Tax Revenue Sustainability and ICT Adoption: Evidence from ARDL and Markov Chain Models

Grayson Kisinga[1], Mashaka Mkandawile[2] and Severine Sirito Kessy[3]

Abstract

In contemporary society, Information and Communication Technology (ICT) is widely recognised as an important tool for improving tax administration and revenue mobilisation. However, empirical evidence on the impact of ICT adoption on tax revenue remains inconclusive, with existing studies reporting mixed findings. Against this background, this study examines the long-run and short-run relationships between ICT investment, ICT imports, internet usage, broadband penetration, economic growth, and tax revenue in Tanzania over the period 1997–2022. The study employs the Autoregressive Distributed Lag (ARDL) bounds testing approach to examine cointegration and estimate dynamic relationships, complemented by a Markov Chain model to assess the sustainability of tax revenue over time. The ARDL bounds test results confirm the existence of a long-run relationship among the variables. Long-run estimates indicate that ICT investments, ICT imports and broadband penetration have a positive and significant influence on tax revenue, while internet usage has a negative effect, highlighting challenges associated with taxing digital economic activities under existing tax systems in developing countries. Economic growth is found to positively influence tax revenue, reinforcing its role as a key macroeconomic control factor. The Markov Chain analysis reveals that tax revenue converges to a stable state after approximately four years, with a 0.628 probability of remaining in an increasing revenue state and a 0.372 probability of transitioning to a declining state. These findings suggest that while ICT adoption can enhance tax revenue sustainability, its effectiveness depends on complementary policy and institutional reforms. The study recommends that governments strengthen digital tax administration systems, modernise tax laws to accommodate online transactions, and integrate ICT strategies into fiscal planning to improve long-term revenue performance.

Keywords: Tax revenue; ICT adoption; ARDL model; Markov chain model

Introduction

Accurate tax revenue forecasting is a critical component of national budget preparation and fiscal planning, as it enables governments to align expenditure commitments with available resources (Koniagina, 2020; Glenday, 2013). In many countries, tax revenue constitutes the dominant source of public finance, accounting for up to 95% of domestic government revenue, thereby making reliable revenue projections essential for effective fiscal policy and macroeconomic stability (Chikwede, 2022; European Central Bank, 2014; Khahro et al., 2020). Sustained growth

[1] University of Dar es salaam Business School, Tanzania
Email: gkisinga@gmail.com
[2] University of Dar es salaam Business School, Tanzania
[3] University of Dar es salaam Business School, Tanzania

in tax revenue allows governments to finance development programmes, expand public infrastructure, and improve social services such as health and education, ultimately enhancing overall welfare. However, tax revenue mobilisation is influenced by multiple interrelated factors, including economic growth, taxpayer compliance, institutional capacity, fiscal policy, and the adoption of Information and Communication Technology (ICT) (Gomero, 2022). ICT adoption has increasingly been recognised as a key instrument for improving tax administration and revenue performance. ICT-related investments include digital infrastructure projects such as broadband expansion, electronic tax filing systems, and digital connectivity programmes that enhance information flow and administrative efficiency (Kim et al., 2010). In developing economies, however, tax authorities continue to face substantial challenges, including outdated infrastructure, limited technical expertise, digital divides, and weak data management systems (Mills, 2017). Although ICT investments may impose short-term fiscal costs through implementation expenses and tax incentives, existing evidence suggests that they can enhance productivity, innovation, and compliance, thereby contributing to higher tax revenue in the long run (Mayer et al., 2020; Nikiforova, 2022). In this study, ICT investment refers to expenditure on the development and deployment of ICT infrastructure and systems, including hardware, software, and digital platforms used in tax administration, and is conceptually distinct from ICT imports, which capture the value of imported ICT goods.

Alongside ICT adoption, economic growth remains a fundamental determinant of tax revenue performance. Expansion in economic activity increases incomes, profits, and transaction volumes, which collectively broaden the tax base and improve governments' revenue-generating capacity. ICT adoption is widely recognised for enhancing productivity, business efficiency, and market expansion, thereby supporting economic growth and reinforcing fiscal capacity (Qiang et al., 2009; Vu et al., 2020; Sawng et al., 2021). Accordingly, economic growth is incorporated in this study as a control variable to account for broader macroeconomic conditions that influence tax revenue dynamics. Despite the importance of these factors, tax revenue forecasting remains inherently uncertain due to the complex and stochastic nature of economic systems (Kupelian & Loughbridge, 2017). Consequently, a wide range of quantitative methods has been employed to model and predict revenue dynamics. Previous studies have applied time-series techniques to forecast tax revenue (Streimikiene et al., 2018), as well as advanced approaches such as neural networks and grey models to improve predictive accuracy (Sheng et al., 2021). Markov Chain models have also been applied in diverse contexts, including income dynamics, market share analysis, and regime-switching behaviour, due to their ability to capture probabilistic transitions between different system states (Cai, 1994; Hamilton, 2010; Kovacs, 2018; Li & Xing, 2021; Yan et al., 2018).

More recently, Markov Chain analysis has been used to study ICT investment strategies, financial sustainability, and technological transitions by modelling systems as evolving across discrete states over time (Abed-Allah Migdadi, 2017; Haller et al., 2020; Rekova et al., 2020; Zatonatska et al., 2022). In the context of public finance, several scholars have examined tax-related dynamics and fiscal behaviour using probabilistic and regime-based approaches, including applications of Markov chain models in public finance and revenue forecasting (Haller et al., 2020; Zohrah et al., 2024). However, empirical evidence remains mixed regarding the impact of ICT adoption on tax revenue, and existing studies have largely focused on short-term effects or single methodological approaches. Guided by the Technology–Organization–Environment (TOE) framework, which emphasises the role of technological infrastructure in shaping organisational and fiscal outcomes, this study addresses an important gap in the literature by examining the sustainability of tax revenue in the context of ICT adoption. Specifically, the study combines the Autoregressive Distributed Lag (ARDL) model with a Markov Chain approach to capture both long-run relationships and probabilistic revenue dynamics. Unlike previous studies, this research establishes cointegration between tax revenue and ICT-related variables and uses the estimated relationships to assess tax revenue sustainability over a ten-year horizon. By integrating dynamic econometric analysis with stochastic modelling, the study provides new insights into how ICT adoption influences tax revenue performance over time, offering valuable implications for policymakers and tax authorities in developing economies.

