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# Can adoption of digital technologies ease household burdens? New evidence from West Africa using a C-S ARDL approach

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**Abstract**

Technology adoption is essential for sustainable development, particularly in shaping a country's growth. While many studies have explored technology use in sub-Saharan Africa, few have examined how it affects household burdens in West Africa. This study fills that gap by analyzing the impact of technology adoption on household burdens across 12 West African countries between 1996 and 2020. It focuses on four key technologies: mobile and cellular use, internet access, clean fuel and cooking technologies, and electricity access. Using a panel data analysis method (the pooled mean group estimator of the ARDL model), the study finds that, in the long run, increased internet use, clean fuels, and access to electricity significantly reduce household burdens. However, in the short term, the effects of clean fuels and electricity access are not statistically significant. Overall, the results show that technology adoption can reduce household burdens, but the extent of its impact varies by country, depending on how widely and effectively the technology is adopted. The study highlights the need for strong policies that promote infrastructure development, technology access, and user acceptance—especially for internet services, clean fuels, and modern cooking technologies—to improve household well-being in the region.



*Keywords*: Technology adoption, Household burden, Internet users, Mobile subscribers, Energy

## 1. Introduction

The core objective of the United Nations Sustainable Development Goals (SDGs), introduced in 2015, is to foster a sustainable global future by 2030. Given its pivotal role, technology serves as a critical enabler in achieving these targets. It functions as a key driver of economic growth, a metric for assessing sustainable development, and a facilitator of global integration. While technology intersects with all seventeen SDGs, it is expected to exert a particularly significant impact on nine of them (SDG 1, SDG 3, SDG 4, SDG 6, SDG 7, SDG 8, SDG 9, SDG 11, and SDG 12). Besides, technological innovation and its diffusion have remarkably transformed consumer behavior, productivity, and living standards globally, offering substantial potential for sustainable outcomes. The United Nations [1] acknowledged the role of technology in advancing the SDGs and recommended that governments, industries, and international organizations eliminate barriers to development cooperation. It further advocated for the promotion of research in technology and the facilitation of knowledge transfer mechanisms. Additionally, it emphasized the importance of adopting best practices and context-specific technologies aligned with local economic conditions. Megan [2] highlighted that contemporary governments and firms have capitalized on cutting-edge technologies to develop innovative business models, enhance sustainability, and elevate the overall quality of life for citizens.

Consequently, Allen [3] reported the rapid diffusion of technology across Africa, resulting in internet access for approximately a quarter of the population and contributing 8.5% to the continent's gross domestic product (GDP). The study further highlighted that certain African countries have leveraged internet penetration to achieve measurable improvements in the well-being of their citizens. In terms of technological innovation and the adaptation of existing technologies, the World Health Organization [4] noted that Africa accounted for 12.8% of global technological innovations during the COVID-19 pandemic. Among African nations, South Africa led with 13%, followed by Kenya (10%), Nigeria (8%), and Rwanda (6%). Despite these advancements, there remains a pronounced gap in technology adoption between sub-Saharan Africa and the rest of the world [5]. This digital divide, according to the Broadband Commission [6], is further exacerbated within countries, where disparities are evident across socioeconomic groups in terms of both access to coverage and the quality of services provided.

The commission further noted that rural households and lower-income families, on average, exhibit lower rates of internet access. Hence, there is evidence of a funding gap that needs accelerated investment. Despite these disparities, Africa is projected to align with global trends by 2030, with three-quarters of the African population expected to be internet users by 2030. In West Africa, the World Bank [7] reported relatively high levels of mobile technology adoption, despite ongoing development challenges. The sub-region has demonstrated a rapidly expanding technology ecosystem, even amid rising mobile data costs. The adjusted cost of living in West Africa ranks among the highest in comparison to other African sub-regions and globally [8]. Specifically, the average cost of data-only mobile broadband in West African countries stood at $8.50, compared to $5.50 in East Africa. Niger and Guinea-Bissau are ranked among the top 10 most expensive countries globally for data-only mobile broadband [9]. Alleviating household burdens or reducing poverty remains a fundamental dimension of development and is the top priority of the UN SDGs. Notably, the West African region includes some of the world's poorest nations, such as Sierra Leone, Nigeria, Niger, Chad, Mali, Togo, and Liberia [10].

Given the relatively high rate of technology and internet adoption in sub-Saharan Africa, particularly in West Africa, alongside its elevated costs and the persistent high levels of poverty in the region, this study aims to investigate whether technology adoption has contributed to reducing household burdens in this context. Specifically, the research seeks to answer the question: Has the adoption of technology reduced poverty in West Africa? The contribution of this paper to the literature is twofold. First, it provides empirical evidence on the impact of digital technology adoption on household burdens. Second, it introduces novel variables into the discourse on digital technology adoption and household burden, including clean fuels and cooking technologies, access to electricity, mobile subscriptions, and internet users. The selection of West Africa as the focus of this study is based on three key considerations: the reported high levels of technology adoption, the significant cost of technology usage, and the region's elevated poverty rates.

