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Examining the Nexus between ICT Adoption, and Economic Growth in Oman: jeopardize environment sustainability

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Abstract

This study evaluated the sustainability of ICT adoption and economic development. The study looked at the ICT indicators that have the effects economic growth. Using a dataset for a period of 1975-2021 of ICT indicators (mobile cellular subscriptions (MCS), fixed broadband subscriptions (FBS), fixed telephone subscriptions (FTS), people using the internet (PUI) and GDP taken from the Oman Telephone Regulatory Authority and the World Bank Data Group. The ICT indicators served as the dependent variable, and GDP was chosen as the independent variable. The study employs unit root test, vector error correction model (VECM), and ARIMA for forecasting. The study revealed that fixed broadband subscriptions (FBS) have a significant positive long-term impact on Oman's GDP growth. Forecasts predict a steady decline in real GDP growth, turning negative by 2054.The study suggests projected decline in GDP growth without substantial mitigation measures underscores the urgent need for policies that balance economic development.

Keywords: *Ict, Fixed Broadband Subscription, Fixed Telephone Subscription, Mobile Cellular Subscription, People Using Internet, Gdp.*

JEL: O33, O47, C53, O11

Introduction

The knowledge economy is based on information and communication technology, or ICT. Global economies are rapidly becoming more digital, which emphasizes how important ICT is as a driving force behind economic development. In order to promote connectivity and facilitate effective resource allocation, ICT has proven to be essential. However, depending on the nation's technological infrastructure, policies, and economic structure, the benefits of ICT adoption are not seen consistently across regions. The ICT sector helps boost the economic growth of the Sultanate of Oman and address sustainability goals, particularly through Oman Vision 2040 highlights digital transformation as an essential means of economic diversification, *(Oman-Vision-2040).* With initiatives including the National Digital Economy Program (NDEP) and collaborations in digital skills development, ICT's contribution to Oman's GDP is expected to increase to 3% by 2025 and 10% by 2040. In Oman, the ICT sector is defined by four key performance indicators FTS, FBS, MCS, and MBS that underscore the sector's substantial impact on the nation's GDP. (Oxford Business Group (2024). Abdul-Wahab (2015) found that

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Oman's carbon dioxide (CO_2) emissions had grown over the last 40 years. Despite economic growth, Oman has not yet achieved sustainable development (Alam,2022). However, Oman has committed to reducing GHG emissions by 2% by 2030 (MOECA, 2015). Naseem (2023) notes several factors driving the need for a transition toward sustainable practices: the trend toward modernization, internet surveillance (IS), an inadequate focus on quantum circular economic growth, and their impact on environmental sustainability. According to You et al. (2024), Oman has invested in ICT infrastructure as part of its Vision 2040 strategy, striving to diversify its economy beyond oil. Alshubiri (2023) found that, through infrastructure, societal empowerment, technological growth, and digitalization, Oman's digital economy benefits productivity and strengthens the monetary system, supporting economic growth and environmental sustainability. Abdel-Gadir (2020) found that economic growth and energy consumption increased Oman's CO_2 emissions. However, the potential future impact of internet usage on emissions should not be dismissed. Al- Shammari et al. (2022) explored cointegration and causal relationships among ICT, CO_2 emissions, economic development, trade, and total population across GCC countries. They found no significant relationship between trade and CO_2 emissions, although a negative correlation was identified between population growth and CO_2 emissions. Given Oman's Vision 2040 and its commitment to net-zero emissions, it is crucial to understand the present and future impacts of each ICT indicator on economic growth and environmental stability. Al-Busaidi (2020) identified significant positive short- and long-term relationships between digitalization and productivity. Meanwhile, in Bangladesh, Focusing on GCC (Gulf Cooperation Council) countries, Al-Shammari et al. (2022) also found a positive relationship between CO_2 emissions, ICT, and economic development Additionally, Wiranatakusuma (2024) proposed that ICT growth, especially through mobile cellular subscriptions (MCS), contributes to GDP in Indonesia, even though this comes with trade-offs, including the unexpected negative impact of fixed telephone services (FTS) on the gross domestic product (GDP). Finally, Sridhar and Sridhar (2009) found strong correlations between telecommunications infrastructure, mobile networks, and labor productivity, with positive implications for national income levels in ASEAN countries. According to Appiah-Otoo (2024), energy-intensive ICT components, such as data centers and mobile networks, are big contributors to carbon emissions, creating a trade-off between economic and environmental goals. Similarly, Lee and Brahmasrene (2014) found that although ICT boosts economic growth, it also increases CO_2 emissions. The same study identified a significant inverse bidirectional relationship between economic growth and CO_2 emissions in the ASEAN region, highlighting the need for a balanced approach to ICT development and sustainability. According to Díaz-Roldán (2021), ICT contributes to per capita economic growth in European countries. Furthermore, higher investment in the ICT sector is associated with lower GHG emissions. However, technological inefficiency remains a substantial barrier to achieving sustainable environmental goals. While there is a large body of research on ICT and economic development, there are gaps in our understanding of the short- and long-term effects of ICT indicators (fixed broadband subscriptions (FBS), fixed telephone subscriptions (FTS), mobile cellular subscriptions (MCS), and population using the internet (PUI)) on Oman's GDP. Despite growing attention to digitalization, few studies have addressed ICT's implications on Oman's economic. Moreover, no studies have examined future trends or assessed how all ICT indicators align with Oman's Vision 2040. This study aims to fill these gaps by applying various AI-driven models and econometrics techniques to establish causal relationships among ICT adoption and GDP of Oman.

