancy, mortality rates, measles vaccination rates, population health, Internet users	Panel data	185 countries/ 2015 -2018	Found the negative impact of Internet access and online information use to be higher in low-income countries than in high-income countries.

This research examines 22 studies related to the literature and discusses studies that have examined the effects of ICT use on health outcomes. With regard to the technique studies used for examining the relationship between ICTs and health, Chandrasekhar et al. (2001) used theoretical; Booth et al. (2001) used empirical; Mahmud et al. (2013) used qualitative analysis; Kim et al. (2010), Štaras et al. (2013), Reinecke et al. (2017), Haluza and Jungwirth (2015) used surveys; Damant et al. (2017) used ASCOT and WHOQOL modeling techniques; Majeed and Khan (2019), Rana et al. (2018), Adeola and Evans (2018), Tavares (2018), Dutta (2019), Ibeneme et al. (2020), Kouton et al. (2021), Zhang et al. (2022), and Viorela and Achim (2022) used panel data; and Afroz et al. (2020) used time series analysis techniques. In Turkey, 4 studies related to the literature were examined. In these studies, Yucel and Erkut (2003), Ömürbek et al. (2009), Top and Dilek (2013), and Kırılmaz et al. (2018) used SPSS statistical analysis techniques.

When generally evaluating the studies' results, the effect of ICT use on health outcomes are seen to vary. Studies showing a positive effect include Chandrasekhar et al. (2001), Štaras et al. (2013), Majeed and Khan (2019), and Adeola and Evans (2018); studies showing a negative effect include Booth et al. (2001), Kim et al. (2010), and Reinecke et al. (2017); and studies showing both positive and negative effects include Tavares (2018), Rana et al. (2018), and Damant et al. (2017). When generally evaluating the results from the studies on Turkey, the effect of ICT use on health outcomes are also seen to vary, with one study from Kırılmaz, et al. (2018) finding a positive impact, and the studies from Ömürbek and Altın (2009) and Top and Dilek (2013) finding negative impacts.

No study in the literature has examined the effect of ICT on health outcomes in BRICS countries and Turkey (BRICS-T). Therefore, this study is expected to contribute to the literature by showing what kind of effect ICT has on health outcomes in the sample of BRICS-T countries. At the same time, examining this effect on health outcomes by adding economic, technological, social, and environmental factors is also important.

### 3. Dataset and Method

#### 3.1. Dataset

The study analyzes the effects of ICT on health outputs using data on BRICS-T countries for the period 1990-2018. The analyzed models were created by adapting Majeed and Khan's (2019) study. The current study uses life expectancy at birth as the dependent variable alongside seven independent variables (i.e., income level, number of physicians, education level, carbon dioxide [CO<sub>2</sub>] emissions, number of mobile subscribers, number of fixed telephone subscribers, and number of Internet subscribers). Of these variables; income level, number of physicians, education level, and CO<sub>2</sub> emissions were used as control variables, and the numbers of mobile, fixed telephone, and internet subscribers were used to represent ICT, which is the subject of the study.

Economic growth is a key factor that plays an important role in determining health status. Increases in economic growth led to increases in individual income and improved access to adequate nutrition, shelter, education, and health services, resulting in better health outcomes. This study uses data on GDP per capita (in 2010 USD) to measure economic growth, which is expected to positively affect life expectancy.

Another important determinant of health is health facilities. This study uses the number of doctors per 1,000 people in the population for this determinant. With more doctors, people will have to wait less for treatment and medical attention, as better access will be had for healthcare facilities and services. Therefore, the number of doctors is expected to positively affect life expectancy.

Education is assumed to play an important role in improving health status. Well-educated people can get good jobs and therefore high incomes. In addition, educated persons are aware of health-related information and avoid risky behaviors. Education level is measured by the gross secondary school enrollment rate and is expected to positively affect life expectancy.

Air pollution causes changes in the environment that threaten the well-being and health of current and future generations and increasing air pollution causes health hazards. This environmental variable is measured by CO<sub>2</sub> emissions and is expected to affect life expectancy negatively.

This study addresses the effects of ICT use on health outcomes. In this context, the hypotheses of the study are as follow:

*H<sub>0</sub>: Health outcomes are not based on ICT use.*

*H<sub>1a</sub>: Health outcomes are based positively on ICT use.*

*H<sub>1b</sub>: Health outcomes are based negatively on ICT use.*

The theoretical relationships between ICT and health outcomes show both positive and negative effects. Therefore, empirically determining whether the positive or negative effects of ICT on health outcomes are predominant and whether these effects differ depending on the ICT measures used are important. Of course, the null hypothesis may be true, in which case, ICT does not affect the dependent variable.

The variables and descriptive statistics used in the study are given in Tables 2 and 3.

**Table 2.** Variables Used in the Model

Variable	Description	Source
<b>Lifetime</b>	Life expectancy at birth, total (years)	World Bank
<b>Income</b>	GDP per capita in constant 2010 USD	World Bank
<b>Health</b>	Number of doctors per 1,000 people	World Bank
<b>Education</b>	Human capital index (%)	Penn World Table
<b>CO<sub>2</sub></b>	Carbon dioxide emissions in metric tons per capita	World Bank
<b>Mobile</b>	Number of mobile phone subscribers per 100 people	World Bank
<b>Fixed Phone</b>	Fixed telephone subscribers per 100 people	World Bank
<b>Internet</b>	Number of Internet users per 100 people	World Bank

**Note:** All variables are used in the form of natural logarithms.

**Table 3.** Descriptive Statistics

	Lifetime	Income	Health	Education	CO <sub>2</sub>	Mobile	Fixed	Internet
<b>Mean</b>	1.829	3.688	.125	.358	.554	.926	1.020	.524
<b>Max.</b>	1.888	4.181	.821	.533	1.165	2.219	1.502	1.907
<b>Min.</b>	1.727	2.760	-.390	.172	-.191	-3.69	-.235	-3.953
<b>SD</b>	.0386	.3990	.241	.087	.364	1.387	.432	1.334
<b>Obs.</b>	174	174	166	174	174	168	174	160

### 3.2. Method

Before examining the cointegration relationships between series, the study examines whether cross-sectional dependence (CSD) is present among the panel countries using the tests developed by Breusch-Pagan (1980) and Pesaran et al., (2008). Next, the cross-sectionally augmented Dickey-Fuller (CADF) test developed by Pesaran (2007), a second-generation unit root test, is used due to the presence of CSD among the countries forming the panel, followed by examining whether the coefficients of the independent variables vary from country to country using the homogeneity test developed by Pesaran and Yamagata (2008). The study analyzes the cointegration relationship between series for the variables using the Durbin-Hausman (Durbin-H) test developed by Westerlund (2008), due to CSD and series being stationary at the different levels  $I(0)$  and  $I(1)$ , which takes all these conditions into account. Finally, due to the presence of a cointegration relationship between series, the cointegration coefficients for the countries and the panel are generally calculated with the panel ARDL (PMG and MG) estimators.