Most studies on technology adoption in sub-Saharan Africa have focused on its implications for economic growth and inequality, with comparatively little attention given to poverty. There appears to be a scholarly consensus on the relationship between technology and both poverty reduction and inequality in the region. While Emara [11] and Muchdie [12] identified a positive impact of technology on poverty reduction, Mirza et al. [13], Zia [14], and Njangang et al. [15] highlighted the adverse effects of technology on inequality. Despite the abundance of studies on technology adoption, research within the specific context of West Africa remains limited. Moreover, the impact of technology adoption on household burdens is notably under-represented in the empirical literature. Some existing studies on technology adoption in West Africa include Carlos et al [8], Jeremiah and Osabuohien [16], and Ahuru et al. [17]; however, none of these works directly examine the effect of technology adoption on household burdens. This gap in the literature motivates the present study, as more studies on this focus area are critical. Notably, Carlos et al. [8] explored technology adoption broadly, while Jeremiah and Osabuohien [16] investigated the relationship between technology and inclusive growth. Ahuru et al. [17] focused on the link between information and communication technology (ICT) and unemployment, and Azuh et al. [18] considered innovation from a human development perspective in West Africa.

Overall, this study is designed to refine existing knowledge by providing new insight into the contribution of some dimensions of digital technology to alleviating household burden in West Africa. Its policy frameworks will be sustainable and comprehensive, aimed at improving household welfare in Africa, with a particular focus on the West African sub-region. The findings and policy recommendations of this investigation are intended to enhance household livelihoods through technological adoption. The study provides critical insights for policymakers in the region, guiding strategic actions to reduce household burdens in alignment with the Sustainable Development Goals (SDGs). Additionally, the study informs broader policy adjustments aimed at alleviating poverty and addressing other household challenges in the sub-region. The research also has significant implications for the implementation of the SDGs, as it provides an empirical evaluation of progress within the West African context.

The structure of the study is as follows: The next section reviews the relevant theoretical and empirical literature. Section 3 details the methodology, including data descriptions, model specification, and estimation techniques. The penultimate section presents and discusses the empirical findings, while the final section summarizes the study and offers policy recommendations.

## 2. Literature

### 2.1. Theoretical literature

The Schumpeterian endogenous innovation theory identifies innovation as the cornerstone of economic change and development. Schumpeter [19] and Becker et al. [20] presented the theory as an extension of the endogenous growth model, incorporating technology, socioeconomic conditions, institutions, and other conventional growth determinants as key components of economic development. Solo [21] acknowledged Schumpeter's concept of innovation as a dynamic force within the economy, acting as the source of credit, interest, profit, and business cycles. Govindan [22] observed that the resurgence of neo-Schumpeterian models of technological innovation and development reaffirms the historical significance of Schumpeter’s work on economic transformation driven by technological change.

Similarly, Romer [23], in his model of endogenous technological change, argues that technology fosters growth through intentional investments aimed at maximizing profit. Thus, the endogenous growth theory advocates for investment in innovation, technology, and human capital as primary drivers of economic expansion. According to this framework, the size of the economy is contingent upon the magnitude of investments in technology and other growth factors. Furthermore, it is posited that the rate of economic growth directly influences income levels and other key economic indicators. While Schumpeter's theory emphasizes the introduction of new technologies, Strassman [24] critiqued Schumpeter's notion of "creative destruction," arguing that it is not always accurate. Strassman contended that old technologies and production methods often persist in industries undergoing technological transformation, coexisting with newer innovations rather than being entirely replaced.

### 2.2. Empirical literature

Carlos [8] empirically examined mobile internet adoption in West Africa between 2018 and 2019. The study employed a linear probability model and identified low household consumption and high service charges as the region's primary constraints to mobile internet adoption. Jeremiah and Osabuohien [16] investigated the relationship between mobile technology adoption and inclusive growth in West Africa. Using the system generalized method of moments, they found that mobile cell subscriptions had a statistically insignificant effect on inclusive growth in the region. This lack of significance may be attributed to low-income levels and the high costs associated with acquiring technology, which, in turn, affect the number of subscribers and contribute to overall growth in the sub-region. Furthermore, Azuh et al. [18] explored the nexus between innovation and human development in West Africa from 2004 to 2014, applying fixed and random effects estimation models. Their findings indicated that research and development exert a significant positive impact on human development. Mora and Rivera [25], using the experimental technique in Mexico, confirmed that access to the internet contributes to poverty reduction, including people living in rural areas. Similarly, Zhang et al. [26] found that internet use had the capability to suppress poverty and vulnerability in rural China.

Ahuru et al. [17] utilized the pooled mean group estimator to investigate the impact of information and communication technology (ICT) on unemployment within the West African Monetary Zone (WAMZ). The research revealed a significant inverse relationship between ICT adoption and unemployment. This underscores the job-creating potential of ICT. The establishment of ICT business ventures by firms and individuals has contributed to a reduction in the unemployment rate. Meanwhile, Ayesha et al. [27] employed the system generalized method of moments (GMM) to assess the effects of technology penetration on poverty and inequality, evaluating the efficacy of linear, non-linear, and synergy effect models across 86 countries from 2005 to 2020. Their findings indicate that the impact of technological penetration varies among countries, largely depending on income levels. Furthermore, the study highlights that the positive relationship between technology and income inequality disproportionately affects low-income countries. Kakeu et al. [28] focused on the contribution of technological innovation in poverty alleviation in Africa. They found technological innovation useful in reducing poverty in Sub-Saharan Africa, with a low rate of urbanization, and supported poverty in countries with a high rate of urbanization. Gadisa and Getahun [29] examined the influence of technology adoption on the income of 210 farmer households in the Dendi district of Ethiopia. Using the propensity score matching method and logistic regression model, they found that households that adopted agricultural technology reported higher incomes compared to non-adopters. This suggests that improved agricultural technologies, such as high-yielding seedlings, are likely to yield greater returns under favorable weather conditions, quality land, and other agricultural factors. From Bangladesh, Kannari et al. [30] studied mobile phones, income diversification, and poverty decrease. The outcome indicates that mobile phone ownership correlates with the level of income and, at the same time, reduces poverty.