Research Questions

How does ICT adoption impact Oman's GDP?

What are the projected trends and potential impacts of ICT adoption on GDP over the next 20 years?

Which ICT variables have the greatest or least impact on GDP growth

Study Objectives

To assess the impact of ICT adoption on Oman's GDP.

To project the trends and potential impacts of ICT adoption on GDP growth over the next 20 years.

Study Hypotheses

H (1): Higher levels of ICT adoption will contribute to the higher economic growth of Oman.

H (2): The continued growth of ICT adoption will benefit Oman's GDP, fostering economic development and innovation in the future.

Research Methodology

This study examines annual data on GDP growth rate (GDPGR), and ICT indicators per 100 people, mobile cellular subscriptions (MCS), fixed broadband subscriptions (FBS), fixed telephone subscriptions (FTS), and population using the internet (PUI). The dataset spans from 1975 to 2021, from the World Data Organization and the Telecommunications Regulatory Authority of Oman. Here, economic growth (GDPGR) is used as the dependent variables while MCS, FBS, FTS, PUI indicators act as the independent variables. The study applied a combination of methodologies to empirically address each research question.

Objectives 1

The study used a statistical time series, the vector error correction model (VECM), which was contingent on the data meeting the conditions of the unit root and cointegration tests (Dickey & Fuller, 1979). The VECM was built on the vector autoregressive (VAR) model but was specifically adapted to data that exhibited cointegration, indicating a long-term equilibrium relationship among the variables, despite short-term deviations (Johansen, 1991). The VECM adjusts for these deviations by including error-correction terms, restoring long-term balance. This model helped capture the linear interdependencies among ICT adoption and GDP, enabling an evaluation of their collective impact on Oman's economic growth.To accurately apply the VECM model, the optimal lag length was identified using four criteria: the Akaike information criterion (AIC), Schwarz Bayesian information criterion (SBIC), Hannan- Quinn criterion (HQC), and final prediction error (FPE). Furthermore, Johansen and Juselius' (1990) cointegration tests (the maximum eigenvalue and trace tests) were used to determine the number of cointegration vectors to understand the long-term relationship among variables. If the cointegration results indicated long-term relationships among ICT adoption, economic growth, this allowed for further modeling with the VECM to capture short-term dynamics and long-term equilibrium adjustments.

Objectives 2

The study applied Box and Jenkins' (1970) auto-regressive integrated moving average (ARIMA) modeling technique to capture temporal patterns for short- and medium-term predictions. ***SPSS' advanced AI tools and machine-learning algorithms (MLAs)*** were employed to enhance forecasting accuracy, refining the model and dynamically adjusting its parameters. This approach offered insights into the potential impacts of ICT adoption on emission reductions and economic growth during 2022–2054. ARIMA models require stationary data; thus, stationarity tests—particularly the augmented Dickey-Fuller (ADF) test—were conducted on the GDPGR to determine whether differencing was necessary. Non-stationary data (as indicated by a gradual decay in autocorrelation plots) were transformed using first differencing to achieve stationarity. The ARIMA model was then applied at the first difference, using the I(1) component. ARIMA Model has four stages first is Identification *phase which* involves determining the structure and parameters that best fit the time series data by analyzing its autocorrelation patterns. Correlograms of both autocorrelation (ACF) and partial autocorrelation (PACF) functions were used to guide the selection of model parameters for the ARIMA model, particularly the autoregressive AR(p), differencing(I), and moving average MA(q) components. Second is *Model estimation stage where t*he orders for the p, d, and q components of the ARIMA model were determined by analyzing the ACF and PACF plots of GDPGR. In third *Diagnostic checking* stage several diagnostic checks were performed to identify the optimal ARIMA model for forecasting GDP growth. Last is *Forecasting where a* forecast was generated for economic growth for 2022–2054, using the fitted ARIMA model.

Empirical Analysis

Result -Objectives 1

Step 1: Identification of the Optimal Lag Length

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1436.4270	NA	1.20e+21	65.56485	65.80815	65.65508
1	-1054.4990	642.3326	1.81e+14*	49.84088	51.54397	50.47246*
2	-980.0803	104.8631	3.46e+13*	48.09456*	51.25744	49.26751*
3	-916.2443	72.54909*	1.26e+13*	46.82929*	51.45198	48.54360*

Table 1-Lag Length Criterion

Source: *own compilation*

Table 1 presents the log-likelihood (LogL), LR (Likelihood Ratio) test statistic, final prediction error (FPE), Akaike information criterion (AIC), Schwarz criterion (SC), and Hannan-Quinn criterion (HQ) for various lag lengths. Most criteria (indicated with asterisks*), specifically LR, FPE, AIC, and HQ, ***indicate that three lags are optimal.***

Step 2: Unit Root Test for Assessing the Stationarity of the Series

Variables	P-value at level	P-value at first difference
Fixed Broadband Subscription-FBS (per 100 people)	0.684**	0.000*
Fixed telephone subscriptions (per 100 people)-FTS	0.7165**	0.000*
GDP growth rate -GDPGR-Annual	0.006**	0.000*
Papulation using the internet per 100 people-PUI	0.9278**	0.000*
Mobile cellular subscriptions (per 100 people)-MCS	0.5716**	0.000*

Table 2-Unit Root Test

Source: *own compilation,***=NS (non-stationary), *=S (stationary)

Table 2 presents the *p*-values of the augmented Dickey-Fuller (ADF) test, which was conducted to examine the stationarity of each variable at both the level and at the first difference. The results of the unit root test revealed that GDPGR, FTS, FBS, FTS, PUI, and MCS, become stationary after differencing, indicating they are integrated of order ***one, I(1), which is the assumption for applying VECM.***

Step 3: Johnson Cointegration Test-*H0 = There is no cointegration*

If TV(Trace Value) > critical value, H0 is rejected as there is integration. If EV(Eigen Value)> critical value, H0 is rejected as there is integration.

