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NEXUS BETWEEN INFORMATION AND COMMUNICATION TECHNOLOGIES AND PUBLIC HEALTH EXPENDITURES: EVIDENCE FROM TÜRKİYE

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ABSTRACT

Although the role of health-specific technologies has been extensively studied, the broader impact of general ICT (Information and Communication Technologies) adoption on public health expenditures remains unclear. This study investigates the long-run relationship between ICT (i.e., mobile cellular subscriptions per 100 people) and public health expenditures in Türkiye. Using annual time series data, an Autoregressive Distributed Lag (ARDL) model is estimated to analyse the long-term effects of ICT, GDP per capita, population aged 65 and over, and urbanization on public health expenditures. The findings show that ICT usage has a positive long-run relationship with public health expenditures. Additionally, the proportion of the population aged 65 and over and urbanization both positively influence public health expenditures in the long term. In contrast, GDP per capita demonstrates a negative association. The results highlight the importance of ICT infrastructure, population aging, and urban development in shaping public health financing. Policymakers should consider these structural factors in designing sustainable and inclusive public health expenditure strategies.

Keywords: ARDL Model, Public Health Expenditures, ICT, Mobile Phone Subscriptions, Türkiye

BİLGİ VE İLETİŞİM TEKNOLOJİLERİ İLE KAMU SAĞLIK HARCAMALARI ARASINDAKİ İLİŞKİ: TÜRKİYE ÖRNEĞİ

ÖZ

Sağlığa özgü teknolojilerin rolü kapsamlı bir şekilde incelenmiş olsa da, genel BİT kullanımının kamu sağlık harcamaları üzerindeki daha geniş etkisi belirsizliğini korumaktadır. Bu çalışma, Türkiye'de BİT (100 kişi başına mobil hücresel abonelik) ile kamu sağlık harcamaları arasındaki uzun vadeli ilişkiyi araştırmaktadır. Yıllık zaman serisi verileri kullanılarak, BİT, kişi başına GSYİH, 65 yaş ve üzeri nüfus ve kentleşmenin kamu sağlık harcamaları üzerindeki uzun vadeli etkilerini analiz etmek için ARDL model kullanılmıştır. Bulgular, BİT kullanımının kamu sağlık harcamalarıyla uzun vadede pozitif bir ilişkiye sahip olduğunu göstermektedir. Ek olarak, 65 yaş ve üzeri nüfus oranı ve kentleşme, uzun vadede kamu sağlık harcamalarını olumlu yönde etkilemektedir. Buna karşılık, kişi başına GSYİH negatif bir ilişki göstermektedir. Sonuçlar, kamu sağlık finansmanının şekillenmesinde BİT altyapısının, nüfus yaşlanmasının ve kentsel kalkınmanın önemini vurgulamaktadır. Politika yapıcılar, sürdürülebilir ve kapsayıcı kamu sağlık harcama stratejileri tasarlarken bu yapısal faktörleri dikkate almalıdır.

Anahtar Kelimeler: : ARDL Model, Kamu Sağlık Harcamaları, ICT, Mobil Telefon Aboneliği; Türkiye

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INTRODUCTION

The digital transformation of society has introduced new determinants into the dynamics of public health financing. Among these, the diffusion of Information and Communication Technologies (ICT) has drawn increasing attention for its potential to indirectly influence public healthcare demand and government spending. In countries such as Türkiye, where the state is the primary provider and financer of healthcare services, public health expenditure constitutes a key component of the national budget and a central indicator of health system performance. Therefore, it becomes crucial to investigate how shifts in demographic structure, urbanization, income levels, and particularly ICT with trends in government healthcare expenditures.