In a different context, Muchdie [12] explored the dimensions of technological change and human development in Indonesia from 2004 to 2013. Based on path model analysis, they indicated that technological progress has a direct negative impact on human development; however, they also noted that technological advancements positively influence human development through pathways of poverty reduction and economic growth. Xiaowei and Lingwen [31] investigated the impact of technological innovation on China’s economic growth from 1990 to 2019. By employing ordinary least squares (OLS) and weighted least squares (WLS) models, their empirical findings revealed that increased government expenditure on science and technological innovations has significantly contributed to economic growth.

Hooks et al. [32] employed a random effects panel model to explore the factors influencing technological adoption rates in 15 countries from 2010 to 2019. Their findings indicated that countries characterized by globalization and enhanced cybersecurity facilitate business operations more effectively. Additionally, they noted that nations with low levels of political violence and terrorism are more inclined to adopt new technologies compared to others. Shah and Krishnan [33] investigated the relationship between information and communication technology (ICT), gender inequality, and income inequality across 86 countries from 2013 to 2016. Utilizing cross-lagged panel analysis, they found that ICT has the potential to reduce gender inequality. However, they emphasized that the effectiveness of ICT in mitigating gender inequality varies according to the developmental status of the countries involved. Burch et al. [34] examined the work and personal determinants of mobile technology adoption among community-dwelling older adults. Using a mixed-methods approach, their results suggested that inequalities in income and occupation prior to retirement are associated with varying levels of mobile technology proficiency. The study further indicated that many participants employed compensatory secondary control strategies, which hindered their adoption and usage levels of mobile technology. Njangang [15] investigated the effect of ICT on wealth inequality in 45 developed and developing countries during the period from 2000 to 2017.

By employing the generalized method of moments, the study revealed that ICT tends to exacerbate wealth inequality. Conversely, the findings suggested that democratic governance mitigates the increasing effect of ICT on wealth inequality. In a study focused on eradicating poverty in Sri Lanka, Dasanayaka [35] concluded that without a comprehensive approach to integrating and distributing new technologies to impoverished populations, substantial investments in research development, innovations, technology transfer, and acquisition would be insufficient for alleviating poverty. Zang et al. [36] examined the impact of mobile phone use on energy poverty by adopting the Ordinary least squares technique. They established a significant negative impact of mobile phone use and energy poverty. Shita et al. [37] examined the effects of fertilizer adoption on poverty and income distribution in North Western Ethiopia using the propensity score matching technique and dose-response function. Their results indicated that the adoption of fertilizer significantly increased household per-adult consumption expenditure. The study also affirmed that the utilization of improved agricultural tools led to higher household incomes and a substantial reduction in poverty incidence. Jin et al. [38] investigated internet adoption and poverty in rural China from 2014 to 2018 using the difference-in-difference approach. Findings reveal a varying degree of poverty reduction among rural dwellers across regions.

Zahao et al. [39] examined the dynamic influence of digital and technological advancements on sustainable economic growth among 21 partner countries in the Asian region along the Belt and Road initiative from 2004 to 2020. The study employed a two-step generalized method of moments (GMM) approach and found that increases in the e-government development index, ICT exports, and the growth of internet users significantly and positively impact sustainable economic growth. This outcome suggests that digital and technological advancements are beneficial for sustainable economic growth. Similarly, Mirza et al. [13] explored the relationship between technology-driven inequality, poverty, and resource depletion. Utilizing the social-ecological model, they discovered that a positive feedback loop between wealth and technology can lead to local inequality, extensive resource degradation, and increased poverty levels. Dercon and Christiaensen [40] investigated the interplay between consumption risk, technology adoption, and poverty traps in Ethiopia. Their findings indicated that credit constraints and suboptimal consumption outcomes during poor harvests deterred fertilizer application, while the absence of insurance or alternative means to stabilize consumption left some households trapped in low-return scenarios.

From this review, it is evident that previous investigations have paid insufficient attention to the peculiarities of the West African region regarding technological adoption. Likewise, prior studies have overlooked the impact of technology adoption with emphasis on household burdens in this sub-region. Thus, our study aims to address this critical gap in the empirical literature. Moreover, unlike previous investigations, this study employed advanced panel data techniques that are robust to cross-sectional dependencies and slope heterogeneities. These enhanced estimators include the pooled mean group (PMG) estimator and the cross-sectional autoregressive distributed lag (CS-ARDL) model.

## 3. Methodology

### 3.1. Data descriptions and sources

The focus of this study is to ascertain the influence of technology on household burdens. The study utilized the proportion of the population living below the poverty line as a proxy for household burden across 12 countries in West Africa. To ensure a comprehensive assessment, datasets spanning the years 1996 to 2020 were analyzed. The selection of this date range is based on data availability. Table 1 presents detailed information regarding the description and sources of the relevant panel data series.