Theoretical Framework

TOE framework provides a comprehensive theoretical lens for understanding the dynamics of ICT adoption in the context of tax revenue mobilization. The availability and sophistication of ICT infrastructure play a critical role in enabling tax authorities to adopt and effectively utilise digital technologies for revenue generation. The implementation of automated tax collection, processing, and enforcement systems requires adequate technological infrastructure, including hardware, software, and communication networks. Within the TOE framework, the adoption of digital tax administration tools such as electronic filing, electronic payment systems, and electronic fiscal devices (EFDs) is shaped by technological factors (e.g., the functionality and reliability of digital systems), organisational factors (e.g., institutional readiness and managerial commitment), and environmental factors (e.g., regulatory frameworks and market conditions) (Park & Choi, 2019).

Hypothesis Development

ICT Investment, ICT imports and Tax Revenue

ICT-related investments are widely recognised for their potential to enhance economic efficiency and administrative capacity, which may translate into improved tax revenue performance. By improving productivity, reducing compliance costs, and strengthening tax administration systems, ICT investment can increase business profitability and taxable economic activity, thereby supporting tax revenue mobilisation (Vu et al., 2020; Sawng et al., 2021). Similarly, ICT imports may contribute to tax revenue directly through customs duties and indirectly through the diffusion of digital technologies that support economic activity and innovation (Adedeji & Lipede, 2023). However, empirical evidence on the fiscal effects of ICT adoption remains inconclusive. Studies such as Olaoye and Atilola (2018) and Mallick (2021) report insignificant or mixed impacts of ICT infrastructure on tax revenue, suggesting that institutional capacity, regulatory frameworks, and the structure of digital markets play an important role in shaping outcomes. In addition, the shift towards digital trade raises concerns about potential revenue losses arising from tariff exemptions and difficulties in taxing cross-border digital transactions, particularly in developing economies (Choudhury, 2020; Suominen, 2017; Teltscher, 2002). Given these mixed theoretical and empirical insights, the net effect of ICT investment and ICT imports on tax revenue remains ambiguous. Accordingly, the following non-directional hypotheses are proposed:

H1a: *ICT investment positively influences tax revenue.*
H1b: *ICT imports positively influence tax revenue.*

Broadband Penetration and Tax revenue

Broadband penetration and internet usage represent key dimensions of digital infrastructure that can affect tax revenue through their influence on economic activity and market structure. Broadband infrastructure facilitates high-speed connectivity, enabling firms to optimise operations, adopt new technologies, expand into new markets, and improve productivity (Qiang et al., 2009; Fazlioglu et al., 2026). These effects may broaden the tax base by stimulating investment, employment, and entrepreneurial activity (Katz, 2018; Stephens et al., 2022). At the same time, increased internet usage may alter consumption patterns and business models in ways that complicate tax collection. The expansion of e-commerce and digital platforms can weaken traditional tax bases if regulatory and enforcement mechanisms are not adequately adapted to digital transactions, particularly in developing economies where digital activities are harder to monitor (Teltscher, 2002; Choudhury, 2020). Several studies note that online transactions, cross-border digital trade, and platform-based business models can erode conventional tax bases and reduce tax compliance when tax systems lag behind technological change (Suominen, 2017; OECD, 2015). As a result, the fiscal implications of broadband penetration and internet usage may differ, reflecting both revenue-enhancing and revenue-eroding effects. Given these contrasting mechanisms, the direction of their impact on tax revenue remains an empirical question.

H2a: *Broadband penetration has a positive effect on tax revenue.*
H2b: *Internet usage has a positive effect on tax revenue.*

Economic Growth and Tax Revenue

Economic growth is a fundamental determinant of tax revenue performance, as expansions in output, income, and consumption increase the taxable base. Higher levels of economic activity raise corporate profits, household incomes, and transaction volumes, thereby strengthening governments' capacity to mobilise tax revenue. Consistent with public finance theory and empirical evidence, economic growth is expected to exert a positive influence on tax revenue performance (Qiang et al., 2009; Vu et al., 2020). In this study, economic growth is included as a control variable to account for broader macroeconomic conditions that influence tax revenue dynamics alongside ICT-related factors. Accordingly, the following hypothesis is proposed:

H3: *Economic growth has a positive effect on tax revenue.*

Methodology and Approaches

This study adopts a positivist research philosophy, as it relies on observable and quantifiable data to examine the relationships between ICT adoption and tax revenue performance (Saunders et al., 2009). A deductive research approach is employed, whereby hypotheses derived from established theoretical and empirical literature are empirically tested using time-series data. The study follows a time-series research design, which is appropriate for analysing dynamic relationships among variables over time and for capturing both short-run and long-run effects. Time-series analysis enables the assessment of how changes in ICT-related variables and economic growth influence tax revenue trajectories and supports forecasting based on historical patterns (Hudson et al., 2019). Accordingly, this design is well suited to the application of the ARDL and Markov Chain models used in the study. The data collection process was guided by the research objectives and the selection of key variables relevant to tax revenue performance. The variables considered in this study include total tax revenue, ICT investment, ICT imports, internet usage, broadband penetration, and economic growth. These variables were carefully identified to capture both technological and macroeconomic factors influencing tax revenue dynamics. ICT investment is measured as expenditure on ICT-related infrastructure and systems, including hardware, software, and digital applications utilised in tax administration. ICT imports are measured separately as the value of imported ICT goods, allowing the study to distinguish between domestic ICT investment efforts and externally sourced technology. Economic growth is measured by gross domestic product (GDP) and is included as a control variable to account for overall macroeconomic conditions influencing tax revenue performance (Park & Choi, 2019; Vu et al., 2020). Internet usage and broadband penetration are used to capture the extent of digital connectivity and access to ICT infrastructure. The operational definitions of all variables are summarised in Table 1. The study relies on secondary time-series data for the Tanzanian economy. Data on tax revenue were obtained from the Tanzania Revenue Authority (TRA), while data on ICT-related variables and economic growth were sourced from the World Bank (WB). These sources were selected due to their reliability, consistency, and widespread use in empirical economic research.

Following data collection, the time-series data were subjected to a sequence of statistical and econometric analyses to address the study's research objectives and test the proposed hypotheses. Descriptive and preliminary analyses were first conducted to examine the basic characteristics of the data. Subsequently, the Autoregressive Distributed Lag (ARDL) modelling approach was employed to estimate both short-run and long-run relationships between ICT-related variables, economic growth, and tax revenue. The ARDL model is particularly suitable for time-series data with mixed orders of integration and allows for the assessment of dynamic adjustments over time. In addition, a Markov Chain model was applied to analyse the sustainability and probabilistic dynamics of tax revenue by examining transitions between different revenue states. This approach complements the ARDL analysis by providing insights into the likelihood of changes in tax revenue regimes over time. The ARDL estimations were conducted using Stata 14, while the Markov Chain analysis was implemented using Maple 2022.

Table 1: Operationalization of Variables

Variable	Dimensions/ Indicators	Indicative measures elaborations	Source
Tax Revenue	Total tax revenue	Revenue generated from various types of taxes in a particular country(Hill et al., 2022)	TRA
ICT investment	Investment cost on ICT items	Hardware and software (Leung & Fan, 2002; Rahman et al., 2021)	TRA
ICT import	ICT goods imports (% total goods imports)	Hardware and software (ITU, 2016; World Bank, 2018)	WBD
Internet Usage	Individual using Internet (%of population)	The % of individuals within a certain population that use the internet(Dutta & Lanvin, 2021)	WBD
Broadband Penetration	Fixed broadband subscriptions (per 100 people)	High-speed internet connectivity enables quick data transmission, e.g., DSL, cable, fiber optics (World Bank, 2009)	WBD
Economic growth	Gross Domestic Product (GDP)	The aggregate earnings of a nation's inhabitants during a designated timeframe(Kohli, 2003)	NBS

ARDL Model Specification

The Autoregressive Distributed Lag (ARDL) model was employed to analyse the dynamic interactions between tax revenue and ICT-related variables. Prior to estimation, the stationarity properties of the time-series data were examined using the Augmented Dickey–Fuller (ADF) unit root test to ensure that none of the variables were integrated of order I(2), a key requirement for the ARDL bounds testing approach (Afzal et al., 2010; Shrestha & Bhatta, 2018).

Cointegration Test

The ARDL bounds testing procedure was used to examine the existence of a long-run cointegrating relationship among the variables. This approach is appropriate when the explanatory variables are a mixture of I(0) and I(1) processes. The bounds test involves estimating an unrestricted error correction model and computing an F-statistic to test the joint significance of the lagged level variables. If the computed F-statistic exceeds the upper critical bound, the null hypothesis of no cointegration is rejected, indicating the presence of a stable long-run relationship among the variables (Pesaran et al., 2001).

ARDL Model Estimation

The functional relationship between tax revenue and the explanatory variables is expressed as:

$$TR_t = F(INV_t, IMP_t, INT_t, BRD_{t,}, GDP_t) \ldots \quad (1)$$

Where TR_t denotes total tax revenue, INV_t represent ICT investment, IMP_t denotes ICT imports, INT_t represents internet usage, BRD_t denotes Broadband Penetration and GDP_t represents Economic Growth.

Following Pesaran et al. (2001), the ARDL model is specified as

$$\Delta TR_t = a_0 + \sum_{i=1}^{p} b\Delta TR_{t-i} + \sum_{i=1}^{p} c\Delta INV_{t-1} + \sum_{i=1}^{p} b\,\Delta BDR_{t-1} + \lambda_1 TR_{t-1} + \lambda_2 INV_{t-1} + \lambda_3 BRD_{t-1} + U_t \ldots \quad (2)$$

Where i are indices of lags; $i = 1,2 \ldots.p, p$ is the optimum lag length, t denotes the time periods $t = 1,2 \ldots\ldots, T$ and U_t is the error term.

λ's represents the long-run dynamics of the variables. The cointegration can be established when λ is not equal to zero for the level variable in equation 2 above and F-test is used to test the joint significance of lag level variables.