Internet penetration, as one of the most important proxies for ICT diffusion, has become a central variable in health economics research. While internet access is not a direct component of public healthcare budgets, its impact on health service demand, policy responsiveness, and health system management suggests a plausible indirect link to public expenditure trends (Buntin et al., 2011; Kruse & Beane, 2018). Previous studies have demonstrated that increased internet connectivity correlates with more informed health-seeking behaviour among citizens, potentially increasing the demand for publicly funded services, including diagnostics, outpatient visits, and preventive screenings (Chang et al., 2021; Shao & Dou, 2022). This behavioural shift can increase financial pressure on governments, particularly in countries such as Türkiye, that aim to maintain universal access to healthcare, especially where services is free or heavily subsidized. Moreover, access to digital platforms can influence the utilization patterns of public healthcare by reducing barriers to information, facilitating appointment scheduling, and improving awareness of entitlements, thereby driving up service use and, by extension, government spending (Chaudhry et al., 2006; Kavandi et al., 2024). In this study, mobile cellular subscriptions per 100 inhabitants are used as a proxy for ICT diffusion. Unlike broadband-based indicators, mobile subscriptions are considered more appropriate in contexts where mobile networks serve as the primary means of internet access. Given the widespread adoption of smartphones and mobile broadband, this measure effectively reflects the population's potential to interact with digital health services.

For example, in Türkiye, MHRS (Central Physician Appointment System), which is considered as one of the important digitalization steps taken within the framework of the "health transformation program" in Türkiye, started to serve all over the country in 2012. Prior to the MHRS implementation, many hospitals were using their own appointment systems. With MHRS, it is planned to carry out outpatient services with appointments in Public Hospitals from a single centre. Although there are similar examples at regional level in the world, it is the first physician appointment system carried out from a single centre throughout the country. Among the most important objectives of MHRS are to ensure equal and fair access of patients to health services and to facilitate the organization of appointments between patients and doctors. The MHRS mobile application was launched in 2013. Hence, MHRS can provide services to citizens at 99.6% accessibility level through Alo 182 call center, internet, mobile applications, hospitals and family physicians (Central Physician Appointment System, 2025).

At the macro level, technological advancement is frequently associated with increased public health expenditure, even when not explicitly itemized within budgetary frameworks (Sorenson et al., 2013). This relationship underscores the role of broader technological diffusion—measured through proxies such as internet usage—as an external, demand-side determinant of public health spending (Murthy & Ketenci, 2017).

Demographic and structural factors—such as population aging, urbanization, and rising income levels—are significant determinants of public health expenditure. Population aging is associated with increased utilization of healthcare services, leading to higher public health spending (Navarro-García & Sarria-Santamera, 2023). Urbanization contributes to elevated healthcare costs due to increased demand for medical services in urban areas (Shao et al., 2022). Additionally, higher income levels correlate with greater health expenditures, reflecting increased access to and consumption of healthcare services (Gemma et al., 2019).

The impact of ICT on health expenditure varies across different contexts and is not always straightforward. While some studies suggest that digital expansion leads to short-term efficiency gains and cost containment (Lee & Dowd, 2013), others report a net increase in public spending due to increased service uptake (Kavandi et al., 2024). In middle-income countries, such as Türkiye, the ICT-health expenditure relationship may exhibit different dynamics due to differing healthcare infrastructure maturity and policy environments (Kavandi et al., 2024).

This study contributes to this growing literature by empirically investigating the relationship between ICT and health expenditures in Türkiye over the period 1990–2022. Using the Autoregressive Distributed Lag (ARDL) bounds testing approach, the analysis focuses exclusively on government health spending, incorporating mobile cellular subscriptions per 100 people as a proxy for digital engagement while controlling for economic growth, aging population, urbanization, and structural shocks such as COVID-19.

1. Data and Methodgy

1.1. Data and Variables

This study investigates the relationship between Information and Communication Technologies (ICT) and public health expenditures in Türkiye over the period 1990–2022. Annual time series data are employed, sourced primarily from the

World Development Indicators (WDI) for all variables except public health expenditures which is gathered from OECD[1]. The dependent variable is the natural logarithm of public health expenditures as a share of GDP (LNHEX). The main independent variable is the natural logarithm of ICT usage (LNICT), proxied by mobile cellular subscriptions (per 100 people). Control variables include the natural logarithm of GDP per capita, (constant 2015 US$) (LNGDPPC), the natural logarithm of the urban population share (LNURBANPOP), and the proportion of the population aged 65 and above (LNPOP65). A dummy variable (COVID) is included to control for structural shocks during the COVID-19 pandemic.