Table 1. Data descriptions and sources

| Variable | Description | Sources |
|---|---|---|
| Poverty (*POVT*) | Share of the population below the poverty line | Our World in Data (OWID) |
| Mobile cellular subscription (*MOCS*) | Number of mobile cellular subscribers per 100 persons | Our World in Data (OWID) |
| Internet users (*INTU*) | Percentage of the population using the internet | Our World in Data (OWID) |
| Clean fuel and technologies for cooking (*CFTC*) | The proportion of the population with primary reliance on clean fuel and technologies for cooking. | Our World in Data (OWID) |
| Access to electricity (*ACCE*) | Percentage of the population with access to electricity | Our World in Data (OWID) |
| Education (*SCEN*) | School enrolment, primary (% gross) | World Development Indicators (WDI) |
| Sampled countries | | |
| Benin, Burkina Faso, Cabo Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Mali, Niger, Nigeria, Senegal, and Togo | | |

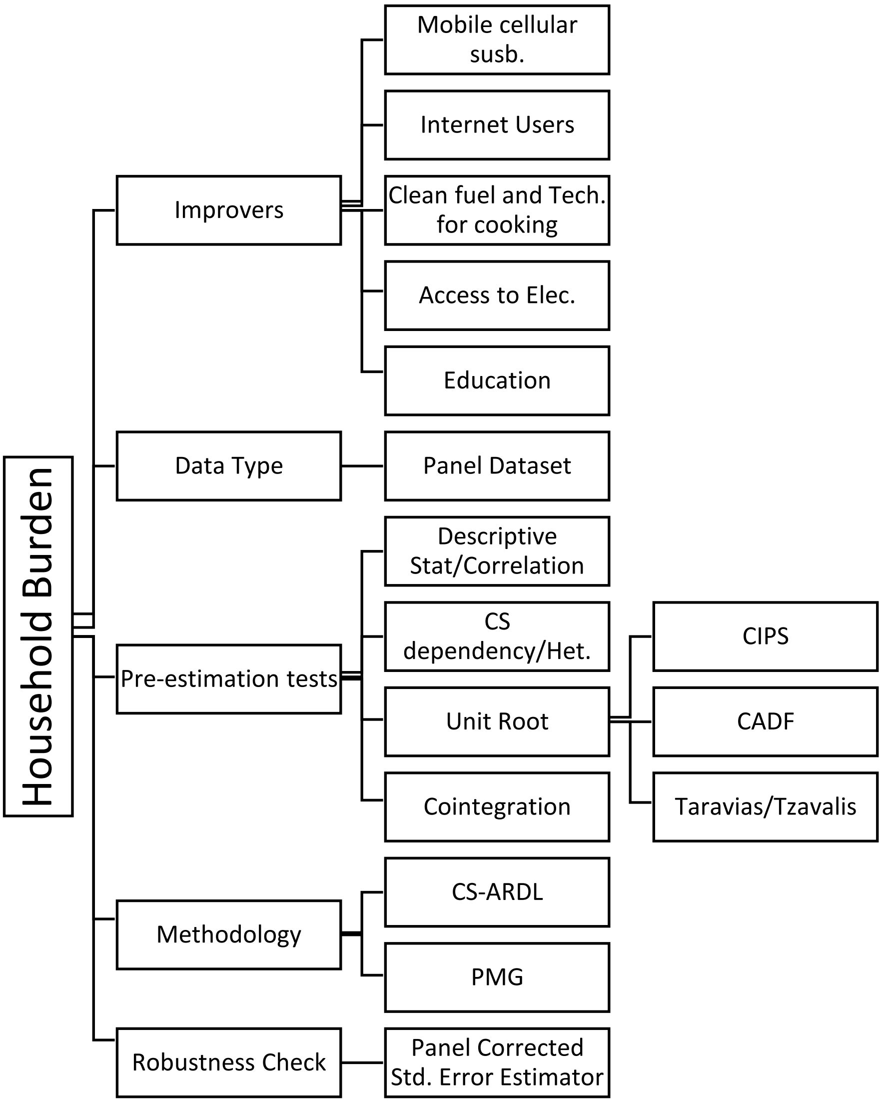


Figure 1. Methodological framework

#### 3.1.1. Model specification

The study adapted the Schumpeterian model for its empirical estimations. Accordingly, the Schumpeterian model considers three basic factors of growth, where; $A$ is, $S$ is socioeconomic factors, including institutions, and these are the traditional determinants of growth. Our study suggests that an increase in growth rate, $Y$ resulting from $A$ will reduce poverty. Hence, we hypothesize that poverty. $POV = f(Ai, Si, Xi)$. Focusing on $A$ and decomposing technology, the following model subsists:

$$POVT = (MOCS, INTU, CFTC, ACCE, SCEN) \quad (1)$$

where POVT depicts the poverty rate (a proxy for household burden), MOCS denotes mobile cellular subscribers, INTU depicts internet users, CFTC represents clean fuel and technology for cooking, while ACCE is access to electricity. Essentially, these control variables were enlisted based on their notable influence on the predicted variables [41], [42], [43]. Likewise, their inclusion will help to overcome omitted variable bias and skewed estimates and ensure the internal validity of the findings. Employing the panel ARDL estimation technique and introducing SCEN (school enrolments) as a control variable, our operating model becomes:

$$\Delta POVT_t = \phi + \sum_{i=1}^{k} \vartheta_i POVT_{t-i} + \sum_{i=1}^{l} \theta_i \, \Delta MOCS_{t-1} + \sum_{i=1}^{m} \lambda_i \Delta INTU_{t-1} + \sum_{i=1}^{n} \chi_i \Delta CFTC_{t-1} + \sum_{i=1}^{p} \zeta_i \, \Delta ACCE_{t-1} + ƛ_1 MOCS_{t-1} + ƛ_2 INTU_{t-1} + ƛ_3 CFTC_{t-1} + ƛ_4 ACCE_{t-1} + ƛ_5 SCENE_{t-1} + \varepsilon_t \quad (2)$$