Error Correction Model

After establishing cointegration, this study utilized ARDL error correction representation to estimate long-run relationships and short-run dynamics. Cointegration raises concerns about short-run fluctuations and long-run equilibrium adjustment speed. Fluctuations are particularly noticeable as a result of specific policy changes and the time it takes for them to become effective. An error correction term (ECT) in equation (3) captures these short-run modifications and provides significant information regarding long-run equilibrium changes:

$$\Delta TR_t = a_0 + \sum_{i=1}^{p} b_i \Delta TR_{t-i} + \sum_{i=1}^{p} c_i \Delta INV_{t-i} + \sum_{i=1}^{p} d\Delta IMP_{t-1} + \sum_{i=1}^{p} e_i\,\Delta INT_{t-i} + \sum_{i=1}^{p} f_i\,\Delta BRD_{t-i} + \sum_{i=1}^{p} g_i\,\Delta GDP_{t-i} + Au_{t-i} + v_t \ldots \quad (3)$$

The coefficients $a_i$tog_i capture the short-run dynamics, with Δ showing how changes in independent variables affect the dependent variable TR in the short term. p represents the optimal lag length based on the Akaike information criterion(AIC). The term Au_{t-i} capture the error correction term, is typically derived from long term relationship between variables in the model. This term adjusts for any disequilibrium in the long run relationship between TR and the independent variables. The coefficient A measures the speed at which the system recovers to equilibrium after a shock.$\boldsymbol{v_t}$ is the white noise error term, representing random shocks or error not explained by the model.

Markov Chain Model
The Markov Chain model is employed in this study to analyse the sustainability and long-term dynamics of tax revenue by modelling transitions between discrete revenue states over time. A Markov process is characterised by the memoryless property, whereby the probability of transitioning to a future state depends solely on the current state and not on the sequence of prior states. This property makes the Markov Chain particularly suitable for analysing stochastic systems such as tax revenue performance, where future outcomes depend on current conditions.

State Space Definition
The state space represents the set of possible tax revenue conditions in which the system may exist. In this study, tax revenue is categorised into discrete states reflecting different revenue performance regimes. Let the state space be denoted as:

$$S = S_1, S_2, \dots \dots \dots \dots, S_n$$

where each S_i represents a distinct tax revenue state. These states remain fixed throughout the analysis and form the basis for estimating transition probabilities.

Transition Probability Matrix
The dynamics of tax revenue are governed by the transition probability matrix PPP, whose elements P_{ij} represent the probability of moving from state S_i at time t to state S_j at time $t+1$. The transition matrix satisfies the conditions:

$$P_{ij} \geq 0 \text{ and} \sum_{j=1}^{n} P_{ij} = 1$$

This study assumes a time-homogeneous Markov Chain, implying that transition probabilities remain constant over time. The k-step transition matrix is obtained as:

$$P^{(k)} = P^k$$

which provides the probabilities of transitioning between states over multiple periods.

Prediction and Long-Run Behaviour
Given an initial state probability vector $S(0)$, the distribution of tax revenue states after k periods are obtained as:

$$S(k) = S(0)P^k$$

The long-run behaviour of the system is examined through the stationary distribution π, which satisfies:

$$\pi = \pi P \text{ and } \sum_i \pi_i = 1$$

When the transition matrix is regular (irreducible and aperiodic), the Markov Chain converges to a unique stationary distribution, representing the long-run probabilities of tax revenue being in each state, regardless of the initial condition.

Relevance to Tax Revenue Sustainability
In this study, the stationary distribution provides a probabilistic assessment of tax revenue sustainability by indicating the likelihood that tax revenue will remain in, or transition to,

favourable or unfavourable revenue states over time. By complementing the ARDL results, the Markov Chain model offers additional insights into the stability, predictability, and long-term risks associated with tax revenue performance following ICT adoption.

Data Analysis and Interpretation

Descriptive Statistics

The analysis begins with descriptive statistics to summarise the basic characteristics of the time-series data used in the study. Table 2 reports the minimum, maximum, mean, and standard deviation for tax revenue, ICT investment, ICT imports, internet usage, broadband penetration, and economic growth over the study period. The results indicate substantial variation across all variables, as reflected by the wide range between minimum and maximum values and relatively large standard deviations for several series, particularly total tax revenue, ICT investment, internet usage, and GDP. This variation suggests pronounced changes in economic activity, ICT adoption, and tax revenue performance over time. To stabilise the variance and ensure comparability across variables, all series were transformed into logarithmic form prior to econometric analysis, which is standard practice in time-series modelling. The study utilises annual data covering the period 1999–2021, yielding 25 observations. Given the limited sample size, the maximum lag length in the ARDL model was restricted to two lags to avoid over-parameterisation and preserve degrees of freedom. In addition, diagnostic and stability tests were conducted to assess model robustness and reliability.

Table 2: Summary Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Total tax revenue	25	0.51	17.62	6.23	5.98
ICT investments	25	0.41	22.22	7.86	7.70
ICT imports	25	3.08	6.92	4.62	1.11
Internet usage	25	0.01	31.63	6.47	8.63
Broadband penetration	25	0.11	0.50	0.32	0.12
GDP	25	8.15	161.53	59.16	51.63

Goodness of fit test

The goodness of fit of the ARDL model is assessed using the coefficient of determination alongside diagnostic and stability tests. The estimated model in Table 6 reports an R-squared value of 0.905, indicating that the explanatory variables and their dynamic adjustments jointly account for a substantial proportion of the variation in tax revenue. The adjusted R-squared of 0.7678 remains relatively high after controlling for the number of regressors and lag structures, which is typical in dynamic time-series models. In addition, the error correction term is negative and statistically significant, confirming convergence towards long-run equilibrium. Combined with the absence of serial correlation and the stability of parameters as confirmed by the CUSUM and CUSUMQ tests, these results suggest that the ARDL model is well specified and provides a reliable representation of tax revenue dynamics in the context of ICT adoption.

Diagnostic and Stability Test

The diagnostic and stability tests are essential for assessing the reliability and validity of the ARDL model results. In this study, model adequacy was evaluated using the Breusch–Godfrey serial correlation test and the CUSUM and CUSUM of squares (CUSUMQ) stability tests. The Breusch–Godfrey test results in Table 3 indicate no evidence of serial correlation in the residuals, confirming that the model is correctly specified. Furthermore, the CUSUM and CUSUMQ plots, presented in Figure 1, remain within the 5% critical bounds throughout the sample period, suggesting parameter stability. These results confirm the long-run stability of the estimated ARDL and error correction models.