This study employs a quantitative time-series research design to examine the relationship between information and communication technologies (ICT), proxied by mobile phone subscriptions, and public health expenditure in Türkiye. The analysis is based on annual data covering the period 1990-2022, obtained from World Bank, OECD.

From a methodological perspective, the study adopts the Autoregressive Distributed Lag (ARDL) bounds testing approach to cointegration, as developed by Pesaran, Shin, and Smith (2001). The ARDL model is particularly suitable for this analysis because it allows for the estimation of both short-run and long-run dynamics regardless of whether the variables are integrated of order I(0) or I(1), provided that none is integrated of order I(2). Additionally, ARDL is appropriate for small sample sizes and helps address potential endogeneity issues through the inclusion of lagged variables.

Table 1. Descriptive Statistics

	HEX	ICT	GDPpc	URBANPOP	POP_OVER_65
Mean	3.028	55.686	8315.572	68.363	6.702
Maximum	4.423	105.807	14055.103	77.022	9.719
Minimum	1.466	0.058	5101.207	59.203	4.740
Std. Dev.	0.778	41.160	2726.637	5.476	1.381
Observations	33	33	33	33	33

The Table 1 presents the summary statistics for five key variables — HEX (Health Expenditure), ICT (Information and Communication Technology usage), GDPpc (GDP per capita), URBANPOP (Urban Population rate), and POP_OVER_65 (percentage of the population aged 65 and above) — based on 33 observations. On average, Health expenditure (HEX) is 3.028, with values ranging from 1.466 to 4.423 and a standard deviation of 0.778, indicating moderate variability. the ICT shows a mean value of 55.686, ranging widely from 0.058 to 105.807, and a high standard deviation of 41.160, suggesting substantial dispersion across observations. GDP per capita averages at 8,315 USD, with a minimum of 5,101 USD and a maximum of 14,055 USD, and a standard deviation of 2,726 USD, highlighting notable differences among the units analyzed. Urban population rates (URBANPOP) average 68.363%, with relatively lower variation (standard deviation of 5.476), fluctuating between 59.203% and 77.022%. Lastly, the elderly population (POP_OVER_65) has a mean of 6.702%, a minimum of 4.740%, a maximum of 9.719%, and a relatively low standard deviation of 1.381, suggesting less pronounced variation among the observations.

1.2. Econometric Approach: ARDL Model

To assess the short-run and long-run relationships among the variables, the Autoregressive Distributed Lag (ARDL) bounds testing approach developed by Pesaran et al. (2001) is employed. The ARDL method is particularly suitable for small sample sizes and for models in which the variables are integrated of different orders, i.e., I(0) and I(1), but not I(2). Prior to estimation, the stationarity of each variable is tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests.

The general form of the ARDL (p, q1, q2, ..., qk) model is specified as (Eq. 1):

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \sum_{j=0}^{q_1} \gamma_j \Delta X_{1,t-j} + \cdots + \sum_{j=0}^{q_k} \delta_j \Delta X_{k,t-j} + \varphi_1 Y_{t-1} + \varphi_2 X_{1,t-1} + \cdots \varphi_{k+1} X_{k,t-1} + \varepsilon_t \qquad (1)$$

where Y_t denotes the dependent variable (LNHEX), X_k are the explanatory variables (LNICT, LNGDPPC, LNPOP65, LNURBANPOP), and Δ represents the first-difference operator. The coefficients on the differenced terms represent short-run dynamics, while the lagged level terms capture long-run relationships.

1.3. Bounds Test for Cointegration

To examine the existence of a long-run relationship among the variables, the bounds test for cointegration is applied. The null hypothesis of the test is that there is no long-run relationship among the variables. The computed F-statistic is compared with critical values provided by Pesaran et al. (2001). If the F-statistic exceeds the upper bound of the critical value, the null hypothesis is rejected, indicating cointegration.

1.4. Error Correction Representation

[1] Ethics committee approval is not required for this study as the data are entirely sourced from publicly available and open-access databases, specifically the WDI and OECD. All scientific research and publication ethics rules are strictly adhered to during the preparation and writing of this manuscript.