#### 3.2.1. Testing Cross-Sectional Dependence

Analyses that are made without taking CSD between series into account affect the analysis results when CSD is present between series (Pesaran, 2004). Therefore, testing for the presence of CSD for the series and the overall panel is necessary prior to starting the analyses.

CSD was tested among the series using Berusch-Pagan's (1980) LM test; Pesaran's (2004) CD test; and Pesaran et al.'s (2008) corrected LMadj (LM) tests. The Berusch-Pagan (1980) LM test can be used when the time dimension is greater than the cross-section dimension ( $T > N$ ), while the Pesaran (2004) CD test can be used when either the time or cross-section dimension is larger ( $T > N$  or  $N > T$ ). However, due to these tests possibly being biased when the group mean and individual means are non-zero, the adjusted LM test is used. The findings related to the tests are given in Table 4.

**Table 4.** Results from the Cross-Section Dependency Tests

Variables/ Tests	Lifetime	Income	Mobile	CO <sub>2</sub>	Health	Education	Internet	Fixed	Panel
LM	57.237 (0.00)	42.500 (0.00)	49.122 (0.00)	35.028 (0.00)	48.751 (0.00)	47.032 (0.00)	60.864 (0.00)	34.402 (0.00)	119.845 (0.00)
CDLM1	7.711 (0.00)	5.021 (0.00)	6.230 (0.00)	3.657 (0.00)	6.162 (0.00)	5.848 (0.00)	8.374 (0.00)	3.542 (0.00)	19.142 (0.00)
CDLM	-0.827 (0.20)	-2.717 (0.00)	-1.855 (0.03)	-3.048 (0.00)	-3.423 (0.00)	-3.240 (0.00)	0.483 (0.31)	-1.924 (0.02)	-3.117 (0.00)
LMadj	29.018 (0.00)	18.603 (0.00)	6.759 (0.00)	43.692 (0.00)	0.156 (0.43)	-0.491 (0.68)	9.161 (0.00)	20.630 (0.00)	4.010 (0.00)

According to the findings, because the probability values of the series and the panel are less than 0.05 in general, the hypothesis stating no CSD to be present is rejected, with CSD being determined to be present. In this case, CSD is present among the countries making up the panel. For this reason, unit root tests that take into account CSD were applied while performing the unit root analysis for the series used in the study. The second-generation panel unit root test, which also takes into account CSD, was used in the next step.

Due to CSD being determined to be present in the variables used in this study, the stationarity of the series was examined with the CADF test, one of the second-generation unit root tests that was developed by Pesaran (2007). The test can be done for each country (in each cross-section unit) in the series making up the panel. In this way, test statistics can be calculated both for the panel as a whole and for each country separately. The stationarity of each country is tested by comparing the obtained test statistic values with the CADF critical table values from Pesaran's (2007) study. If the



CADF critical table value is greater than the CADF statistic, the null hypothesis is rejected and only that country's series is concluded to be stationary.

The basic CADF regression is constructed as follows:

$$\Delta Y_{it} = \alpha_i + p_i Y_{it-1} + d_0 \bar{Y}_{t-1} + d_1 \Delta \bar{Y}_t + \varepsilon_{it} \quad (1)$$

where  $\bar{Y}_t$  is the mean of all  $N$  observations with  $t$  referring to time. After estimating the CADF regression, the unit root for the overall panel (cross-sectionally augmented IPS, or CIPS) can be obtained by taking the average of the unit-roots of each cross-section (Pesaran, 2007, pp. 268–276).

$$CIPS = \frac{1}{N} \sum_{i=1}^N CADF_i \quad (2)$$

Accordingly, the null and alternative hypothesis of the CADF and CIPS test is formed as follows:

$$H_0: p_i = 0 \text{ for all } i$$

$$H_a: p_i < 0 \text{ (} i = 1, 2, \dots, N_i \text{) and } p_i = 0 \text{ (} i = N_{i+1}, N_{i+2}, \dots, N \text{)}$$

The unit root statistics (CADF) for each country forming the panel and the test statistics (CIPS) for the panel as a whole are given in Table 5.

**Table 5.** CADF Unit Root Test Results

Countries/ Variables	Brazil	China	India	Russia	Turkey	South Africa	Panel (CIPS)
Life expectancy	0.42	1.45	-1.08	-4.27*	-1.99	-0.51	-0.99
$\Delta$	1.28	-2.30	-4.53*	-2.38	-10.8*	-2.83	-3.60*
Income Level	-1.78	-2.22	-0.41	-5.20*	-1.72	-2.78	-2.35*
$\Delta$	-1.74	-2.10	-2.56	-2.55	-2.36	-2.77	-2.35*
Mobile	-15.0*	-2.07	-7.42*	-5.29*	-1.48	-15.2*	-7.75*
$\Delta$	-6.62*	-2.01	-2.15	-2.72	-4.62*	-5.57*	-3.95*
CO <sub>2</sub> emissions	-1.71	-3.47*	-2.69	-4.96*	-2.26	-2.77	-2.98*
$\Delta$	-0.74	-0.90	-2.87	-1.65	-3.70*	-4.16*	-2.34*
Health	-3.82*	-3.13	-4.19*	-3.25	-2.97	-3.11	-3.41*
$\Delta$	-6.20*	-3.98*	-6.28*	-5.60*	-4.34*	-3.68*	-5.01*
Education level	-2.39	-4.19*	-3.32	-7.54*	-5.83*	-2.87	-4.36*
$\Delta$	-5.08*	-2.60	-2.63	-6.19*	-5.74*	-3.61*	-4.31*
Internet	-1.79	-2.47	-1.45	-2.58	-3.71*	-0.70	-2.12
$\Delta$	-6.36*	-5.45*	-5.19*	-10.7*	-6.31*	-1.12	-5.85*
Fixed Line	-3.05	-2.56	-2.47	-1.44	-1.35	-3.35*	-2.37*
$\Delta$	-2.42	-2.87	-3.37*	-2.89	-1.55	-4.68*	-2.96*

**Note:** \* shows the series to be stationary at  $p < .05$ ,  $\Delta$  is the difference operator, indicating the variable to show the difference. The critical values for countries and the overall panel are taken from Pesaran's (2007) study. The critical value in the fixed model is 3.36 for countries and 2.33 for the overall panel. The critical value in the fixed and trend models is 3.87 for countries and 2.86 for the overall panel. The fixed model was used as the test model for the lifetime expectancy variable and the trend model as the test model for the other variables.