#### 3.1.2. Estimation procedures

##### 3.1.2.1. Cross-sectional dependence (CD) test

In modeling a panel data set, an issue of great importance is the cross-sectional dependency of the units forming the panel. This is experienced when the error terms of the cross sections are related, as specified in Equation 3 standard panel data model.

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \quad (3)$$

The null hypothesis assumes that the error term ($\varepsilon_{it}$) is independent and identically distributed over time and across units, i.e. $Cov(\varepsilon_{it}, \varepsilon_{ij}) = 0$. However, the alternative hypothesis is that the error term may correlate across units ($Cov(\varepsilon it, \varepsilon ij) \neq 0$). Whereas the null hypothesis assumes no cross-sectional dependence, the alternative hypothesis assumes that panels are affected by shocks from other panels, translating to cross-sectional dependence (CD).

Laszlo and Patrick [44] observed that time series in macroeconomic applications involving country or regional data tend to be contemporaneously correlated. Consequently, cross-sectional dependence can arise due to spatial spillover effects, unobserved common factors, and omitted commonly observed variables. Ignoring cross-sectional dependence in panel analysis can lead to spurious results and biased estimates. Therefore, this study adopts a combination of cross-sectional dependence (CD) test criteria based on insights from prior studies [45]. The tests employed include the Breusch and Pagan Lagrange multiplier (LM) test, Pesaran scaled LM test, bias-corrected scaled LM test, Pesaran CD test, and Friedman test. The rationale for this combination is to address the limitations of individual test criteria. For instance, while the Breusch and Pagan test is most suitable for this study, given that the time period (T) exceeds the number of countries (N), the Pesaran CD test serves as an alternative.

***Panel unit-root test***

The presence of cross-sectional dependence in a panel data set alters the use of the first-generation panel unit-root test and necessitates the second-generation unit-root test. The first-generation panel unit-root tests, such as [46-51], have been criticized since they assumed no CD among panels. Therefore, the second-generation unit-root tests are designed to address the challenges of cross-sectional dependence in panel series. Hence, this study adopted the cross-sectional augmented Dickey-Fuller (CADF) and cross-sectional augmented Im, Pesaran, and Shin (CPIS) processes among several second-generation panel unit-root test toolkits. Thus, Pesaran [52] proposed these two second-generation panel unit-root (CADF and CIPS) procedures. The test criteria have a common assumption of cross-sectional correlation due to the presence of an unknown common factor. The Pesaran CADF and CIPS assume $r = 1$ that the error term has an unobserved common factor structure accounting for the cross-sectional dependence. The CADF is based on the cross-sectional augmented Dickey-Fuller test, where the standard Dickey-Fuller regressions are augmented with cross-sectional averages of lagged levels and first differences of individual series. This standard panel unit-root test is based on the simple averages of individual cross-sectional augmented ADF statistics. Notably, Equation 4 is a demonstration of the typical CADF specification.

$$\Delta y_{it} = \alpha_i + \rho_i y_{it-1} + \delta_i \bar{y}_{t-1} + \sum_{j=0}^{k} \delta_{ij} \Delta \bar{y}_{it-j} + \sum_{j=0}^{k} \Delta y_{it-j} + \varepsilon_{it} \qquad (4)$$

where, $\bar{y}_{t-1} = (\frac{1}{N})\sum_{i=1}^{N} y_{it-1,} \Delta\bar{y}_t = (\frac{1}{N})\sum_{I-1}^{N} y_{it}\, t_i(N,T)$ is the t-statistic estimate of $\rho_i$ used for computing individual ADF statistics.

On the other hand, the CIPS is a simple average of individual CADF statistics as follows:

$$CIPS = (\frac{1}{N})\sum_{I=1}^{N} ti(N,T) \qquad (5)$$

CIPS is a cross-sectional augmented IPS and is the CADF for the individual cross-sectional unit given by the t-ratio of CADF regression.