Hypothesized No. of Cointegrating Equations (CE)	Eigenvalue	Trace Statistic	Critical Value (0.05)	Prob.**	Integration
None	0.652704	108.8223	69.81889	0.0000	Yes
At most 1	0.579119	64.44432	47.85613	0.0008	Yes
At most 2	0.379119	31.22927	29.79707	0.0340	Yes
At most 3	0.297200	15.49417	15.49471	0.0501	No
At most 4	0.144118	3.844465	3.841466	0.0477	No

Table 3: Trace Test

Source: *own compilation,**The trace test indicates the presence of three cointegrating equations at the 5% level.***

Hypothesized No. of Cointegrating Equations (CE)	Eigenvalue	Max-Eigen Statistic	Critical Value (0.05)	Prob.**	Integration
None	0.652704	44.37832	33.87687	0.0013	Yes

At most 1	0.579119	33.21504	27.58434	0.0075	Yes
At most 2	0.379119	15.73511	21.13162	0.2448	No
At most 3	0.297200	11.64971	14.26460	0.1311	No
At most 4	0.144118	3.844465	3.841466	0.0477	No

Table 4: Maximum Eigenvalue Test

Source: *own compilation*, ***maximum eigenvalue test suggests two cointegrating equations at the 5% level.***

The trace test suggested three cointegrating equations while the maximum eigenvalue test suggested two (Tables 3 and 4). Both tests rejected the null hypothesis of no cointegration. This confirmed cointegration among the variables, a **prerequisite for applying the VECM.**

Step 4: Results of the VECM—Objective 1

H(1): Higher levels of ICT adoption will contribute to the higher economic growth of Oman, as reflected in an increase in the GDP growth rate.

	Cointegrating equation/ Long Run relationship				**Error correction estimate/ Short run diagnostic**			
Co- Integrating eq -1	Coefficient	Standard Error	t-Value (>1.94) at 5 % and 1.64 at 10 %	Significance (5% /10%level)	Adjustment Coefficient	Adjustment SE	Adjustment t-statistic (<0.05=significant)	Interpretation
GDPGR	1.000	(Normalized)	-	-	0.002147	0.02698	0.0795	***NS***; very slow adjustment to equilibrium.
FTS	1.045	1.94064	0.54	*NS*	-0.004947	0.00235	-2.105	*S, adjustment; corrects downward to equilibrium.*
FBS	*38.45*	22.4697	*1.71*	*Significant at 10% level (1.64)*	-0.003486	0.00054	-6.455	*HS, adjustment; rapidly corrects to equilibrium.*
MCS	-1.638	1.44665	-1.13	*NS*	0.005483	0.02126	0.258	***NS***; does not adjust to restore equilibrium.
PUI	-5.134	3.37162	-1.52	***NS***	0.002	0.00693	0.378	***NS***; does not adjust to restore equilibrium.

Table 5: VECM Model Results

Source: *own compilation,*

Sample (adjusted): 547, Obs.: 43

after adjustment. NS(Not significant),S(significant),HS(highly significant)

$$[\Delta GDPGR_t = \alpha + \beta GDPGR_{t-1} + \sum_{i=1}^{p-1} \Gamma \Delta Y_{t-1} + 1.0456 \cdot FTS_t + 38.4501 \cdot FBS_t - 1.63897 \cdot MCS_t + 13.34795 \cdot PUI_t + 115.32 + \epsilon_t]$$

..............................VECM Model ......Eq. 2

This VECM model (Eq. 2) captures how changes in **GDRGR** relate to various economic indicators in the long and short run. Each term's coefficient (1.0456 (FTS), 38.45 (FBS), -1.63 (MCS), and

13.34 (PUI)) indicates the direction and magnitude of that variable's impact on GDP growth. **FBS** had the greatest effect on GDPGR, with a one-unit increase in **FBS leading to a 38.4501% increase in GDPGR. Meanwhile, FTS had the lowest impact (1.045%) on** GDPGR. Overall, the findings suggest that among the studied variables, **FBS is the most influential**, making it a critical focus for policy interventions aimed at boosting GDP growth. At the same time, enhancing the contributions of other variables like FTS and PUI could provide additional support to economic performance.

Long-Term Relationship (Cointegrating Equation)

Table 5 presents the results of the ICT variables' long-term impacts on GDPGR. The results indicate that ***FTS does not*** **meaningfully influence GDP growth**, indicating that changes in FTS are unreliable predictors of GDP growth over time. Simultaneously, ***FBS had a coefficient of 38.45061, which is statistically significant at the 10% level. This indicates a strong positive relationship with GDP***, likely driven by its role in enhancing productivity and innovation. Neither MCS (-1.638971) nor PUI (-5.134799) were statistically significant, indicating that they do not substantially impact GDP growth in the long run.