If cointegration is established, the error correction model (ECM) is estimated to capture both short- and long-run dynamics. The error correction term (ECT) represents the speed at which the system returns to equilibrium following a short-term shock. A statistically significant and negative coefficient of the ECT confirms the presence of a stable long-run relationship.

1.5. Error Correction Representation

After estimating the ARDL and ECM models, a series of diagnostic tests are conducted to ensure the robustness of the results. These include tests for serial correlation, heteroskedasticity, and normality of residuals. Additionally, the CUSUM and CUSUMSQ tests are employed to assess the stability of the model coefficients over the sample period.

2. Empirical Results

2.1. Unit root test

Before examining the potential cointegration among the variables, it is essential to determine their respective levels of integration. To this end, the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) and the Phillips-Perron (PP) test (Phillips & Perron, 1988) were employed. In both tests, the null hypothesis posits the presence of a unit root—indicating non-stationarity—while the alternative hypothesis suggests stationarity of the series. The unit root test results, presented in Table 3, reveal that all variables, except for ICT, are non-stationary in their levels. However, after taking the first differences, all series become stationary. These findings indicate a combination of I(0) and I(1) processes among the variables, thus justifying the application of the ARDL bounds testing approach.

Table 2. Unit Root Results

Variables	Augmented Dickey-Fuller (ADF)				Phillips-Perron (PP)			
	Level		First Difference		Level		First Difference	
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
lnHEX	-1.204	0.892	-4.534	0.005	-1.303	0.869	-4.556	0.005
lnICT	-6.159	0.000	--	--	-3.783	0.000	--	--
lnGDPpc	0.584	0.987	-5.656	0.000	1.806	0.999	-6.469	0.000
lnPOP65	-0.493	0.878	-3.732	0.000	0.898	0.994	4.312	0.000
lnURBANPOP	-2.027	0.274	-7.787	0.000	2.227	1.000	-11.447	0.000

2.2. ARDL Bound testing

This study utilizes the Autoregressive Distributed Lag (ARDL) model to analyze the relationship between Information and Communication Technologies (ICT) and health expenditures in Türkiye from 1990 to 2022. The model incorporates control variables such as GDP per capita, urbanization, the proportion of the elderly population, and a COVID-19 dummy variable.

To investigate the presence of a long-run relationship among the variables, we conducted a bounds test using an ARDL model with the lag structure (2,2,0,0,1) under the model specification of an unrestricted constant and restricted trend (Case IV). Table 3 reports the calculated F-statistic along with the corresponding critical values from Narayan (2005), which are adjusted for small sample sizes. The F-statistic exceeds the upper bound of the critical values, leading to a rejection of the null hypothesis of no cointegration. This result confirms the existence of a long-term equilibrium relationship among health expenditures, economic growth, ICT, urban population and population over 65 in the context of Türkiye.

Table 3. Co-integration Results of Bound Testing

Model	k	F-statistics	Decision	Lower bound	Upper bound
ARDL(2,2,0,0,1)	4	10.303	Yes	I(0)	I(1)
10% significance				2.68	3.53
5% significance				3.05	3.97
1% significance				3.81	4.92

Narayan (2005) provided the critical value constraints for lower I(0) and higher I(1). The following are the critical values for the boundaries test: Case III: unrestricted constant and restricted trend (k = 4); the optimal lag duration is chosen automatically based on SC.

2.3. ARDL Results

Table 4 presents both the long-run and short-run estimation results. Notably, all of the long-run coefficients are statistically significant, indicating robust relationships among the variables over the long term.