**3.1.2.2. Panel cointegration test**

The panel cointegration test is a natural follow-up to the panel unit-root test and is essential to avoid spurious results. Several panel cointegration procedures have been proposed in panel econometric modelling. Our study employs Pedroni [53], [54], who introduced seven test statistics for cointegration criteria. Pedroni proposed two alternative hypotheses: the homogeneous alternative, where $(\rho_i = \rho) < 1$ all cross-sections are termed the within-dimension or panel statistics tests. The heterogeneous alternative, where $(\rho_i < 1)$ for all cross-sectional units is referred to as the between-dimension or group statistics test. Hence, the Pedroni test has the advantage of accommodating homogeneous and heterogeneous panels. It can be conducted with or without a constant and or time trend. The test can include common time dummies to address simple cross-sectional dependency. This is applied by time demeaning the data for each individual and variable [55] (Equation 6).

$$\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} X_{it} \qquad (6)$$

Pedroni's entire test statistics are residual-based tests collected from the following regressions:

$$y_{i,t} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots\ldots\ldots.\beta M_{it} + e_{it} \qquad (7)$$

$$\Delta y_{i,t} = \sum_{m=1}^{M} \beta_{mi} \Delta X_{mit} + \upsilon_{it} \qquad (8)$$

$$\hat{e}_{i,t} = \hat{\eta}_i, \hat{e}_{it-1} + \hat{\mu}_{it.} \qquad (9)$$

$$\hat{e}_{it} = \hat{\eta}_i \hat{e}_{it-1} + \sum_{p=1}^{p} \hat{\eta}_{ip-k} + \hat{\mu}_{it} \qquad (10)$$

where i = 1, 2,..., N is the number of individuals in the panel, t = 1, 2,..., T is the number of periods, m = 1, 2,..., M is the number of regressors, and k = 1, 2,..., K is the number of lags in the ADF regression.

Furthermore, Westerlund [56] developed an alternative test based on four error-correction-based panel cointegration tests. These tests allow for significant heterogeneity in both the long-run cointegrating relationships and the short-run dynamics. Additionally, they account for dependence within and across cross-sectional units [57]. Similar to the tests proposed by Pedroni [53], [54], the Westerlund [56] test demonstrates favorable small-sample properties, exhibiting minimal size distortions and high power relative to other widely used residual-based panel cointegration tests. Two of the tests are designed to evaluate the alternative hypothesis that the panel is cointegrated as a whole, while the other two assess the alternative hypothesis that at least one unit is cointegrated.

#### 3.1.2.3. Pool means group (PMG) and Panel ARDL models

As previously mentioned, this study employs the pooled mean group (PMG) estimator of the autoregressive distributed lag (ARDL) technique. These steps are undertaken primarily to provide new insights into the literature on technology adoption and household burdens in West African countries, as well as to achieve the study's defined objectives. The panel ARDL methodology has the capacity to estimate both long-run and short-run dynamics, accommodate different orders of integration, and permit varying lag orders. The PMG estimator facilitates greater parameter heterogeneity compared to standard estimation procedures commonly used in empirical studies [58]. It enforces common long-run relationships across groups while allowing for heterogeneity in long-run responses and intercepts [59], [41].

In its general form, the panel ARDL is presented as follows:

$$\Delta Y_i = \sum_{k=1}^{P=1} \psi_{ik} \Delta y_{it-k} + \sum_{k=0}^{q-1} \lambda_{ik} \Delta \delta_{it-k} + \chi_i (y_{it-1} + \vartheta'_i \beta_{it}) + \alpha_i + \varepsilon_{it} \qquad (11)$$

where $\lambda_{ik}, \delta_{it-k}$ = short-term coefficients and $\chi_i$ = group-specific error correction coefficient which < 0

while the ARDL error correction model is presented as follows:

$$\Delta POVT_t = \psi_0 + \sum_{i=1}^{k} \vartheta_i \Delta POVT_{t-1} + \sum_{i=1}^{p} \zeta_i \, \Delta MOCS_{t-1} \sum_{i=1}^{v} \varphi_i \, \Delta INTU_{t-1} + \sum_{i=1}^{m} \lambda_i \Delta CFTC_{t-1} + \sum_{i=1}^{l} \theta_i \, \Delta ACCE_{t-1} + \sum_{i=1}^{l} \psi\text{i} \, \Delta SCENt_{t-1} + \delta u_{t-1} + \tau_t \qquad (12)$$

where $\delta$ is the error correction term, and the error term is defined as:

$$u_{t-1} = (POVT_{t-1} - \chi_0 - \gamma_1 MOCS_{t-1} - \gamma_2 INTU_{t-1} - \gamma_3 CFTC_{t-1} - \gamma_4 ACCE_{t-1} - \gamma_5 SCEN_{t-1}) \quad (13)$$

In addition to the PMG estimator of the ARDL, the study further employed the Cross-sectional ARDL and the panel-corrected error estimator to ensure consistency and robust analysis

## 4. Results and discussions

### 4.1. Results

Table 2. Descriptive statistics and correlation matrix

| **Statistics** | **Descriptive statistics** | | | | | |
|---|---|---|---|---|---|---|
| | POVT | MOCS | INTU | CFTC | ACCE | SCEN |
| Mean | 3.613 | 3.307 | 0.579 | 1.485 | 3.471 | 4.001 |

| **Statistics** | | **Descriptive statistics** | | | | |
|---|---|---|---|---|---|---|
| | POVT | MOCS | INTU | CFTC | ACCE | SCEN |
| Maximum | 4.410 | 5.024 | 4.167 | 4.394 | 4.545 | 4.605 |
| Minimum | 0.748 | -6.946 | -6.948 | -1.203 | 1.456 | 1.183 |
| Std. Dev. | 0.676 | 2.740 | 2.456 | 1.523 | 0.681 | .702 |
| Skewness | -1.850 | -1.155 | -.856 | .3150 | -.726 | -2.134 |
| Kurtosis | 6.692 | 3.310 | 3.254 | 1.889 | 2.707 | 7.127 |
| **Correlation matrix** | | | | | | |
| POVT | 1.00 | | | | | |
| MOCS | -0.449<br>0.000 | 1.00 | | | | |
| INTU | -0.553<br>0.000 | 0.426<br>0.000 | 1.00 | | | |
| CFTC | -0.642<br>0.000 | 0.340<br>0.000 | 0.4385<br>0.000 | 1.00 | | |
| ACCE | -0.686<br>0.000 | 0.487<br>0.000 | 0.365<br>0.000 | 0.443<br>0.000 | 1.00 | |
| SCEN | -0.339<br>0.000 | 0.220<br>0.000 | 0.267<br>0.000 | 0.2670<br>0.000 | 0.281<br>0.000 | 1.00 |