When examining the results in Table 5, the series are seen to be at the stationary level for the variables of income level, number of mobile subscribers, CO<sub>2</sub> emissions, number of doctors, and education level as well as the fixed variables for the overall panel. On the other hand, the variables of life expectancy and number of Internet subscribers are not at stationary levels but do become stationary once their first difference is taken into account, namely I(1). Thus, some of the series are stationary at I(1), while others are stationary at I(0). If the dependent variable is stationary at I(1) and the independent variables are stationary at I(1) or I(0), Westerlund's (2008) Durbin-H method can be used for panel cointegration analysis. Therefore, because the variables in the study meet these conditions, a cointegration analysis can be performed. Before performing the cointegration analysis,

whether the slope coefficient in the cointegration equation is homogeneous or not needs to be determined. To do this, the Delta test developed by Pesaran and Yamagata (2008) is used. This test can be calculated in two different ways as  $\Delta$  and  $\Delta adj$  respectively for large and small samples. Accordingly:

$$\text{For large samples: } \Delta = \sqrt{N} \left( \frac{N^{-1}\tilde{S}-k}{\sqrt{2k}} \right) \tag{3}$$

$$\text{For small samples: } \Delta adj = \sqrt{N} \left( \frac{N^{-1}\tilde{S}-E(\tilde{Z}_{iT})}{\sqrt{\text{var}\tilde{Z}_{iT}}} \right) \tag{4}$$

where  $N$  (section),  $T$  (time), and  $k$  show the number of explanatory variables, and  $S$  shows the Swamy statistic. The null hypothesis of the calculated  $\Delta$  and  $\Delta adj$  tests (i.e.,  $H_0: \beta_1 = \beta_2 = \dots = \beta_n = \beta$ ) states the coefficients of the panel's sections to be homogeneous (Pesaran and Yamagata, 2008). The results from the test are shown in Table 6.

**Table 6.** Homogeneity Test Results

Test	Models		Test Statistics	Probability Value	
Pesaran and Yamagata (2008)	Model I	For large samples	$\Delta$	8.279	0.000
		For small samples	$\Delta adj$	9.630	0.000
	Model II	For large samples	$\Delta$	12.007	0.000
		For small samples	$\Delta adj$	13.893	0.000
	Model III	For large samples	$\Delta$	9.132	0.000
		For small samples	$\Delta adj$	10.683	0.000

The probability values of the tests in Table 6 calculated for all models are less than 0.05, both the probability value for the test statistic  $\Delta$  calculated for large samples and the probability value of the test statistic  $\Delta adj$  calculated for small samples. In this case, the null hypothesis  $H_0$ , which states the slope coefficients to be homogeneous, is rejected. Therefore, the constant term and slope coefficients were determined to be heterogeneous. Thus, the cointegration interpretations are valid for the group.

The long-term relationships between the variables were established using the Durbin-H panel cointegration method developed by Westerlund (2008). This method states that, provided the dependent variable is stationary at I(1), panel cointegration analysis can be performed if the independent variables are stationary at I(1) or I(0). The existence of the cointegration relationship is tested separately under the group and panel dimensions:

$$\text{For the Group dimension: } DH_g = \sum_{i=1}^n S_i (\tilde{\Phi}_i - \bar{\Phi}_i) \sum_{t=2}^T \check{e}_{it-1}^2 \tag{5}$$

$$\text{For the Panel dimension: } DH_p = \overline{S_n} (\tilde{\Phi} - \bar{\Phi}) \sum_{i=1}^n \sum_{t=2}^T \widehat{e}_{it-1}^2 \tag{6}$$

The hypotheses for the test are as follows:

$H_0$ : No cointegration relationship exists ( $i = 1, 2, \dots, n$ )

$H_1$ : A cointegration relationship exists ( $i = 1, 2, \dots, n$ )

The hypotheses are rejected or accepted by comparing the obtained test statistics with the critical values from the normal distribution table. Accordingly, when the obtained test statistic is greater than 1.645 (at the 5% significance level),  $H_0$  is rejected and a cointegration relationship is determined to exist. Table 7 presents the results from applying the Durbin-H test.

**Table 7.** Durbin-H Panel Cointegration Test Results

		Statistics Value	Probability Value	Critical Value (5% significance)	Determination
Model I	Durbin-H Group Statistics	1.455	0.073	1.645	No cointegration relationship exists.
	Durbin-H Panel Statistics	7.565	0.000	1.645	A cointegration relationship exists.
Model II	Durbin-H Group Statistics	1.034	0.151	1.645	No cointegration relationship exists.
	Durbin-H Panel Statistics	6.386	0.000	1.645	A cointegration relationship exists.
Model III	Durbin-H Group Statistics	-0.533	0.703	1.645	No cointegration relationship exists.
	Durbin-H Panel Statistics	1.203	0.114	1.645	No cointegration relationship exists.

According to the results in Table 7, the panel statistics in Models I and II exceed the critical value of 1.645, and the group statistics exceed the critical value of 1.645. In this case, hypothesis H<sub>0</sub> is rejected only for the panel statistics in Models I and II, and a cointegration relationship has been determined to exist. The cointegration coefficients for Models I and II, for which a cointegration relationship is found for the panel in general, can be interpreted between series. Despite a statistically weak cointegration relationship existing, the cointegration coefficients is estimatable. Cointegration coefficients for the panel can be obtained using Pesaran and Smith's (1995) mean group (MG) estimator and Pesaran et al.'s (1999) pooled mean group (PMG) estimator.

The MG estimator states the coefficients to differ between countries in the short and long term. Meanwhile, the PMG estimator assumes the constant term, short-term, and error correction coefficients to differ across countries and the long-term coefficients to be homogeneous (Blackburne and Frank, 2007). The basic error correction equation used in the PMG and MG estimators is shown below.

$$\Delta y_{it} = \mu_i + \phi_i (y_{i,t-1} - \theta_i' x_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}^* \Delta x_{i,t-j} + \varepsilon_{it} \quad (7)$$

where  $\phi_i = -\left(\frac{\beta_i}{\theta_i}\right)$  and shows the balance and long-term relationship between  $y_{it}$  and  $x_{it}$ , and  $\lambda_{ij}^*$  and  $\delta_{ij}^*$  represent the short-term coefficients of the dependent variable and the explanatory variables' lags, respectively. In order to be able to mention a long-term relationship, the error correction coefficient must meet the condition of  $\phi_i < 0$ . Therefore, a statistically significant and negative error correction coefficient ( $\phi_i$ ) also shows a cointegration relationship to exist between  $y_{it}$  and  $x_{it}$ . At the same time,  $\phi_i$ , which expresses the error correction coefficient, also measures the rate at which  $y_{it}$  adjusts toward the long-term equilibrium of a unit change in  $x_{it}$ ' (Mamun, et al., 2013).