Table 4. Long-run and Short-run Estimation Results

Variables	Coefficient	Std. error	t-statistics	Prob
Long-run				
lnICT	0.12	0.013	9.137	0.000
lnGDPpc	-0.722	0.114	-6.285	0.000

lnPOP65	1.480	0.233	6.339	0.000
lnUrbanpop	8.163	2.860	2.853	0.009
Short-run				
D(lnICT)	-0.152	0.032	-4.747	0.000
D(lnUrbanpop)	-123.643	12.105	-10.213	0.000
ECM(-1)	-1.251	0.111	-11.209	0.000
Diagnostic tests				
R^2	0.900			
Adjusted R^2	0.880			
F-statistic	45.155 (0.000)			
DW	1.709			
Jarque–Bera	0.861 (0.771)			
x^2 Reset	0.113 (0.911)			
x^2 LM	2.786 (0.114)			
x^2 BPG	1.112 (0.429)			

The ARDL model reveals a statistically significant positive long-run relationship between ICT and health expenditures (β = 0.12, p < 0.01). This suggests that increased ICT adoption correlates with higher health expenditures over time, potentially due to investments in digital health infrastructure and the integration of advanced technologies into healthcare services. This finding aligns with Rana et al. (2020) and Zhang et al. (2022), reporting that ICT penetration would have an increasing effect on public health expenditure for 38 low-income countries and China, respectively.

Additionally, the proportion of the population aged 65 and over and urbanization are positively associated with health expenditures in the long run. An aging population typically requires more healthcare services, and urban areas often have greater access to healthcare facilities, leading to higher utilization rates. These findings are consistent with previous research highlighting demographic shifts as significant contributors to increased healthcare spending (Boz et al., 2020; Shao et al., 2022; Zhang et al., 2022).

Interestingly, GDP per capita exhibits a negative long-run relationship with health expenditures (β = -0.722, p < 0.01). This may suggest that as income levels rise, health expenditures as a proportion of GDP may decline, possibly due to improved efficiency in healthcare delivery or shifts in spending patterns. However, this contrasts with some studies indicating a positive relationship between economic growth and health expenditures, suggesting that the relationship may be context-dependent (Fedeli, 2015; Lago-Peñas et al., 2013).

The error correction term (ECT) is negative and highly significant (β = -1.251, p < 0.01), confirming the existence of a stable long-run relationship and a rapid adjustment mechanism. In the short run, ICT coefficients are negative and significant, indicating cost-reducing effects possibly driven by efficiency gains through digitalization. For instance, the use of e-health records and automated diagnostics may initially reduce transaction costs and administrative overhead.

GDP per capita also displays a dynamic short-run pattern—initially decreasing health expenditures, followed by positive effects in lagged terms. This result may reflect reallocation effects during income shocks or delays in healthcare consumption behavior as income rises. Urbanization has a short-term negative effect on health expenditures. Although counterintuitive, this might be explained by infrastructure bottlenecks or lagging health service expansion relative to population growth in urban centers.