Table 2 presents the outcomes of the summary statistics and correlation matrix. All series are normally distributed and do not exhibit extreme values, with the exception of internet users and clean fuel and technology for cooking. The correlation matrix indicates negative and moderate correlations between poverty and mobile subscribers, as well as between poverty and internet users, with a weak correlation observed with school enrollment. Conversely, the correlation between poverty and clean fuel and technology for cooking, as well as access to electricity, is relatively strong and negative. Although the correlations between poverty and other variables are not particularly strong, they remain relevant for the objectives of this study.

#### 4.1.1.1. Cross-sectional dependence

Table 3. Cross-sectional dependency and slope heterogeneity results

| **Panel A** | | |
|---|---|---|
| Variables | T-Stats. | |
| POVT | 24.739*** | |
| MOCS | 39.027*** | |
| INTU | 39.446*** | |
| CFTC | 13.403*** | |
| ACCE | 32.63*** | |
| SCEN | 7.29*** | |
| **Panel B** | | |
| Slope Heterogeneity test | | |
| | $\tilde{\Delta}$ | $\tilde{\Delta}_{Adjusted}$ |
| Model | 16.121*** | 18.205*** |

*** implies a rejection of the null hypothesis of no cross-sectional dependency at a 1 % significance level.

### 4.2. Unit root and cointegration tests

The outcomes of both cross-sectional dependency and slope heterogeneity tests (Table 3) gave credence to reject the null hypothesis of cross-sectional independence and slope homogeneity among the series. Thus, upon confirming significant cross-sectional dependencies and heterogeneous slopes of the variables, the study evaluated the stationarity of the variables using CIPS and Pesaran CADF unit root criteria, as shown in Table 4.

Table 4. CIPS and CADF panel unit root tests

| | **Variable** | **CIPS (Levels)** | | | **CADF (Levels)** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | t-bar | Cv10 | Cv5 | Cv1 | t-bar | Cv10 | Cv5 | Cv1 | p-value |
| POVT | -1.844 | -2.14 | -2.25 | -2.45 | -2.03 | -2.14 | -2.25 | -2.45 | 0.18 |
| MOCS | 3.943* | -2.14 | -2.25 | -2.45 | -4.22** | -2.14 | -2.25 | -2.45 | 0.00 |
| INTU | -4.075* | -2.14 | -2.25 | -2.45 | -2.66** | -2.14 | -2.25 | -2.45 | 0.00 |
| CFTC | -1.686 | -2.14 | -2.25 | -2.45 | -1.44 | -2.14 | -2.25 | -2.45 | 0.88 |
| ACCE | -2.456* | -2.14 | -2.25 | -2.45 | -2.01 | -2.14 | -2.25 | -2.45 | 0.19 |
| SCEN | -2.895* | -2.14 | -2.25 | -2.45 | -1.81 | -2.14 | -1.25 | -2.45 | 0.45 |
| | **CIPS FIRST DIFF** | | | | **CADF FIRST DIFF** | | | | |
| | t-bar | Cv10 | Cv5 | Cv1 | t-bar | Cv10 | Cv5 | Cv1 | p-value |
| POVT | -3.911* | -2.14 | -2.25 | -2.45 | -2.90* | -2.14 | -2.25 | -2.45 | 0.00 |
| MOCS | - | -2.14 | -2.25 | -2.45 | - | - | - | - | - |
| INTU | - | -2.14 | -2.25 | -2.45 | - | - | - | - | - |
| CFTC | -2.978* | -2.14 | -2.25 | -2.45 | -2.30* | -2.14 | -2.25 | -2.45 | 0.03 |
| ACCE | - | - | - | - | -4.89* | -2.14 | -2.25 | -2.45 | 0.00 |
| SCEN | - | - | - | - | 3.034* | -2.14 | -2.25 | -2.45 | -0.00 |

**, * refers to significant at 1%, 5% and 10% levels, respectively.

The results of the stationarity tests indicate that mobile and cellular subscribers, as well as internet users, are stationary at levels using both criteria, while poverty is stationary at the first difference according to both methods. All other variables that exhibited a unit root process at levels were found to be stationary at the first difference as well. To address the limitations of the diagnostic criteria, this study employed two diagnostic tests. Additionally, the Karavias and Tzavalis [60] structural-break panel unit root test was utilized to account for the impact of structural shocks. This test also offers the advantage of identifying the presence or absence of cross-sectional dependency, sectional heteroskedasticity, and normally distributed errors.