Table 3: Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob> chi2
1	0.006	1	0.9404

Ho: no serial correlation

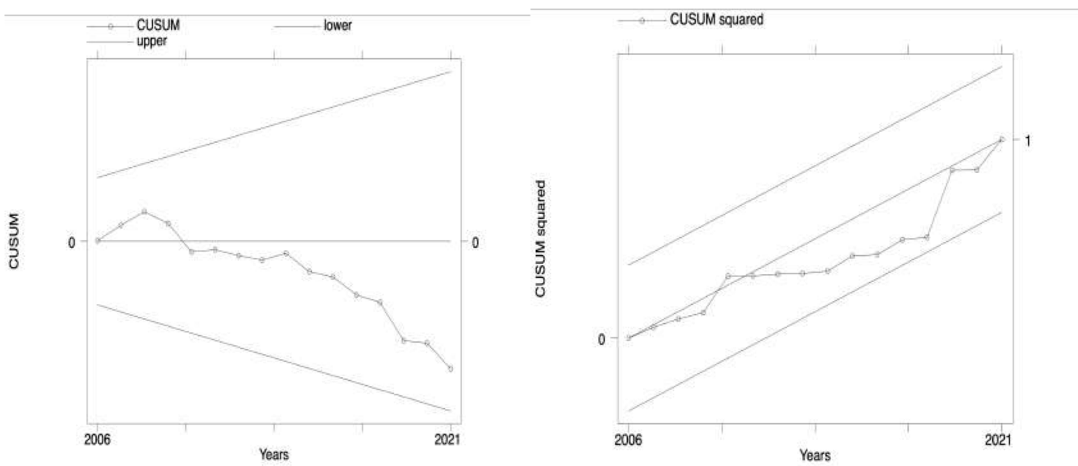

Figure 1: CUSUM and CUSUMQ Test

Unit root test

Prior to estimating the ARDL model, the stationarity properties of all variables were examined to ensure the absence of unit roots of order two, I(2), which would invalidate the ARDL bounds testing approach. Accordingly, the Augmented Dickey–Fuller (ADF) unit root test proposed by Dickey and Fuller (1979) was applied to all six variables. The tests were conducted both at levels and first differences, with specifications including a trend and a drift, as reported in Table 4. The null hypothesis of the ADF test is that the series contains a unit root. This null is rejected when the test statistic is statistically significant at the 5% level. The results indicate that tax revenue, ICT investment, ICT imports, and GDP are non-stationary at levels but become stationary after first differencing, implying integration of order one, I(1). In contrast, internet usage and broadband penetration are stationary at levels under at least one specification, indicating integration of order zero, I(0). Overall, the unit root test results confirm that none of the variables is integrated of order two. The presence of a mixture of I(0) and I(1) variables justifies the use of the ARDL modelling framework and the bounds testing approach to cointegration in this study.

Table 4: Unit root test

Variable	ADF				Decision
	At level		At First difference		
	Include Trend	Include Drift	Include Trend	Include Drift	
Tax Revenue	0.9952	0.0715	0.4564	0.0466	(1)
ICT Investment	0.6738	0.2184	0.0016	0.0001	(1)
ICT imports	0.1865	0.1644	0.0126	0.0004	(1)
Internet usage	0.0000	0.0001	0.0002	0.0000'	(0)
Broadband penetration	0.8575	0.0076	0.0063	0.0037	(0)
GDP	0.876	0.1127	0.4173	0.0229	(1)

ARDL Bound test

After establishing that the variables are integrated of mixed orders, I(0) and I(1), the ARDL bounds testing approach was employed to examine the existence of a long-run relationship among the variables, as reported in Table 5. Given this combination of integration orders, the Johansen cointegration technique is not appropriate. The ARDL bounds test, based on the error correction representation proposed by Pesaran et al. (2001), is well suited for such cases. The results in table 5 indicate that the computed F-statistic (7.988) exceeds the upper critical bound at all conventional significance levels, leading to the rejection of the null hypothesis of no cointegration. This confirms the presence of a stable long-run relationship among the variables. Consequently, the long-run coefficients and the associated error correction model (ECM) were estimated to capture both long-run equilibrium relationships and short-run dynamics.

Table 5: ARDL Bound test

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H0: no levels relationship                F =  7.988
                                          t = -5.463

Critical Values (0.1-0.01), F-statistic, Case 3

      | [I_0]   [I_1]  | [I_0]   [I_1]  | [I_0]   [I_1]  | [I_0]   [I_1]
      |   L_1     L_1  |  L_05    L_05  | L_025   L_025  |  L_01    L_01
------+----------------+----------------+----------------+--------------
  k_5 |  2.26    3.35  |  2.62    3.79  |  2.96    4.18  |  3.41    4.68
accept if F < critical value for I(0) regressors
reject if F > critical value for I(1) regressors

Critical Values (0.1-0.01), t-statistic, Case 3

      | [I_0]   [I_1]  | [I_0]   [I_1]  | [I_0]   [I_1]  | [I_0]   [I_1]
      |   L_1     L_1  |  L_05    L_05  | L_025   L_025  |  L_01    L_01
------+----------------+----------------+----------------+--------------
  k_5 | -2.57   -3.86  | -2.86   -4.19  | -3.13   -4.46  | -3.43   -4.79
accept if t > critical value for I(0) regressors
reject if t < critical value for I(1) regressors

k: # of non-deterministic regressors in long-run relationship
Critical values from Pesaran/Shin/Smith (2001)
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Table 6: ARDL Model Estimation