The panel ARDL ( $p, q$ ) model was created to measure the effect that ICT in the countries making up the panel and the overall panel have on health output and is expressed as follows:

$$\Delta \ln life_{it} = \mu_i + \phi_i g_{i,t-1} + \beta_i' (\ln income_{it} + \ln health_{it} + \ln education_{it} + \ln CO2_{it} + \ln ICT_{it}) + \sum_{j=1}^{pi} \lambda_{ij} \ln life_{i,t-j} + \sum_{j=0}^{qi} \delta_{ij} (\ln income_{it-j} + \ln health_{it-j} + \ln education_{it-j} + \ln CO2_{it-j} + \ln ICT_{it-j}) + \varepsilon_{it} \quad (8)$$

In this equation, time  $t = 1, 2, \dots, T$  and countries  $i = 1, 2, \dots, N$ ;  $\mu_i$  represents the fixed effects;  $j$  is the lag number;  $\phi_i$  is the error correction coefficient;  $\beta_i$  represents the long-term coefficients;  $\lambda_{ij}$  represents the lag from the dependent variable; and  $\delta_{ij}$  represents the short-term coefficients.

In panel ARDL models, the decision about which estimator is more efficient is made according to the Hausman test. As Pesaran et al. (1997) stated in their study, however, the Hausman test could not be calculated in the model because  $V^{\theta^{MG}} - V^{\theta^{PMG}}$  are not defined as positive.

Policy relevance was considered when determining whether the MG or PMG estimator is more effective. This is because the BRICS-T countries were assumed to have common long-term policies while having different short-term policies. Given this information, the results for the PMG estimator are likely to be more reliable. Therefore, the PMG estimator results have been interpreted for the panel as a whole. Table 8 presents the panel ARDL results obtained by considering the cross-section dependency.

**Table 8.** Panel ARDL Analysis Results

<i>Panel Estimation</i>			
<b>Dependent variable (lifetime)</b>	<i>Model I</i>	<i>Model II</i>	<i>Model III</i>
<b>Long-term coefficients</b>	<i>PMG</i>	<i>PMG</i>	<i>PMG</i>
<b>Income</b>	3.47* (0.55)	-0.16* (0.05)	0.06* (0.01)
<b>Health</b>	-0.37*** (0.21)	0.26*** (0.05)	-0.002 (0.02)
<b>Education</b>	-0.44* (0.05)	-0.34* (0.05)	0.001 (0.02)
<b>CO<sub>2</sub></b>	-1.23* (0.09)	0.12* (0.09)	-0.04* (0.01)
<b>Mobil</b>	-0.72* (0.07)		
<b>Fixed</b>		-0.24* (0.04)	
<b>Internet</b>			-0.16* (0.01)
<b>Error correction coefficient</b>			
<b>Ø</b>	-0.18*	-0.27	-0.78**
<b>Short-term coefficients</b>			
<b>ΔIncome</b>	0.64* (0.16)	-0.04* (0.05)	0.04* (0.01)
<b>ΔHealth</b>	-0.07* (0.01)	0.07* (0.07)	-0.001* (0.01)
<b>ΔEducation</b>	-0.08* (0.02)	-0.09* (0.09)	0.001* (0.01)
<b>ΔCO<sub>2</sub></b>	-0.22* (0.17)	0.03* (0.03)	-0.03* (0.01)
<b>ΔMobile</b>	-0.13* (0.08)		
<b>ΔFixed Telephone</b>		-0.07* (0.06)	
<b>ΔInternet</b>			-0.12* (0.01)
<b>C</b>	0.42 (0.48)	-0.08 (0.35)	0.05 (0.53)

**Note:** \*\*\*, \*\*, \* denote the respective confidence levels of 0.01, 0.05, and 0.10.

Table 8 shows the error correction coefficients in Models I and III to be negative and statistically significant. The significantly negative error correction coefficient shows that the short-term deviations stabilize in the long term. These deviations will be corrected in 5.5 years for Model I and in 1.2 years for Model II. In other words, 0.18% of the disequilibrium in Model I in one period and 0.78% in Model II will be corrected in the next period, allowing for the approaches to long-term equilibrium.

In Model I, all variables are statistically significant in both the long and short terms. Of the variables of income level, number of physicians, education level, and CO<sub>2</sub> emission, which are used as control variables in the study, number of physicians and education level do not support the theoretical expectation either in the short or long term. Accordingly, the effect of a 1% unit increase in income on health outcomes is 3.47% in the long term and 0.64% in the short term. The effect of a 1% unit increase in CO<sub>2</sub> emissions on health outcomes is -1.23% in the long term and -0.22% in the short term. A 1% unit increase in number of physicians having a coefficient sign opposite to the theoretical expectation reduces health outcomes by -0.37% in the long term and -0.07% in the short term. Similarly, the effect of a 1% unit increase in human capital on health outcomes is -0.44% units in the long term and -0.08% units in the short term.

Although the statistical significance of the control variables and their compatibility with theoretical expectations are important, the ICT-related variables the study uses are the numbers of mobile, fixed-line telephone, and Internet subscribers. Model I includes the number of mobile subscribers. Accordingly, a 1% unit increase in the number of mobile subscribers results in a -0.72% long-term decrease and a -0.13% short-term unit decrease in health outcomes.

Although the error correction coefficient in Model II has a negative sign, it is not statistically significant. For this reason, despite the coefficients of the variables being statistically significant, they are unable to be interpreted correctly.

In Model III, all variables are statistically significant, both in the long term (except for number of doctors and education level) and in the short term. All the control variables (i.e., income level, education level, and CO<sub>2</sub> emissions) except for number of physicians support the theoretical expectations regarding both the short and long term. Accordingly, the effect of a 1% unit increase in income level on health outcomes is 0.06% in the long term and 0.04% in the short term. The effect of a 1% unit increase in education level on health outcomes is not statistically significant in the long term, it does have a 0.001% unit increase in the short term. The effect of a 1% unit increase in CO<sub>2</sub> emissions on health outcomes is -0.04% in the long term and -0.03% in the short term. The number of Internet subscribers is another variable representing ICT and has a negative sign in both the long and short term. Accordingly, the effect of a 1% unit increase in the number of Internet subscribers on health outcomes is -0.16% in the long term and -0.12% in the short term.

In addition to the importance of evaluating the results of the whole panel, making comments on a country-by-country basis to evaluate the results specifically for Turkey and comparing these with other countries will also be important.