Short-Term Dynamics (Error Correction Model)

Table 5 reports a *0.002147 adjustment coefficient for GDP growth. As this is not statistically significant,* this result indicates that GDP growth does not adjust rapidly to deviations from equilibrium. This implies that *short-term shocks in ICT variables do not lead to quick GDP corrections*, with GDP remaining stable despite economic fluctuations. The -0.004947-adjustment coefficient for fixed telecoms (*t*-statistic = -2.105) indicates a downward adjustment in the short run but no significant long-term impact on GDP. ***FBS exhibited a highly significant coefficient of -0.003486 (t-statistic = -6.455), reflecting rapid correction of deviations and supporting strong long-term GDP growth***. By contrast, MCS had an insignificant adjustment coefficient of 0.005483, indicating slow responses to shocks, while internet usage had a coefficient of 0.002623,which was also not significant. Overall, FBS was the most impactful ICT variable for restoring equilibrium, followed by FTS, supporting long-term GDP growth while components such as mobile and internet usage showed slower or less significant short-term adjustments.

Model Diagnostics

Metric	Value
R-squared-GDPGR	0.3387
Adjusted R-squared (GDPGR)	-0.0685
Adjusted R-squared (FTS)	0.3348
Adjusted R-squared (FBS)	*0.9420*
Adjusted R-squared (MCS)	0.6988
Adjusted R-squared (PUI)	0.8378
F-statistics (Prob.)	0.832282 (0.6423)

Table 6: Results of the Model Diagnostic Test

Source: *own compilation*

Table 6 shows the model's ability to *explain short-term variations in* GDPGR. A negative adjusted R-squared suggested that the predictors (FBS, FTS, PUI, and MCS) did not contribute to GDPGR. *FBS had a high adjusted R-squared of 0.9420, implying strong explanatory power*, while FTS performed poorly, with a much lower adjusted R-squared. The F-statistics of 0.832282 and *p*-value of 0.6423 indicated that the model was not statistically significant ($p > 0.05$). This means that the ***independent variables collectively do not explain all the variation in the dependent variable (GDPGR) in the short run.***The analysis demonstrated that FBS has a positive, significant, long-term relationship with GDPGR, indicating that increased broadband access enhances economic output in the long run. By contrast, FTS, MCS, and PUI did not significantly impact GDPGR in the long run. FBS was essential for maintaining equilibrium and driving sustained economic growth, with strong responsiveness to economic shocks, contributing to system stabilization. Moreover, FTS contributed to short-term adjustments but had no lasting impact on GDP, indicating that the independent variables collectively have limited explanatory power for GDPGR in the short run.The key conclusion is that **FBS has a significant, positive, long-term effect on Oman's GDPGR**, **supporting the hypotheses** related to its positive economic impact and essential role in stabilizing economic growth. Other ICT variables, including **FTS and MCS, were less influential** in the long run and primarily contributed to short-term adjustments without lasting economic impact, which **did not support our hypothesis**.

Result -Objective 2

H(2): The continued growth of ICT adoption will benefit Oman's GDP, fostering economic development and innovation in the future.

To achieve this objective, ARIMA modeling was applied to generate a reliable GDP forecast.

Step 1: Stationarity of the series)

This was confirmed by the ADF unit root test results, shown in ***Table 2***, leading to the application of first-order differencing (d = 1) for the ARIMA modeling. As the ARIMA model follows the Box-Jenkins methodology, this process comprises four stages to ensure accurate predictions: identification, estimation, diagnostic checking, and forecasting.

Step I1: Identification Stage of ARIMA —GDPGR

Lag	***Autocorrelation-Threshold of 0.05***	***Std. Err or***	***Box- Ljun g Stati stic***	***df***	***p-value***	***Autocorrelation Sig.***	***Box-Ljung Sig.(p<0.05=sig nificant)***
1	*0.475*	0.1	11.3 17	1	< 0.001	S-moderate positive correlation	S
2	-0.009	0.1	11.3	2	0.003	NS-weak correlations.	S
3	-0.035	0.1	11.3	3	0.010	NS-weak correlations.	S
4	0.030	0.1	11.4	4	0.022	NS-weak correlations.	S
5	-0.001	0.1	11.4	5	0.043	NS	S
6	0.062	0.1 33	11.6 51	6	0.070	NS	NS
7	***0.125-thresh hold***	***0.1***	***12.5***	***7***	***0.084***	NS	NS
8	0.315	0.1	18.4	8	0.018	S	S
9	0.267	0.1	22.7	9	0.007	S	S
10	0.057	0.1	22.9	10	0.011	NS	S
11	-0.120	0.1	23.8	11	0.013	NS	S
12	-0.030	0.1	23.9	12	0.021	NS	S
13	0.048	0.1	24.0	13	0.030	NS	S
14	-0.024	0.1	24.1	14	0.044	NS	S
15	-0.013	0.1	24.1	15	0.063	NS	NS
16	0.127	0.1	25.3	16	0.064	NS	NS

Table 7 Autocorrelation Significance and Ljung-Box Significance (GDPGR)