ARDL(1,2,2,0,2,1) regression

Sample: 1999 - 2021		Number of obs =	23
		R-squared =	0.9050
		Adj R-squared =	0.7678
Log likelihood =	55.196855	Root MSE =	0.0351

D.lnTotalTax	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
lnTotalTax						
L1.	-1.058092	.1937	-5.46	0.000	-1.496272	-.6199127
LR						
lnICTinvest	.151229	.0601066	2.52	0.033	.0152585	.2871995
lnICTimport	.3558966	.1262037	2.82	0.020	.0704039	.6413893
lnInternetUsage	-.1187787	.0415002	-2.86	0.019	-.2126587	-.0248987
lnBroadband	.3608458	.1014242	3.56	0.006	.1314082	.5902833
lnGDP	1.421795	.1659814	8.57	0.000	1.046319	1.797271
SR						
lnICTinvest						
D1.	-.1298516	.0505784	-2.57	0.030	-.2442679	-.0154354
LD.	-.0741788	.0355583	-2.09	0.067	-.1546173	.0062596
lnICTimport						
D1.	-.2844153	.1151235	-2.47	0.036	-.5448427	-.0239879
LD.	-.1471554	.0938176	-1.57	0.151	-.3593856	.0650748
lnBroadband						
D1.	-.2911917	.1136333	-2.56	0.031	-.5482482	-.0341353
LD.	-.25822	.0776523	-3.33	0.009	-.4338817	-.0825582
lnGDP						
D1.	-1.117075	.4333778	-2.58	0.030	-2.097444	-.1367066
_cons	1.42549	.3993882	3.57	0.006	.5220107	2.328969

The results in Table 6 indicate that, in the long run, ICT investment has a positive and statistically significant effect on tax revenue ($\beta = 0.60$, $p = 0.000$), thereby supporting Hypothesis H1a. This implies that a 1% increase in ICT investment is associated with an approximate 0.60% increase in total tax revenue. In contrast, the short-run dynamics show that a 1% increase in the first difference of ICT investment reduces tax revenue by 8.4%, suggesting that ICT investments may exert short-term fiscal pressure before generating long-term revenue gains. Similarly, ICT imports exhibit a positive and significant long-run effect on tax revenue, supporting Hypothesis H1b. Specifically, a one-unit increase in ICT imports raises total tax revenue by 0.36 units in the long run. However, the short-run results indicate that a 1% increase in the first difference of ICT imports reduces tax revenue by 28%, reflecting short-term adjustment costs associated with acquiring and installing ICT infrastructure. Long-run internet usage is found to have a negative and statistically significant effect on tax revenue ($\beta = -0.12$, $p = 0.019$), thereby contradicting Hypothesis H2b, which expected a positive relationship. The negative coefficient suggests that increased digital connectivity does not automatically translate into higher tax revenue under existing tax structures, particularly in developing economies where digital transactions may be weakly regulated and difficult to monitor (Teltscher, 2002; Choudhury, 2020). In contrast, broadband penetration has a positive and significant long-run effect on tax revenue ($\beta = 0.776$, $p = 0.003$), supporting Hypothesis H2a. This indicates that a 1% increase in broadband penetration is associated with an approximate 0.77% increase in total tax revenue

Economic growth exhibits a positive and statistically significant long-run effect on tax revenue, as indicated by the estimated coefficient on GDP ($\beta = 1.422$, $p = 0.000$). This result supports Hypothesis H3, suggesting that increases in economic growth are associated with higher tax revenue mobilisation. The magnitude of the coefficient implies that a 1% increase in GDP leads to an approximately 1.42% increase in total tax revenue in the long run. In the short run, the first difference of GDP also shows a positive and significant effect on tax revenue ($\beta = 1.117$, $p = 0.030$), indicating that improvements in economic activity translate into increased tax collection even in the adjustment period. These findings confirm the central role of economic growth in strengthening the tax base and enhancing revenue performance.

Markov Chain Model

After establishing cointegration among total tax revenue, ICT investment, and broadband penetration, this study proceeds to analyse the long-term dynamics and sustainability of tax revenue using a Markov Chain model. Cointegration implies the existence of a stable long-run equilibrium relationship among the variables, indicating that short-run deviations from equilibrium are corrected over time. This property provides a suitable basis for forecasting tax revenue dynamics beyond the sample period. The Markov Chain model is employed to predict tax revenue behaviour based on transition probabilities derived from historical tax revenue movements. The core idea of the model is that the future state of tax revenue depends only on its current state and not on the sequence of past states. Accordingly, tax revenue dynamics are modelled as a stochastic process in which the state at time t may transition to another state at time $t + 1$ with a certain probability.

Tax Revenue Collection statistics

The analysis adopts a univariate framework focusing exclusively on total tax revenue collected by the Tanzania Revenue Authority over the period 1997–2022. As shown in Table 7, tax revenue movements are classified using first and second differences. The first difference indicates whether tax revenue is increasing or decreasing, while the second difference captures changes in the rate of increase or decrease. A positive second difference implies an acceleration in revenue growth, whereas a negative second difference indicates a deceleration. Based on these dynamics, tax revenue is categorised into three discrete states: Increasing (I), Constant (C), and Decreasing (D). Using the observed transitions between these states, the transition probability matrix and the initial state vector are estimated. These probabilities form the basis for analysing the long-run behaviour and sustainability of tax revenue under existing institutional and technological conditions.