**Table 9.** Short-Term and Error Correction Coefficients for Each Country

<b>Model I (PMG)</b>						
	<i>Brazil</i>	<i>China</i>	<i>India</i>	<i>Russia</i>	<i>Turkey</i>	<i>South Africa</i>
<b>ECT</b>	-0.07* (0.10)	-0.07* (0.01)	-0.25* (0.03)	-0.12* (0.02)	-0.26* (0.03)	-0.34* (0.05)
<b>ΔIncome</b>	0.26* (0.10)	0.23* (0.03)	0.88* (0.12)	0.41* (0.02)	0.90* (0.14)	1.16* (0.19)
<b>ΔHealth</b>	-0.03 (0.10)	-0.02 (0.01)	-0.09*** (0.06)	-0.04*** (0.03)	-0.10 (0.06)	-0.12 (0.08)
<b>ΔEduc.</b>	-0.03* (0.01)	-0.03* (0.01)	-0.11* (0.02)	-0.05* (0.01)	-0.12* (0.02)	-0.15* (0.04)
<b>ΔCO<sub>2</sub></b>	-0.09** (0.04)	-0.08* (0.02)	-0.31* (0.08)	-0.15* (0.03)	-0.32* (0.07)	-0.42* (0.11)
<b>ΔMobil</b>	-0.05* (0.02)	-0.05* (0.01)	-0.18* (0.02)	-0.09* (0.01)	-0.19* (0.02)	-0.24* (0.05)
<b>C</b>	-0.44* (0.15)	-0.31* (0.04)	0.31* (0.12)	-0.53* (0.04)	2.52* (0.36)	0.98* (0.26)
<b>Model II (PMG)</b>						
	<i>Brazil</i>	<i>China</i>	<i>India</i>	<i>Russia</i>	<i>Turkey</i>	<i>South Africa</i>
<b>ECT</b>	-1.00 (NA)	-0.27* (0.05)	0.60*** (0.36)	-0.32* (0.04)	0.38* (0.06)	-1.00 (NA)
<b>ΔIncome</b>	-0.16* (0.05)	0.04* (0.01)	0.10 (0.07)	-0.05* (0.02)	0.06* (0.02)	-0.16* (0.05)
<b>ΔHealth</b>	0.26* (0.05)	0.07* (0.01)	-0.16 (0.10)	0.08*** (0.02)	-0.10* (0.02)	0.26* (0.05)
<b>ΔEduc.</b>	-0.34* (0.05)	-0.09* (0.02)	0.20 (0.13)	-0.11* (0.02)	0.13* (0.02)	-0.34* (0.05)
<b>ΔCO<sub>2</sub></b>	0.12** (0.05)	0.03* (0.02)	-0.07 (0.05)	0.04** (0.02)	-0.04* (0.02)	0.12* (0.05)
<b>ΔFixed</b>	-0.24* (0.04)	-0.07* (0.01)	0.15* (0.08)	-0.08* (0.01)	0.09* (0.01)	-0.24* (0.04)
<b>C</b>	0.75* (0.08)	0.20* (0.03)	-0.28 (0.18)	0.21* (0.03)	0.31* (0.01)	-1.69* (0.18)
<b>Model III (PMG)</b>						
	<i>Brazil</i>	<i>China</i>	<i>India</i>	<i>Russia</i>	<i>Turkey</i>	<i>South Africa</i>
<b>ECT</b>	-1.00 (NA)	-0.77* (0.04)	-0.52*** (0.07)	-0.51* (0.05)	-0.87* (0.03)	-1.00 (NA)
<b>ΔIncome</b>	0.06* (0.01)	0.04* (0.01)	0.03* (0.01)	0.03* (0.01)	0.05* (0.01)	0.06* (0.01)
<b>ΔHealth</b>	-0.002 (0.02)	-0.001* (0.01)	-0.002 (0.01)	-0.001 (0.01)	-0.001 (0.02)	-0.002 (0.02)
<b>ΔEduc.</b>	0.001 (0.01)	0.0004* (0.01)	0.0003 (0.01)	0.0003 (0.01)	0.001 (0.01)	0.001 (0.01)
<b>ΔCO<sub>2</sub></b>	-0.04* (0.01)	-0.03* (0.01)	-0.02* (0.01)	-0.02* (0.01)	-0.04* (0.01)	-0.04* (0.01)
<b>ΔInternet</b>	-0.16* (0.01)	-0.12* (0.01)	-0.08* (0.01)	-0.08* (0.01)	-0.14* (0.01)	-0.16* (0.01)
<b>C</b>	2.37* (0.03)	-0.97* (0.06)	0.78* (0.09)	0.21* (0.03)	-0.94* (0.05)	-0.27* (0.08)

**Note:** \*\*\*, \*\*, \* denote respective confidence levels of 0.01, 0.05, and 0.10.

When analyzing the results by group, error correction coefficients for all countries in Model I are statistically significant and negative. The error correction coefficients for the countries have been calculated as -0.07 for Brazil, -0.07 for China, -0.25 for India, -0.12 for Russian, -0.26 for Turkey, and -0.34 for South Africa.

Meanwhile, the short-term coefficients for variables other than number of doctors are statistically significant in Brazil. Except for education level (-0.03), income level (0.26), and CO<sub>2</sub> emissions (-0.09), the variables support the theoretical expectations. While a 1% unit increase in

income level increases health outcomes by 0.26%, this same unit increase in CO<sub>2</sub> emissions reduces health outcomes by 0.04%. The number of mobile subscribers (-0.05) negatively affects life expectancy in the short term. Accordingly, an increase in the number of mobile subscribers by a unit of 1% reduces health outcomes by 0.05%.

As in Brazil, the variables except for number of doctors are statistically significant in China. Income level (0.23) and CO<sub>2</sub> emissions (-0.09) are the other variables besides education level (-0.03) that support the theoretical expectations. While a 1% unit increase in income level increases health outcomes by 0.23%, this same unit increase in CO<sub>2</sub> emissions reduces health outcomes by 0.09%. The number of mobile subscribers (-0.05) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of mobile subscribers reduces health outcomes by 0.05%.

In India, however, all variables are statistically significant. The variables of number of doctors (-0.09) and education level (-0.11) do not support the theoretical expectations, while the variables of income level (0.88) and CO<sub>2</sub> emissions (-0.31) do. A 1% unit increase in income level increases health outcomes by 0.88%, a 1% unit increase in number of doctors decreases health outcomes by 0.09%, a 1% unit increase in education level decreases health outcomes by 0.11%, and a 1% unit increase in CO<sub>2</sub> emissions decreases health outcomes by 0.31%. The number of mobile subscribers (-0.05) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of mobile subscribers reduces health outcomes by 0.18%.

All variables are also statistically significant in Russia. The variables of number of doctors (-0.04) and education level (-0.05) do not support the theoretical expectations, while income level (0.41) and CO<sub>2</sub> emissions (-0.15) do. Also, a 1% unit increase in income level increases health outcomes by 0.41%, a 1% unit increase in number of doctors reduces health outcomes by 0.04%, a 1% unit increase in education level reduces health outcomes by 0.05%, and a 1% unit increase in CO<sub>2</sub> emissions reduces health outcomes by 0.15%. The number of mobile subscribers (-0.09) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of mobile subscribers reduces health outcomes by 0.09%.