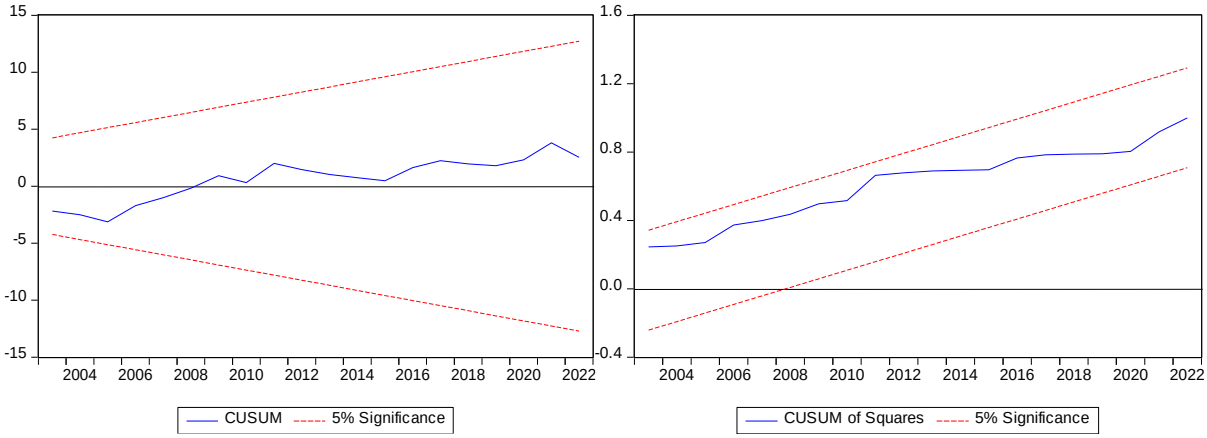

Figure 1. CUSUM and CUSUM of square tests

Diagnostic testing in ARDL models plays a vital role in ensuring the accuracy and reliability of the results. The outcomes of these tests are presented at the bottom of Table 4. Based on the diagnostic checks, the model does not suffer from autocorrelation or heteroskedasticity, and the residuals are normally distributed, indicating no issues with model specification. Additionally, CUSUM and CUSUMSQ tests were conducted to assess the presence of structural breaks in the data, as shown in Figure 1. The results of these tests show that the test statistics lie within the 5% critical bounds,

suggesting that the model coefficients remain stable over the study period. This implies that the estimated parameters are consistent throughout the analysis timeframe.

DISCUSSION AND CONCLUSION

This study examines the relationship between public health expenditures and information and communication technologies in Türkiye between 1990 and 2022. Mobile phone subscription per 100 people was used as a proxy for information and communication technologies. There are several reasons for this. First, mobile phone subscription is the variable with the highest number of observations in the World Bank dataset for the period under study. Second, there is a close relationship between individual mobile phone subscription and public health demand.

Autoregressive Distributed Lag (ARDL) model reveals a statistically significant and positive long-run relationship between ICT and public health expenditures. This finding suggests that increased ICT adoption correlates with higher public health expenditures over time. This result is consistent with previous empirical studies that underscore the fiscal implications of ICT adoption in healthcare systems (Blake et al., 2023; Okunade et al., 2018). Mobile phones enable easier access to health information, remote consultations, and monitoring apps, encouraging more frequent healthcare interactions. For instance, Patrick et al. (2008) found that mobile phones increase patient engagement with healthcare systems, potentially boosting diagnostic and treatment rates. It means that mobile connectivity facilitates the deployment of mobile health applications, including remote monitoring, mobile-based health promotion, and teleconsultation services, which require substantial infrastructure investment and ongoing operational costs (Bhavnani et al., 2008). The integration of such technologies into public health systems has been shown to expand access and improve the efficiency of service delivery, however it also imposes financial demands on governments (Iribarren et al., 2017). Health systems have invested in tools to integrate and interpret data from mobile health devices, requiring upgraded infrastructure, cybersecurity, and analytics platforms—all of which add to expenditure. In a systematic review, Lee et al. (2016) found that mobile health interventions improved healthcare access and outcomes in several countries, but also required the expansion of health infrastructure, data systems, and workforce training, all of which contribute to higher public health expenditures. Similarly, Martínez-Pérez et al. (2013) highlighted how mobile platforms, while improving communication and healthcare delivery, necessitate additional public investment to ensure technological integration, system reliability, and equitable coverage. It is widely known that as access improves through mobile connectivity, the utilization of healthcare services often rises, placing further pressure on public budgets (Humphreys & Smith, 2009; Kouadio et al., 2012).

This study also finds a statistically significant long-run positive relationship between the proportion of the population aged 65 and over and public health expenditures. As the population ages, the demand for healthcare services tends to increase due to the higher prevalence of chronic diseases, greater need for long-term care, and more frequent interactions with the healthcare system (Lopreite & Zhu, 2020; Poudel & Gajurel, 2023; Xu et al., 2007). Public health systems allocate additional resources to accommodate these needs, which contributes to rising government healthcare expenditures (Santos-Jaén et al., 2022).

Moreover, urbanization is also found to have a positive and significant long-run association with public health expenditures. Urban areas often provide better access to healthcare services, more specialized medical facilities, and a wider availability of health technologies, which collectively lead to higher utilization rates and thus greater public spending (Ogunbekun et al., 1999; Shao et al., 2022). Additionally, urban populations tend to have more awareness and expectations regarding healthcare services, which further drives demand (Yadav et al., 2011). Raghupathi et al. (2020) showed that urban density and infrastructure expansion contribute to increased health expenditures by governments seeking to meet the higher service demands in metropolitan regions.