Table 7: Tax State Representation

PERIOD	SALES	1^{ST} DIFFERENCE	2^{nd} DIFFERENCE	STATES
1996/1997	506,630.0			
1997/1998	560,818.1	54,188.13		
1998/1999	616,265.3	55,447.22	1,259.09	Constant(C)
1999/2000	686,602.3	70,336.97	14,889.75	Increasing(I)
2000/2001	834,764.0	148,161.67	77,824.70	Increasing(I)
2001/2002	941,596.5	106,832.52	(41,329.15)	Decreasing(D)
2002/2003	1,107,954.1	166,357.64	59,525.13	Increasing(I)
2003/2004	1,339,195.1	231,241.04	64,883.40	Increasing(I)
2004/2005	1,609,671.9	270,476.78	39,235.74	Increasing(I)
2005/2006	1,930,090.7	320,418.78	49,942.00	Increasing(I)
2006/2007	2,511,160.0	581,069.30	260,650.52	Increasing(I)
2007/2008	3,342,863.2	831,703.19	250,633.89	Increasing(I)
2008/2009	4,019,452.9	676,589.70	(155,113.49)	Decreasing(D)
2009/2010	4,406,910.3	387,457.35	(289,132.35)	Decreasing(D)
2010/2011	5,286,013.0	879,102.71	491,645.36	Increasing(I)
2011/2012	6,466,013.0	1,180,000.02	300,897.31	Increasing(I)
2012/2013	7,654,512.1	1,188,499.07	8,499.05	Decreasing(D)
2013/2014	9,358,404.5	1,703,892.45	515,393.38	Increasing(I)
2014/2015	9,888,445.3	530,040.77	(1,173,851.68)	Decreasing(D)
2015/2016	12,499,665.8	2,611,220.55	2,081,179.78	Increasing(I)
2016/2017	14,126,590.3	1,626,924.51	(984,296.04)	Decreasing(D)
2017/2018	15,191,421.3	1,064,830.91	(562,093.60)	Decreasing(D)
2018/2019	15,511,330.4	319,909.13	(744,921.77)	Decreasing(D)
2019/2020	17,622,822.1	2,111,491.69	1,791,582.56	Increasing(I)
2020/2021	17,624,361.6	1,539.53	(2,109,952.16)	Decreasing(D)

Transition Matrix and State Probabilities

Table 8 presents the observed transitions of tax revenue states over the study period (1997–2021). Each entry represents the number of times tax revenue moved from one state at time *t* to another state at time *t + 1*. The three possible states are Increasing (I), Constant (C), and Decreasing (D).

Table 8: Transition Matrix (Frequency of Transitions)

FROM/TO	I	C	D	Row Total
Increased (I)	7	0	5	12
Constant(C)	1	1	0	2
Decreased(D)	5	0	2	7

Transition Probability Matrix

Transition probabilities are obtained by dividing each cell by its row total, ensuring that the probabilities in each row sum to one. The resulting one-step transition probability matrix is:

$$P = \begin{bmatrix} \frac{7}{12} & 0 & \frac{5}{12} \\ \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{5}{7} & 0 & \frac{2}{7} \end{bmatrix} = \begin{bmatrix} 0.583 & 0 & 0.417 \\ 0.500 & 0.500 & 0.000 \\ 0.714 & 0.000 & 0.286 \end{bmatrix}$$

This matrix shows, for example, that when tax revenue is in an increasing state, there is a 58.3% probability it will remain increasing in the next period and a 41.7% probability it will shift to a decreasing state.

Initial State Distribution

The initial state probability vector is derived from the most recent observed tax revenue movements (Table 9). Out of five observed transitions: 4 periods were in an **Increasing** state; 0 periods were **Constant**; 1 period was **Decreasing**

Table 9: Initial State distribution

2021/2022	TAX	DIFF	STATUS
7	1,509,003.70		
8	1,622,783.10	113,779.40	I
9	1,960,491.20	337,708.10	I
10	1,665,290.70	(295,200.50)	D
11	1,713,469.10	48,178.40	I
12	2,470,303.10	756,834.00	I
TOTAL	10,941,340.90		

Thus, the initial state vector is:

$$S(K) = [P_I \quad P_C \quad P_D]$$
$$S(0) = [0.80 \quad 0.00 \quad 0.20]$$

Forecasting Future Tax Revenue States

Future state probabilities are obtained using the Markov prediction rule:

$$S(t+1) = S(t) \times P$$

Iterative multiplication of the initial state vector by the transition matrix produces the following sequence of state distributions (computed using Maple 2022):

Vector[row] (3, [0.606, 0., 0.394]) (1)
Vector[row] (3, [0.6312199999999999, 0., 0.36878]) (2)
Vector[row] (3, [0.6279413999999999, 0., 0.37205859999999996]) (3)
Vector[row] (3, [0.6283676179999999, 0., 0.37163238199999993]) (4)
Vector[row] (3, [0.6283122096599998, 0., 0.3716877903399999]) (5)
Vector[row] (3, [0.6283194127441998, 0., 0.37168058725579983]) (6)
Vector[row] (3, [0.6283184763432537, 0., 0.37168152365674584]) (7)

$$\text{Vector[row] (3, [0.6283185980753767, 0., 0.37168140192462285])} \tag{8}$$
$$\text{Vector[row] (3, [0.6283185822502007, 0., 0.37168141774979885])} \tag{9}$$
$$\text{Vector[row] (3, [0.6283185843074734, 0., 0.37168141569252594])} \tag{10}$$

The convergence of the state vector demonstrates that the Markov chain satisfies the condition:

$$\pi = \pi \times P$$

indicating the existence of a unique stationary (steady-state) distribution. The stationary distribution implies that, in the long run: The probability that tax revenue will be in an increasing state is approximately 0.628. The probability of a decreasing state is approximately 0.372 and the probability of a constant state converges to zero. The steady state is reached after approximately four iterations, indicating that tax revenue dynamics stabilise relatively quickly following ICT adoption. While the higher probability of remaining in an increasing state suggests a favourable long-term outlook for tax revenue sustainability, the non-negligible probability of decline (37.2%) highlights potential fiscal risks. This underscores the importance of complementary policy measures such as strengthening digital tax regulation and enforcement to mitigate long-term revenue volatility.