In South Africa, all variables except for number of doctors are statistically significant, with education level (-0.15), income level (1.16), and CO<sub>2</sub> emissions (-0.42) supporting the theoretical expectations. A 1% unit increase in income level increases health outcomes by 1.16%, and a 1% unit increase in CO<sub>2</sub> emissions reduces health outcomes by 0.42%. The ICT variable of number of mobile subscribers (-0.24) negatively affects life expectancy in the short term, as in the other countries. Accordingly, a 1% unit increase in the number of mobile subscribers reduces health outcomes by 0.24%.

Finally, all variables except number of doctors are statistically significant in Turkey, just as in Brazil, China, and South Africa. Education level (-0.12) does not support the theoretical expectations, while income level (0.90) and CO<sub>2</sub> emissions (-0.32) do. A 1% unit increase in income level increases health outcomes by 0.90%, while a 1% unit increase in CO<sub>2</sub> emissions reduces health outcomes by 0.32%. The number of mobile subscribers (-0.19) negatively affects life expectancy in the short term, as in the other countries. Accordingly, a 1% unit increase in the number of mobile subscribers reduces health outcomes by 0.19%.

In Model II, the error correction coefficients for countries other than China (-0.27) and Russia (-0.32) are statistically significant and do not meet the requirement of having a negative value. Accordingly, India (0.60) and Turkey (0.38) have a statistically significant but positive sign. In other words, both have a positive sign and are not statistically significant, just as in Brazil (1.00) and South Africa (1.00). Accordingly, all variables are also statistically significant in China. Education level (-0.09) and CO<sub>2</sub> emissions (0.03) do not support the theoretical expectations, while income level (0.04) and number of doctors (0.07) do. A 1%-unit increase in income level increases health outcomes by 0.04%, a 1% unit increase in number of physicians increases health outcomes by 0.07%, and a 1% unit increase in CO<sub>2</sub> emissions increases health outcomes by 0.04%. However, a 1%-unit increase in

education level decreases health outcomes by 0.07%. The number of fixed-line subscribers (-0.07) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of fixed-line subscribers reduces health outcomes by 0.07%.

All variables for Model II are also statistically significant in Russia. The number of doctors (0.08) does not support the theoretical expectations, while income level (-0.05), education level (-0.11), and CO<sub>2</sub> emissions (0.04) do. Accordingly, while a 1% unit increase in the number of physicians increases health outcome by 0.08%, and a 1% unit increase in CO<sub>2</sub> emissions increases health outcomes by 0.04%. However, a 1% unit increase in income level decreases health outcomes by 0.05%, and a 1% unit increase in education level decreases health outcomes by 0.11%. The number of fixed-line subscribers (-0.08) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of fixed-line subscribers reduces health outcomes by 0.08%.

The error correction coefficients for countries other than Brazil (1.00) and South Africa (1.00) in Model III do meet statistically significant and the requirement of having a negative sign. Accordingly, the error correction coefficients were calculated as -0.77 for China, -0.52 for India, -0.51 for Russia, and -0.87 for Turkey. In China, all variables are statistically significant, with number of doctors (-0.001) not supporting and income level (0.04), education level (0.0004), and CO<sub>2</sub> emissions (-0.03) supporting theoretical expectations. A 1% unit increase in income level increases health outcomes by 0.04%, and a 1% unit increase in education level increases health outcomes by 0.0004%, while a 1% unit increase in number of physicians decreases health outcomes by 0.001%, and a 1% unit increase in CO<sub>2</sub> emissions decreases health outcomes by 0.03%. The number of Internet subscribers (-0.12) has a negative impact on life expectancy in the short term. Accordingly, a 1% unit increase in the number of Internet subscribers reduces health outcomes by 0.12%.

In India, all variables except health (-0.002) are statistically significant. The coefficients for income level (0.03), education level (0.0003), and CO<sub>2</sub> emissions (-0.02) support theoretical expectations. A 1% unit increase in income level increases health outcomes by 0.03%, and a 1% unit increase in education level increases health outcomes by 0.0003%, while a 1% unit increase in CO<sub>2</sub> emissions decreases health outcomes by 0.02%. The ICT variable of number of Internet subscribers (-0.08) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of Internet subscribers reduces health outcomes by 0.08%.

In Russia, all variables except health (-0.001) are statistically significant. The coefficients for income level (0.03), education level (0.0003), and CO<sub>2</sub> emissions (-0.02) support the theoretical expectation. A 1% unit increase in income level increases health outcomes by 0.03%, and a 1% unit increase in education level increases health outcomes by 0.0003%, while a 1% unit increase in CO<sub>2</sub> emissions decreases health outcomes by 0.02%. The number of Internet subscribers (-0.08) has a negative effect on life expectancy in the short term. Accordingly, an increase in the number of Internet subscribers by a unit of 1% reduces health outcomes by 0.08%.

Finally, the variables other than number of doctors are statistically significant in Turkey, just as in India and Russia. The coefficients of income level (0.05), education level (0.001), and CO<sub>2</sub> emissions (-0.04) support the theoretical expectation. While a 1% unit increase in income level increases health outcomes by 0.05%, a 1% unit increase in education level increases health outcomes by 0.001%, and a 1% unit increase in CO<sub>2</sub> emissions decreases health outcomes by 0.04%. The number of Internet subscribers (-0.14) has a negative effect on life expectancy in the short term. Accordingly, a 1% unit increase in the number of Internet subscribers reduces health outcomes by 0.14%.

Looking at the results in general, the variable of income level is positive in all countries, and CO<sub>2</sub> emissions are negative. The variable of number of doctors has a negative sign in all models and countries except China in Model II. Similarly, the variable of education level is generally negative in the other models except for Model III. All ICT variables this study uses have negative values and negative short-term effects on life expectancy.



#### 4. Conclusion

The widespread use of ICT leads to good relationships and healthy behaviors among people, improving their health and longevity. In this context, the study has analyzed the impact ICT has on health outcomes in BRICS countries and Turkey (BRICS-T countries), both on a panel and by country basis, using data for the period 1990-2018. The study uses life expectancy at birth as the dependent variable and the following seven independent variables: income level, number of doctors, education level, CO<sub>2</sub> emissions, number of mobile phone subscribers, number of fixed-line telephone subscribers, and number of Internet subscribers. Of these variables, income level, number of doctors, education level, and CO<sub>2</sub> emissions were used as control variables, while the numbers of mobile, fixed-line telephone, and internet subscribers were used to represent the study's subject of ICT.

Three models were created in the study, with the ICT variables of numbers of mobile, fixed-line, and Internet subscribers being added one at a time to each of these models. According to the results obtained for the panel in general, all variables in Model I are statistically significant in both the long and short term. Of the study's control variables, number of physicians and education level do not support the theoretical expectations either in the short or long term. Accordingly, income level increases health outcomes by 3.47% in the long term and 0.64% in the short term, while CO<sub>2</sub> emissions decrease health outcomes by 1.23% in the long term and 0.22% in the short term. Meanwhile, number of physicians has a sign opposite theoretical expectations and reduces health outcomes by 0.37% in the long term and 0.07% in the short term, also education level decreases health outcomes by 0.44% in the long term and 0.08% in the short term. Although the statistical significance of the control variables and their compatibility with theoretical expectations are important, so are the study's ICT-related variables of the numbers of mobile, fixed-line telephone, and Internet subscribers. Model I include the number of mobile subscribers. According to this model, the increase in the number of mobile subscribers reduces health outcomes by 0.72% in the long term and 0.13% in the short term.