Source: *own compilation,* ***NS(Not significant),S(significant***

Table 7 reveals varying patterns and correlations across different lags. The autocorrelation of 0.475 at lag 1 suggests a moderate positive correlation with its previous value, supported by a significant Ljung-Box statistic of 11.317 and a *p*-value of < 0.001. This result implies that the series was not random and had predictive power from past observations. By contrast, lags 2 to 4 showed small autocorrelations ranging from -0.009 to 0.030, reflecting weak correlations. Although the Ljung-Box statistics remained significant (p < 0.05), the low strength of autocorrelation implied slight randomness or white noise characteristics in this range. For lags 5 to 7, the autocorrelation values remained low (-0.001 to 0.125), with *p*-values gradually increasing above 0.05, indicating diminishing significance. The Ljung-Box statistic showed a reduction in significance as lags increased, particularly by lag 7 (*p* = 0.084), suggesting weaker evidence of autocorrelation. Notably, lags 8 and 9 exhibited significant autocorrelations at 0.315 and 0.267, respectively. Both had significant Ljung-Box statistics (*p* = 0.018 and 0.007, respectively), indicating a non-random pattern and possible cyclical components or delayed effects in the series. Finally, from lags 10 to 16, the autocorrelation values fluctuated but remained low (ranging from -0.120 to 0.127), with a decreasing significance for the Ljung-Box statistic, showing *p*-values near or slightly above 0.05. By lag 16, the *p*-value was 0.064, suggesting that serial correlation was no longer significant, supporting the notion of reduced memory at longer lags. ***There was a clear indication of significant autocorrelation at lags 1, 8, and 9,*** indicating that the series may have a cyclical component with short-term memory at lag 1 and periodic influences at lags 8 and 9. Weak autocorrelation was found for other lags, and the Ljung-Box test did not consistently indicate significant autocorrelation, especially beyond lag 10. ***The significant autocorrelations at specific lags (1, 8, and 9) suggested that the ARIMA captured the underlying pattern.***

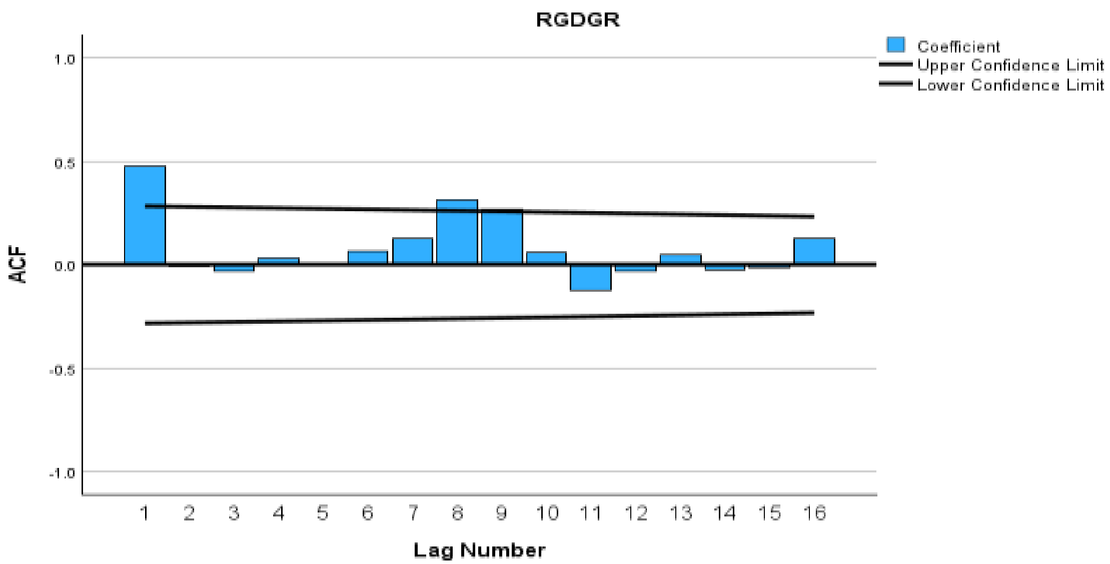

Figure 1: ACF plot—RGDPGR

Moving Average Order (qqq): The ACF plot in Figure 1 shows a ***significant spike at lag 1*** and smaller spikes at lags 8 and 9, followed by tapering values despite a noticeable spike at lag 9. This pattern suggests an MA component that could be modeled with q = 1. However, accounting for lag 9, it may also have been worth experimenting with q = 2q = 2q = 2.

Lag	Partial Autocorrelation	Interpretation ***Threshold=0.05***	Std. Error
1	***0.475***	**Significant, Moderate positive correlation with the previous value**	*0.146*

2	-0.303	Moderate negative correlation.	0.146
3	0.163	weak relationship	0.146
4	-0.040	weak relationship	0.146
5	-0.023	weak relationship	0.146
6	0.136	weak positive correlation	0.146
7	0.020	negligible effect of the seventh lag.	0.146
8	**0.363**	**moderate positive correlation**	0.146
9	-0.100	slight negative correlation,	0.146
10	0.042	slight positive effects	0.146
11	-0.152	negative effects	0.146
12	0.125	slight positive effects	0.146
13	-0.031	negative effects	0.146
14	-0.148	negative effects	0.146
15	0.146	slight positive effects	0.146
16	-0.090	weak negative correlation.	0.146

Table 8: Partial Autocorrelation (GDPGR)

Source: *own compilation*

Table 8 (partial autocorrelation analysis of GDPGR) reports a moderate positive influence from lag 1 (0.475) and a moderate negative effect at lag 2 (-0.303), indicating that these lags significantly impact the current value. Lags 3 to 5 showed weak correlations, and, by lag 6 (0.136), the influence diminished. Lag 8 stood out with a moderate positive correlation (0.363), whereas lag 9 had a slightly negative effect (-0.100). From lags 10 to 16, the coefficients fluctuated with minimal influence, demonstrating weaker correlations in line with the lag increasing, indicating a reduced impact from earlier values***. The partial autocorrelation function (PACF) revealed significant patterns in the series, with lags 1 and 8*** showing notable positive correlations, suggesting that these lags had potential influences. By contrast, the negative correlations at lag 2 and higher lags indicated relationships that varied with time, with influence diminishing as lags increased. This analysis aided in determining the appropriate order for an ARIMA model, particularly in identifying significant lags to include in forecasting.