Discussion of Findings

The findings of this study provide important insights into the long-term sustainability of tax revenue in the context of ICT adoption. Sustainability in tax revenue mobilisation is inherently a long-term process, as the benefits of technological investments often materialise gradually through improved efficiency, compliance, and economic expansion. Consistent with this perspective, the ARDL results reveal that ICT adoption exerts differentiated short-run and long-run effects on tax revenue, highlighting the importance of accounting for dynamic adjustment processes and delayed impacts. The positive and significant long-run effect of ICT investment on tax revenue supports Hypotheses H1a and H1b, indicating that sustained investment in ICT infrastructure enhances governments' capacity to mobilise revenue over time. Although ICT investments may impose short-term fiscal pressures due to high initial costs, their long-run contribution to tax revenue arises from improved tax administration, expanded digital economic activities, and increased formalisation of economic transactions. This finding aligns with Nikiforova (2022) and Lowry (2019), who argue that digital transformation expands taxable economic activities, but contrasts with studies such as Mallick (2021) and Olaoye and Atilola (2018), which report insignificant effects in the short term. The divergence in findings can be attributed to differences in time horizons, institutional readiness, and the ability of tax systems to adapt to digital economic structures.

Regarding ICT infrastructure usage, the results indicate that broadband penetration has a positive and significant long-run effect on tax revenue, supporting Hypothesis H2a, while internet usage exerts a negative effect, leading to the rejection of Hypothesis H2b. Broadband penetration facilitates productivity gains, business expansion, and investment attraction, which collectively broaden the tax base. These results are consistent with Pushkareva (2021) and Stephens et al. (2022), who emphasise the role of broadband infrastructure in promoting economic activity and fiscal capacity. In contrast, the negative effect of internet usage may reflect challenges associated with e-commerce, cross-border digital transactions, and regulatory gaps that undermine traditional tax collection mechanisms when tax laws are not adequately aligned with digital markets. The positive and statistically significant effect of economic growth on tax revenue highlights the role of macroeconomic expansion in strengthening fiscal capacity. Higher levels of economic activity increase household incomes, corporate profits, and transaction volumes, which collectively expand the tax base and improve revenue mobilisation. Accordingly, economic growth is treated as a control variable capturing the broader macroeconomic conditions influencing tax revenue. This finding is consistent with existing literature that emphasises the close relationship between economic growth and tax revenue performance, particularly in developing economies (Qiang et al., 2009; Vu et al., 2020).

The Markov Chain analysis complements the ARDL findings by providing a probabilistic assessment of tax revenue sustainability. The results indicate a 0.628 probability of tax revenue remaining in an increasing state in the long run, suggesting a generally favourable revenue trajectory following ICT adoption. However, the presence of a 0.372 probability of declining tax revenue highlights potential vulnerabilities and underscores the need for adaptive fiscal policies. These findings are consistent with Mapesa et al. (2020) and demonstrate that while ICT adoption enhances revenue sustainability, policy misalignment and structural challenges can still pose risks to long-term revenue performance. Overall, the convergence of evidence from the ARDL and Markov Chain models suggests that ICT adoption can support sustainable tax revenue mobilisation when accompanied by appropriate regulatory frameworks, institutional capacity, and policy responsiveness. The probabilistic nature of the Markov results further underscores the importance of proactive fiscal planning to mitigate downside risks and maximise the long-term benefits of digital transformation.

Conclusion, implication and Further studies

The integration of Information and Communication Technology (ICT) in tax administration has significant potential to enhance the sustainability of tax revenue mobilisation, although its effectiveness depends on institutional, regulatory, and economic contexts. This study employed the ARDL and Markov Chain models to examine both the dynamic relationships and the long-term sustainability of tax revenue in the context of ICT adoption in Tanzania. The ARDL results reveal that ICT investment, ICT imports, and broadband penetration exert positive and significant effects on tax revenue in the long run, while internet usage is associated with a negative long-term effect, reflecting challenges in taxing digitally driven economic activities under existing tax structures. Economic growth, included as a control variable, plays a central role in strengthening the tax base and supporting revenue mobilisation. Unlike many previous studies that focus solely on short-term impacts, this study contributes to the literature by distinguishing between short-run adjustment costs and long-run revenue gains associated with ICT adoption. The findings demonstrate that while ICT-related investments may impose short-term fiscal pressures, their long-term benefits materialise through improved efficiency, productivity, and expansion of taxable economic activities. In addition, the application of the Markov Chain model provides a probabilistic perspective on tax revenue sustainability, showing that tax revenue is more likely to remain in an increasing state over time, although non-negligible risks of revenue decline persist.

From a policy perspective, the results underscore the importance of complementing ICT investments with adaptive tax policies, institutional capacity building, and regulatory frameworks capable of capturing revenue from digital economic activities. Governments and tax authorities should prioritise broadband infrastructure development, modernise tax administration systems, and align tax laws with evolving digital business models to maximise the long-term fiscal benefits of ICT adoption. The probabilistic insights from the Markov Chain analysis further highlight the need for proactive fiscal planning to mitigate potential revenue risks and enhance resilience. For future research, further investigation is recommended to explore the interaction between ICT adoption, governance quality, and institutional capacity in shaping tax revenue outcomes. Comparative cross-country studies and the use of alternative modelling approaches could provide deeper insights into how different policy environments influence the effectiveness of ICT-driven tax reforms. Additionally, future studies may examine specific digital taxation instruments and compliance mechanisms to better understand how tax systems can adapt to the growing digital economy.

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