Although the error correction coefficient in Model II has a negative sign, it is not statistically significant. For this reason, the coefficients of the variables are statistically significant but unable to be interpreted correctly.

In Model III, all variables are statistically significant, both in the long term (except for the variables of number of doctors and income level) and in the short term. With regard to control variables except for the number of physicians, income level, education level, and CO<sub>2</sub> emissions support theoretical expectations in both the short and long term. According to the results, income level increases health outcomes by 0.06% in the long term and 0.04% in the short term. While education level does not affect health outcomes in the long term, it increases health outcomes by 0.001% in the short term. CO<sub>2</sub> emissions decrease health outcomes by 0.04% in the long term and 0.03% in the short term. The ICT variable of number of Internet subscribers has a negative sign in both the long and short term. Accordingly, the number of Internet subscribers reduces health outcomes by 0.16% in the long term and 0.12% in the short term.

When evaluating the results by group, the variable of income level is positive in all countries and the variable of CO<sub>2</sub> emissions is negative. The variable of number of doctors is positive in all models and countries except China in Model II. Similarly, the variable of education level is generally negative in all models except Model III. All ICT variables have negative values and a negative effect on life expectancy in the short term.

In line with the findings, some suggestions can be given to researchers and policymakers. In the context of the recommendations to researchers, the variable of life expectancy that this study used as a health measure does not take into account the quality of life but only considers life span. Therefore, a need is found to create a comprehensive variable that better reflects the variable measuring health.

In the context of recommendations to policymakers, improving income levels attracts attention, as it is the most important indicator for improving health outcomes. In this context, developing policies to improve income levels appears essential as a fundamental indicator of health outcome improvement.

The variable of CO<sub>2</sub> emissions generally has a negative effect on health outcomes across the sampled countries. Prioritizing the prevention of environmental degradation as well as mitigation measures emerges as the main challenge for all countries with regard to improving health outcomes.

The effects from the variables of both education level and number of doctors on health outcomes appear to be negative. This indicates that all countries should focus on remedial measures that ensure fair access to these services and be more inclusive with regard to these indicators.

ICT can be seen to play a negative role in determining public health in both BRICS countries and Turkey. In this direction, ICT can contribute to improving public health if policymakers adopt the right policies that ensure ICT is used inclusively in society with measures that reduce ICT's negative impact, improve health literacy, disseminate health information on preventing diseases, and improve communications between patients and healthcare systems.

## References

- Afroz, R., Muhibbullah, Md. and Morshed, M. N. (2020). Impact of information and communication technology on economic growth and population health in Malaysia. *Journal of Asian Finance, Economics and Business*, 7(4), 155-162. <https://doi.org/10.13106/jafeb.2020.vol7.no4.155>.
- Adeola, O. and Evans, O. (2018). Digital health: ICT and health in Africa. *Actual Problems of Economics*, 10(208), 2018.
- Arhete, L. E. and Erasmus, R. (2016, 15-19 May). Healthcare service delivery: A literature review, *International Association for Management of Technology. IAMOT 2016, Conference Proceedings*, 487-505.
- Benvenuto, M., Sambati, F. V. and Viola, C. (2019). *The impact of internet usage on health-care expenditures and sustainability*. ERAZ 2019, Selected Papers. <https://doi.org/10.31410/ERAZ.S.P.2019.95>.
- Blackburne, E. F. and Frank, M. W. (2007). Estimation of nonstationary heterogeneous panels. *The Stata Journal*, 7(2), 197–208. <https://doi.org/10.1177/1536867X0700700204>.
- Breusch, T. S. and Pagan, A. R. (1980). The lagrange multiplier test and its applications to model specification tests in econometrics. *Review of Economic Studies*, 47(1), 239-53. <https://www.jstor.org/stable/2297111>.
- Booth, S. L., Sallis J. F., Ritenbaugh C., Hill, J. O., Birch, L. L., Frank, L. D., Glanz, K., Himmelgreen, D. A., Mudd, M. and Popkin, B. M. (2001). Environmental and societal factors affect food choice and physical activity: rationale, influences, and leverage points. *Nutr Rev.*, 2001(59), 21–36. <https://doi.org/10.1111/j.1753-4887.2001.tb06983.x>.
- Chandrasekhar, C.P. and Ghosh, J. (2001). Information and communication technologies and health in low income countries: The potential and the constraints. *World Health Organization*, 79(9), 850-855.
- Damant, J., Knapp, M., Freddolino, P. and Lombard, D. (2017). Effects of digital engagement on the quality of life of older people. *Health and Social Care in the Community*, 25(6), 1679–1703. <https://doi.org/10.1111/hsc.12335>.
- Duttaa, U. P., Gupta, H. and Sengupta, P. P. (2019). ICT and health outcome nexus in 30 selected Asian countries: Fresh evidence from panel data analysis. *Technology in Society*, 59(2019), 101184. <https://doi.org/10.1016/j.techsoc.2019.101184>.
- Haluzaa, D. and Jungwirth, D. (2015). ICT and the future of health care: aspects of health promotion. *International Journal of Medical Informatics*, (84), 48-57. <https://doi.org/10.1016/j.ijmedinf.2014.09.005>