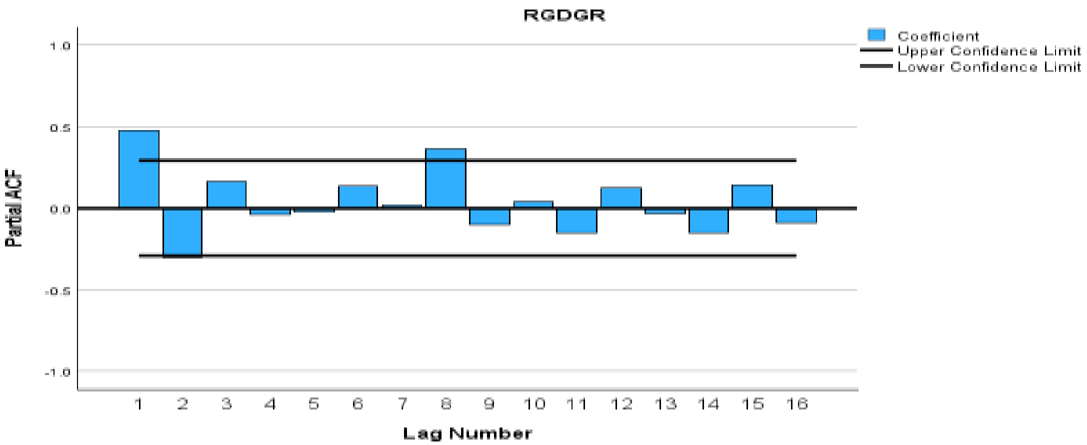

Figure 2: PACF plot—RGDPGR, lag = 16

The PACF ***plot showed a significant spike at lag 1,*** which dropped off and remained mostly within the confidence limits for subsequent lags, except for a few minor spikes (Figure 2). This pattern indicates that the series may be best modeled with an ***AR (1) process, meaning p = 1p = 1p = 1.***

Model estimation—**Stage 2 (GDPGR**): Based on the ACF and PACF plots, an **ARIMA (1, 1, 1)** model appeared suitable, with the differencing order d = 1, as initial differencing had been applied to achieve stationarity in the series. This model included AR and MA terms of 1. Furthermore, experimenting with an **ARIMA (1, 1, 2)** model could be beneficial for examining the potential impact of including the autocorrelation at lag 9, capturing additional dependencies in the series.

The diagnostic stage was as long as necessary to finalize the best model for our forecasting.

Differenced CPI	ARIMA (1,1,1)	ARIMA (1,1,2)
DF-Higher	16	15
Significant coefficient n(more)	.536	*.837*
Adjusted r-square(more)	.086	*.149*
SBIC(minimum)	*3.642*	3.677
Ljung-Box stat (Q18)- less	14.852	9.717

Table 9: Model Comparison

Source: *own compilation*

The metrics in Table 9 indicate that the ***ARIMA (1, 1, 2) model was more suitable for forecasting*** the differenced CPI. This model demonstrated a higher adjusted R-squared compared to ARIMA (1, 1, 1), indicating a better fit to the data. Additionally, the ARIMA (1, 1, 2) model had a lower Ljung-Box Q18 statistic, suggesting that the residuals exhibited less autocorrelation, enhancing the model's forecasting reliability. Although ARIMA (1, 1, 1) had a slightly lower SBIC, the improved fit and reduced residual autocorrelation of ARIMA (1, 1, 2) indicate that it is a more reliable model for accurate, consistent forecasting.

Step 4: Forecasting

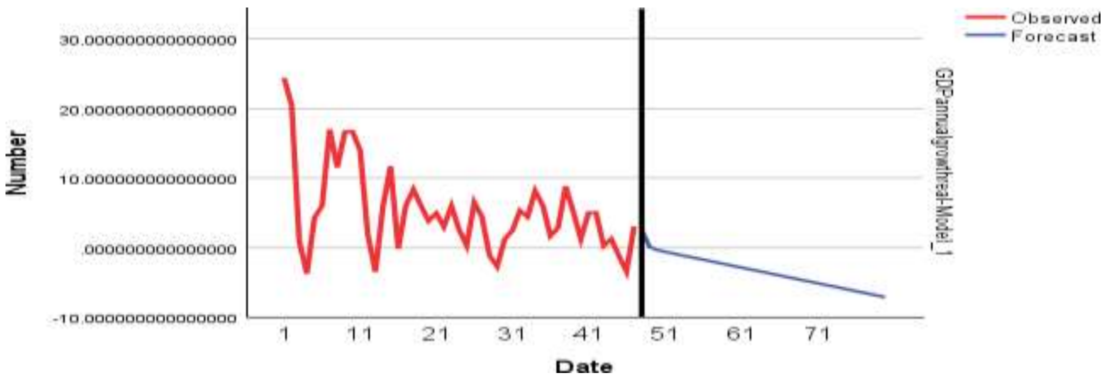

Figure 3: GDPGR—Forecast (2022-2054)

Figure 4 illustrates the observed and forecasted GDPGR over the next 20 years. The observed data, depicted by the red line, exhibited marked volatility with periods of positive and negative growth. Notably, the growth rate declined toward the end of the observed period. ***The forecast, represented by the blue line, suggests that this downward trend will continue, with the projected growth rate even turning negative in the future***, indicating a potential economic downturn or recession on the horizon.