Interestingly, the results of this study reveal a statistically significant negative long-run relationship between GDP per capita and public health expenditures. This finding suggests that as economic wealth increases, the relative burden on public health budgets may decrease. One potential explanation is that rising income levels could lead to increased private healthcare spending, thereby reducing the reliance on publicly funded health services. Increased individual wealth may lead to a greater utilization of private healthcare providers, health insurance schemes, and out-of-pocket services, potentially reducing the demand placed on the public healthcare system (Xu et al., 2007). Additionally, higher income may lead to healthier lifestyles and greater health awareness, potentially lowering public expenditure related to preventable diseases (Larrimore, 2011; Yen et al., 2017). In the Turkish context, where private healthcare options have expanded in recent decades, it is plausible that rising income levels are associated with a substitution effect, diverting demand away from public health services. Therefore, the negative long-run association identified in this study may reflect the combined influence of rising private sector participation, shifting household preferences, and strategic public spending priorities.

This study reveals that ICT usage is positively associated with public health spending over the long term. The study also confirms that demographic and structural factors play crucial roles in shaping health expenditures. Specifically, the proportion of the population aged 65 and over and the level of urbanization both exhibit significant positive long-run relationships with health expenditures. Conversely, GDP per capita is found to have a significant negative long-run association with public health spending.

Although this study provides valuable insights into the relationship between ICT and public health expenditures in Türkiye, several limitations should be acknowledged. First, the study relies solely on mobile cellular subscriptions per

100 people as a proxy for ICT. While this variable is a widely accepted proxy, ICT is a multifaceted concept that also encompasses broadband internet access, digital health records, telemedicine, and health information systems. Future studies could incorporate composite ICT indices to capture a more comprehensive technological landscape.

Second, the analysis is confined to a single country context. Given Türkiye's specific health system structure and economic dynamics, the findings may not be directly generalizable to other developing or developed nations. Finally, while key macroeconomic and demographic variables were included in the study model, other potential determinants of public health expenditures such as out-of-pocket health spending, specific institutional health policy reforms, and advancements in medical technologies were omitted due to data constraints.

The results highlight the complex interplay between technology adoption, demographic shifts, economic development, and healthcare financing. Policymakers should recognize that expanding ICT infrastructure, while beneficial for service efficiency and accessibility, may also require sustained public investment. Moreover, preparing for the fiscal impacts of population aging and urbanization will be essential to ensuring the sustainability of public health systems in Türkiye. In addition, ICT can have both cost-saving and cost-increasing effects, depending on the time horizon. Policymakers in Türkiye should support ICT expansion in healthcare but simultaneously design cost-control measures and monitor long-term spending trajectories. Public-private partnerships and digital health strategies must be aligned with financing frameworks to ensure sustainability. The role of GDP and demographic shifts in shaping health expenditures calls for proactive planning—particularly in preparing for aging populations and urban health service demands. Economic growth alone is not sufficient to contain health spending; targeted health reforms and investment in preventive care will also be critical. Future research could explore the differentiated effects of various ICT subcomponents (e.g., broadband access, digital literacy) and examine whether similar patterns hold in other middle-income countries undergoing digital transformation and demographic transition.

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EXTENDED ABSTRACT

GENİŞLETİLMİŞ ÖZET

BİLGİ VE İLETİŞİM TEKNOLOJİLERİ İLE SAĞLIK HARCAMALARI ARASINDAKİ İLİŞKİ: TÜRKİYE ÖRNEĞİ

Toplumun dijital dönüşümü, kamu sağlığı finansman dinamiklerine yeni belirleyiciler kazandırmıştır. Bu unsurlar arasında Bilgi ve İletişim Teknolojilerinin (BİT) yaygınlaşması, kamu sağlık hizmetleri talebini ve devlet harcamalarını dolaylı olarak etkileme potansiyeliyle giderek daha fazla dikkat çekmektedir. Devletin sağlık hizmetlerinde temel sunucu ve finansör rolünü üstlendiği Türkiye gibi ülkelerde kamu sağlık harcamaları, ulusal bütçenin temel bir bileşenini ve sağlık sistemi performansının merkezi bir göstergesini oluşturmaktadır. Bu bağlamda demografik yapı, kentleşme, gelir seviyeleri ve özellikle BİT düzeyindeki değişimlerin devletin sağlık harcamalarıyla nasıl bir etkileşim içinde olduğunu incelemek büyük önem taşımaktadır. Bu çalışma, 1990–2022 döneminde Türkiye özelinde BİT ile kamu sağlık harcamaları arasındaki uzun dönemli ilişkiyi ampirik olarak inceleyerek literatüre katkı sağlamayı amaçlamaktadır.