- Ibeneme, S., Revere, F. L., Hwang, L-Y, Rajan, S., Okeibunor, J. Muneene, D. and Langabeer, J. (2020). Impact of information and communication technology diffusion on HIV and tuberculosis health outcomes among African health systems. *Informatics*, 7(2), 1-10; <https://doi.org/10.3390/informatics7020011>
- Iverson, S.A., Howard, K. B. and Penney, B. K. (2008). Impact of internet use on health-related behaviors and the patient-physician relationship: a survey-based study and review. *Special Communication, Jaoa*, 108(12). <https://doi.org/10.7556/jaoa.2008.108.12.699>.
- Khan, F.H., Pasha, M.A. and Masud, S. (2021). Advancements in microprocessor architecture for ubiquitous-an overview on history, evolution, and upcoming challenges in a implementation. *Micromachines*, 12(665). <https://doi.org/10.3390/mi12060665>.
- Kırılmaz, H., Kılıç Kırılmaz, S. and Kahraman, M. (2018). Sağlık personelinin bilgi sistemi işlevlerini kullanımları ve örgütsel performansa etkisi. *Strategic Public Management Journal*, 4(8), 62-80. <https://doi.org/10.25069/spmj.474458>.
- Kiberu, V. M., Mars, M. and Scott, R. E. (2017). Barriers and opportunities to implementation of sustainable e-health programmes in Uganda: A literature review. *African Journal of Primary Health Care and Family Medicine*, 9(1), 1-10. <https://doi.org/10.4102/phcfm.v9i1.1277>.
- Kim, Y., Park, J. Y., Kim, S. B., Jung, I. K., Lim, Y. S. and Kim, J. H. (2010). The effects of internet addiction on the lifestyle and dietary behavior of Korean adolescents. *Nutr Res Pract.*, 4, 51-7. <https://doi.org/10.4162/nrp.2010.4.1.51>.
- Kouton, J. and Bétula, R. R. and Lawin, M. (2021). The impact of ICT development on health outcomes in Africa: Does Economic Freedom Matter? *Journal of the Knowledge Economy*, 12:1830-1869.
- Mahmud, A. J., Olander, E., Eriksén, S. and Haglund, B. J. (2013). Health communication in primary health care-A case study of ICT development for health promotion. *BMC Medical Informatics and Decision Making*, 17 (13). <http://www.biomedcentral.com/1472-6947/13/17>.
- Mamun, M. A., Sohog, K. and Akhter, A. (2013). A dynamic panel analysis of the financial determinants of CSR in Bangladeshi banking industry. *Asian Economic and Financial Review*, 3(5), 569-570. <http://aessweb.com/journal-detail.php?id=5002>.
- Majeed, M. T. and Khan, F. N. (2019). Do information and communication technologies (ICTs) contribute to health outcomes? An empirical analysis. *Qual Quant*, 53, 183-206. . <https://doi.org/10.1007/s11135-018-0741-6>.
- May, C. R., Finch, T. L., Cornford, J., Exley, C., Gately, C., Kirk, S., Jenkins, K. N., Osbourne, J., Robinson, A. L., Rogers, A., Wilson, R. and Mair, F. S. (2011). Integrating telecare for chronic disease management in the community: What needs to be done? *Health Services Research*, 2011, 11: 131.
- Ömürbek, N. and Altın, F. G. (2009). Sağlık bilişim sistemlerinin uygulanmasına ilişkin bir araştırma: İzmir örneği. *SDÜ Fen Edebiyat Fakültesi Sosyal Bilimler Dergisi*, 19, 211-232.
- Patterson, D. A. (2020). Information technologies. *Scientific American*, 273(3), (September 1995), 62-67. <https://www.jstor.org/stable/10.2307/24981716>.
- Pesaran, M. H. (1997). The role of economic theory in modelling the long run. *The Economic Journal*, 107 (440), 178-191.
- Pesaran, M. H., Shin, Y. and Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(446), 621-634. <https://doi.org/10.1080/01621459.1999.10474156>
- Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *Discussion*, 1240, 1-42.
- Pesaran, M. H. (2007). A simple unit root test in the presence of cross section dependence. *Journal of Applied Econometrics*, (22), 265-312. <https://doi.org/10.1002/jae.951>.
- Pesaran, M., Ullah, A. and Yamagata, T. (2008). A bias-adjusted lm test of error cross-section independence. *Econometrics Journal*, 11(1), 105-127. <https://doi.org/10.1111/j.1368-423X.2007.00227.x>

- Peseran, M. H. and Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50-93. <https://doi.org/10.1016/j.jeconom.2007.05.010>.
- Rana, R. H., Alam, K. and Gow, J. (2018). Development of a richer measure of health outcomes incorporating the impacts of income inequality, ethnic diversity, and ICT development on health. *Globalization and Health*, 14(72). <https://doi.org/10.1186/s12992-018-0385-2>.
- Reinecke, L., Aufenanger, S., Beutel, M. E., Dreier, M., Quiring, O., Stark, B., Wölfling, K. and Müller, K. W. (2017). Digital stress over the life span: the effects of communication load and internet multitasking on perceived stress and psychological health impairments in a german probability sample. *Media Psychology*, 20(1), 90-115. <https://doi.org/10.1080/15213269.2015.1121832>.
- Rosell, M. C., Sánchez-Carbonell, X., Jordana, C. G. and Fargues, M. B. (2007). Adolescents and information and communications technologies: internet, mobile phone and videogames. *Papeles del Psicólogo*, 2007(28), 196–204. <http://www.cop.es/papeles>.
- Staras, K., Mačiulienė, M. and Stokaitė, V. (2013). Informacinių ir komunikacinių technologijų įtaka sveikatos priežiūros paslaugų teikimui. *Online Sveikatos Politika Ir Valdymas Health Policy And Management*, 1(5), 148–166. <https://doi.org/10.13165/SPV-13-1-5-10>.
- Tavares, A. I. (2018). eHealth, ICT and its relationship with self-reported health outcomes in the EU countries. *International Journal of Medical Informatics*, 112(2018), 104-113. <https://doi.org/10.1016/j.ijmedinf.2018.01.014>.
- Top, S. and Dilek, S. (2013). Sağlık hizmet sektöründe çalışanların kurumsal bilgi paylaşımı algılamasının ilişki analizi yoluyla değerlendirilmesi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 18(1), 283-304.
- Viorela Ligia Vaidean, V. L. and Achim, M. V. (2022). When more is less: Do information and communication technologies (ICTs) improve health outcomes? An empirical investigation in a non-linear framework. *Socio-Economic Planning Sciences*, 80 (2022), 101218.
- Westerlund, J. (2008). Panel cointegration tests of the fisher effect. *Applied Econometrics*, 23(2), 193-233. <https://doi.org/10.1002/jae.967>.
- World Bank (2020). Life expectancy at birth, total (years), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). Individuals using the internet (% of population), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). Fixed telephone subscriptions (per 100 people), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). GDP per capita (constant 2010 US\$), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). School enrollment, secondary (% gross), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). Physicians (per 1,000 people), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). CO2 emissions (metric tons per capita), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- World Bank (2020). Mobile cellular subscriptions (per 100 people), Haziran 29, 2021 tarihinde <https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=TR>.
- Yankın, F. B. (2019). Dijital dönüşüm sürecinde çalışma yaşamı. *Trakya Üniversitesi İktisadi ve İdari Bilimler Fakültesi E-Dergi*, 7(2), 1-38.
- Yücel, D. and Erkut, H. (2003). Bilişim teknolojilerinin çalışma yaşam kalitesi üzerine etkisi. *itüdergisi/d mühendislik*, 2(2), 49-59.
- Zhang, J., Gong, X. and Zhang, H. (2022). ICT diffusion and health outcome: Effects and transmission channels. *Telematics and Informatics*, 67 (2022), 101755.
- Zonneveld, M., Patomella, A. H., Asaba, E. and Guidetti, S. (2020). The use of information and communication technology in healthcare to improve participation in everyday life: a scoping review. *Disability and Rehabilitation*, 42(23), 3416–3423. <https://doi.org/10.1080/09638288.2019.1592246>.