Year	Real GDP annual growth rate -Model-Arima(1,1,2)		
	Forecast	UCL	LCL
2022	2.751	12.719	-7.216
2023	0.188	12.116	-11.739
2024	-0.286	11.680	-12.252
2025	-0.537	11.431	-12.505
2026	-0.765	11.203	-12.733
2027	-0.991	10.977	-12.958
2028	-1.216	10.751	-13.183
2029	-1.441	10.526	-13.407
2030	-1.666	10.300	-13.631
2031	-1.891	10.074	-13.855
2032	-2.116	9.848	-14.079
2033	-2.341	9.622	-14.303

2034	-2.566	9.396	-14.527
2035	-2.791	9.169	-14.751
2036	-3.016	8.943	-14.975
2037	-3.241	8.717	-15.199
2038	-3.466	8.491	-15.423
2039	-3.691	8.264	-15.646
2040	-3.916	8.038	-15.870
2041	-4.141	7.811	-16.094
2042	-4.366	7.585	-16.317
2043	-4.591	7.359	-16.541
2044	-4.816	7.132	-16.765
2045	-5.041	6.906	-16.988
2046	-5.266	6.679	-17.212
2047	-5.491	6.453	-17.435
2048	-5.716	6.226	-17.659
2049	-5.941	6.000	-17.883
2050	-6.166	5.773	-18.106
2051	-6.391	5.547	-18.330
2052	-6.616	5.320	-18.553
2053	-6.842	5.094	-18.777
2054	-7.067	4.868	-19.001

Table 10: Real GDP Annual Growth—Model 1 (ARIMA 1, 1, 2)

Source: *own compilation*

Table 10 presents the forecast from the ARIMA (1, 1, 2) model, which indicated a steady decline in the real GDPGR from 2022 to 2054, with the growth rate progressively turning negative. The upper (UCL) and lower control limit (LCL) for each year show a widening confidence interval over time, highlighting the increasing uncertainty in future forecasts. This overall downward trajectory has important implications for assessing the impact of ICT adoption, as ICT variables, including FBS, FTS, PUI, and MCS, may influence this forecasted trend differently. Introducing widespread and advanced broadband infrastructure may mitigate the declining trend of GDP growth, likely raising the LCL as businesses and sectors integrate more ICT solutions. Given the limited growth potential of traditional telephone lines alone, any positive impact on the GDP may be marginal. Increased internet usage may positively impact GDP growth, slowing or even reversing the declining GDPGR by enhancing productivity and connectivity. This would raise the LCL and perhaps narrow the confidence interval, lessening long-term forecast uncertainty. Mobile subscriptions may not drastically alter the UCLs but will likely contribute to a reduction in the GDP decline rate and stabilize growth, particularly in rural and underserved areas.

Forecast Reliability

Residual (ACF and PACF)

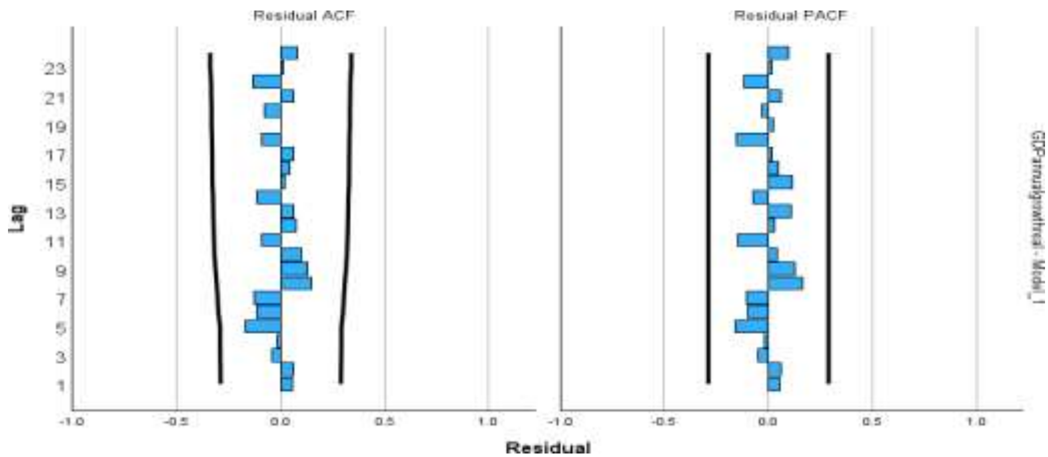

Figure 4: Residual of ACF and PACF

Figure 4 illustrates the residual ACF and residual PACF, indicating that the forecasting model performed well as it captured underlying data patterns and the remaining errors were random. Similarly, the bars in the residual PACF and ACF plot were mostly within the confidence bands, further confirming that the residuals were not significantly correlated with their lagged values.