Çalışmada 1990-2022 yıllarını kapsayan yıllık zaman serisi verileri kullanılmıştır. Bağımlı değişken olan ve GSYH içindeki pay olarak ifade edilen kamu sağlık harcamaları (LNHEX) verisi OECD'den; diğer bağımsız ve kontrol değişkenleri ise Dünya Bankası Kalkınma Göstergeleri (WDI) veri tabanından elde edilmiştir. Analizde Gecikmesi Dağıtılmış Otoregresif (ARDL) Sınır Testi yaklaşımı benimsenmiştir. Modelde temel bağımsız değişken olarak dijital katılımı temsilen 100 kişi başına düşen mobil hücresel abonelik sayısının doğal logaritması (LNICT) kullanılmıştır. Kontrol değişkenleri olarak; kişi başına düşen GSYH'nin doğal logaritması (2015 sabit ABD doları bazında, LNGDPPC), kent nüfusu oranının doğal logaritması (LNURBANPOP) ve 65 yaş ve üzeri nüfus oranının doğal logaritması (LNPOP65) modele dâhil edilmiştir. Ayrıca, COVID-19 pandemisinin yarattığı yapısal şokların etkisini kontrol altına almak amacıyla modele bir kukla değişken (COVID) eklenmiştir.

ARDL modelinden elde edilen bulgular, BİT kullanımı ile kamu sağlık harcamaları arasında uzun dönemde pozitif ve anlamlı bir ilişki olduğunu ortaya koymaktadır. Analiz sonuçları, demografik ve yapısal faktörlerin de sağlık harcamalarının şekillenmesinde kritik bir rol oynadığını doğrulamaktadır. Özellikle 65 yaş ve üzeri yaşlı nüfus oranı ile kentleşme düzeyi, kamu sağlık harcamalarıyla uzun dönemde istatistiksel olarak anlamlı ve pozitif bir ilişki sergilemektedir. Öte yandan, kişi başına düşen GSYH ile kamu sağlık harcamaları arasında uzun dönemde istatistiksel olarak anlamlı ve negatif bir ilişki tespit edilmiştir.

Sonuçlar; teknoloji benimsemesi, demografik değişimler, ekonomik kalkınma ve sağlık finansmanı arasındaki karmaşık etkileşimi göz önüne sermektedir. BİT altyapısının genişletilmesi hizmet verimliliği açısından faydalı olsa da, karar alıcılar bunun sürekli bir kamu yatırımı gerektirdiğinin bilincinde olmalıdır. BİT'in zaman ufkuna bağlı olarak hem maliyet düşürücü hem de maliyet artırıcı etkileri olabileceğinden, dijitalleşme desteklenirken eş zamanlı olarak maliyet kontrol mekanizmaları tasarlanmalıdır. Ekonomik büyüme tek başına sağlık harcamalarını kontrol altına almak için yeterli değildir; artan kentsel hizmet talepleri ve yaşlanan nüfus dikkate alınarak koruyucu sağlık hizmetlerine yönelik proaktif yatırımlar yapılmalıdır. Gelecek çalışmalar, genişbant erişimi gibi BİT alt bileşenlerinin etkilerini analiz edebilir ve benzer eğilimlerin dijital dönüşüm geçiren diğer orta gelirli ülkelerde de geçerli olup olmadığını inceleyebilir.

KATKI ORANI BEYANI, ÇIKAR ÇATIŞMASI BİLDİRİMİ VE YAPAY ZEKA KULLANIM BİLDİRİMİ

AUTHOR CONTRIBUTION, CONFLICT OF INTEREST AND ARTIFICIAL INTELLIGENCE USE DECLARATION

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