The results of the ARIMA modeling indicate that H(3) should be rejected, suggesting that ICT adoption does not lead to economic growth. Moreover, projections show that, over the next 20 years, ICT adoption may contribute to a GDP decline.

Findings and Discussion

The hypothesis that higher ICT adoption will contribute to Oman's economic growth was partially supported.The analysis revealed that FBS exhibits a significant, positive long-term relationship with the country's GDP growth, underscoring the role of advanced ICT infrastructure as a driver of economic growth. This robust association suggests that fixed broadband access is crucial for enhancing economic output and promoting sustained growth. However, other ICT variables—such as FTS, MCS, and PUI—do not significantly impact GDP growth, even in the short run. Among the ICT variables, FBS showed the highest explanatory power, reflected by a high, adjusted R-squared; this demonstrates its significance in predicting economic growth. By contrast, FTS performed poorly, with a much lower adjusted R-squared, indicating a limited contribution to GDP growth. In general, however, the independent variables collectively fail to explain substantial short-term variations in the GDPGR. Moreover, short-term shocks within the ICT sector do not significantly impact Oman's GDP growth. Further analysis highlighted FBS's highly significant adjustment coefficient, indicating rapid correction of deviations from equilibrium and supporting robust long-term GDP growth. By contrast, MCS exhibited an insignificant adjustment coefficient, suggesting slower responses to economic shocks, while PUI also showed an insignificant coefficient, indicating a minimal short- term effect.Overall, FBS emerged as the most impactful ICT variable in restoring equilibrium and supporting long-term GDP growth, with FTS also contributing, although to a lesser extent. However, mobile and internet usage showed slower or reduced significant short-term adjustments, highlighting that ICT adoption alone may be insufficient in driving long-term economic growth. Complementary factors, including infrastructure development and digital literacy, may be necessary to maximize ICT's economic impact in Oman. Initially, we hypothesized that the growing adoption of ICT would positively impact Oman's GDP, fostering economic development and innovation. However, the findings from the ARIMA (1, 1, 2) model forecast indicate a steady decline in real GDP growth between 2022 and 2054, with the growth rate predicted to become progressively negative (-7.067% by 2054). Represented by UCL and LCL, the widening confidence interval highlights a growing uncertainty over time. While advanced broadband infrastructure could mitigate this decline by increasing the LCL, traditional fixed telephone lines showed limited growth potential, implying a minimal positive impact on GDP. By enhancing productivity and connectivity, increased internet usage may offer substantial positive contributions to potentially reverse the downward trend. Similarly, mobile subscriptions could help reduce the GDP decline rate and stabilize growth in underserved areas. However, despite these potential mitigating factors, the ARIMA model's results suggest a rejection of H(3), as ICT adoption alone appears insufficient to sustain economic growth and may instead contribute to a GDP decline over the next two decades. Although short-term shocks in the ICT sector do not affect Oman's GDP, this study recommends prioritizing the sector's expansion to stimulate economic development, given the strong positive impact of fixed broadband on GDP growth. Broadband services are crucial for restoring equilibrium and driving long-term economic growth to rapidly stabilize the system. Efforts to enhance accessibility and affordability include increased investment in broadband infrastructure, especially in underserved areas. Public-private partnerships can accelerate this growth, while digital literacy programs will enable the population and businesses to leverage broadband's benefits. By contrast, FTS supported short-term adjustments but showed no significant long-term impacts on GDP. Although other ICT elements, including mobile and fixed telecom, demonstrated limited long-term effects on GDP, continuous monitoring and improvement in these areas could support complementary growth as broadband access increases. However, their long-term influence, particularly in their role as drivers of digital transformation, should not be overlooked. Policymakers should prioritize and allocate funds to expand broadband networks, particularly in rural and underserved areas. Such investments will enhance access to high- speed internet, enabling more people to benefit from the economic opportunities and stability offered by broadband services, ultimately driving long-term GDP growth. Based on the findings of Objective 2, Oman should prioritize the expansion and enhancement of broadband infrastructure, as it holds the greatest potential for countering GDP decline by increasing productivity, facilitating innovation, and boosting connectivity. Public-private partnerships can be explored as a means of funding and expediting the roll- out of high-speed internet to underserved and rural areas. Moreover, mobile technology can help to stabilize GDP growth in underserved regions, particularly rural areas. Furthermore, the government should support mobile network expansion and affordability to ensure equitable access, boosting economic activities in these regions.

Conclusion

FBS exhibited a significant positive long-term relationship with Oman's GDP growth, demonstrating the highest explanatory power as reflected by a high adjusted R-squared; this emphasizes its importance in predicting economic growth. Model forecasts indicated a steady decline in real GDP growth from 2022 to 2054, with the growth rate becoming progressively negative, projected to be -7.067% by 2054. This study's findings underscore the need to consider sustainable ICT practices and integrate renewable energy to mitigate environmental impacts while fostering digital economic growth. Mobile cellular services and internet usage demonstrated limited responsiveness to deviations from equilibrium, indicating that disequilibrium in these sectors typically persists in the short run and has a lower impact on short-term economic stability. This study provides insights for Oman on how to develop and leverage ICT to enhance the progression of the overall knowledge economy and its pillars and offers guidance on exploiting ICT to generate economic value. The simultaneous forecasted GDP decline (as identified in the previous analysis) combined with rising CO_2 emissions per capita could signal an unsustainable economic model, where emissions growth may fail to contribute to sustainable economic expansion.

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