Table 5. Karavias and Tzavalis' panel unit root test

| Variable | min Z Stat | Bootsrap Crt. Val. | P. Val | Break Date |
|---|---|---|---|---|
| POVT | -10.68 | 4.63 | 0.00 | 2019 |
| MOCKS | -22.28 | 14.53 | 0.00 | 2019 |
| INTU | -22.35 | 14.94 | 0.00 | 2019 |
| ACCE | -17.96 | 7.22 | 0.00 | 1999 |
| CFTC | -7.37 | 1.97 | 0.00 | 1997 |
| SCEN | -18.26 | 6.88 | 0.00 | 1997 |

The Karavias and Tzavalis test presented in Table 5 indicates the rejection of the null hypothesis of all panel time series having unit-root processes without breaks to accept the alternative of some panel series having a stationary process with breaks. The stationarity of the variables and the demonstration of the structural breaks rule out a possible spurious regression and confirm the outcome's reliability for prediction and policy brief.

Table 6. Cointegration test results

| Pedroni | | | Westerlund | | |
|---|---|---|---|---|---|
| Parameter | Statistics | p-value | | Statistics | p-value |
| Modified-Phillips Perron t | 3.890 | 0.001 | Var. Ratio | 1.425 | 0.077 |
| Phillips- Perron t | 2.068 | 0.019 | | | |
| Augmented Dickey-Fuller t | 2.475 | 0.007 | | | |

The study employed two cointegration tests, as illustrated in Table 6, to accommodate different cointegration assumptions. While Pedroni's criteria hypothesize cointegration across panels, the Westerlund procedure hypothesizes cointegration for some panels. Given the outcomes of both procedures, the null hypothesis of no cointegration is rejected. The rejection of the null hypothesis implies a long-run relationship between poverty and the listed predicting variables.

Table 7. Group outcomes with poverty as the dependent variable

| **Pooled Mean Criterion** | | | | | | | |
|---|---|---|---|---|---|---|---|
| Long Run Outcome | | | | Short Run Outcome | | | |
| Variable | Coef. | Std. Error | P. Val. | Variable | Coef. | Std. Error | P. Value |
| MOCS | 0.219*** | 0.034 | 0.000 | MOCS | -.0003 | 0.020 | 0.892 |
| INTU | -0.359*** | 0.047 | 0.000 | INTU | 0.003 | 0.010 | 0.794 |
| ACCE | -0.122 | 0.139 | 0.382 | ACCE | -0.037 | 0.029 | 0.208 |
| CFTC | 0.088 | 0.058 | 0.128 | CFTC | -0.639 | 0.487 | 0.189 |
| SCEN | -0.039 | 0.079 | 0.628 | SCEN | -0.015 | 0.019 | 0.443 |
| | | | | Cons | 0.266 | 0.132 | 0.043 |
| | | | | ECT | -0.081*** | 0.034 | 0.016 |
| **Cross-Sectional ARDL Criterion** | | | | | | | |
| Long Run Outcome | | | | Short Run Outcome | | | |
| Variable | Coef. | Std. Error | P. Val. | Variable | Coef. | Std. Error | P. Value |
| MOCS | 0.037 | 0.032 | 0.245 | MOCS | -0.041 | 0.035 | 0.023 |
| INTU | -0.098 | 0.079 | 0.216 | INTU | -0.156 | 0.114 | 0.169 |
| ACCE | -0.171* | 0.095 | 0.071 | ACCE | 0.182 | 0.111 | 0.102 |
| CFTC | -0.102** | 0.356 | 0.015 | CFTC | -0.287 | 0.432 | 0.506 |
| SCEN | -0.084** | 0.225 | 0.010 | SCEN | -0.001 | 0.275 | 0.997 |
| **Panel Corrected Error Standard Estimator** | | | | | | | |
| Variable | Coef. | Std. Error | P. Val. | | | | |
| MOCS | -0.017 | 0.012 | 0.179 | | | | |
| INTU | 0-.036*** | 0.013 | 0.005 | | | | |
| ACCE | -0.029 | 0.026 | 0.272 | | | | |
| CFTC | -0.203*** | 0.033 | 0.000 | | | | |
| SCEN | 0.001 | 0.011 | 0.942 | | | | |
| Cons | 3.986*** | 0.099 | 0.000 | | | | |

****, **, * imply significant relationship at 1%, 5%, and 10% levels of significance, respectively.*

Table 7 presents the estimates obtained using the cross-sectional Autoregressive Distributed Lag (ARDL) and Pooled Mean Group (PMG) methods for robustness checks. The findings indicate that all dimensions of technology adoption have not significantly reduced household burdens in West Africa. Except for mobile and cellular subscribers, other variables inhibited household burden. Consequently, the null hypothesis of no significant effect is upheld for mobile cellular subscribers and internet users. On the other hand, the null hypotheses of no significant effect are rejected for clean fuel and technology for cooking, internet users, and access to electricity. Furthermore, the model suggests that the household burden associated with technology in the region will significantly return to equilibrium at a rate of 8%.

Table 8. Country-specific outcome

| Variable | Coff. | P.Val | Variable | Coff. | P. Val | Variable | Coff. | P. Val |
|---|---|---|---|---|---|---|---|---|
| **Country** | **Benin** | | | **B/Faso** | | | **Cabo Verde** | |
| **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** |
| MOCS | -0.019* | 0.085 | MOCS | 0.039 | 0.074 | MOCS | -0.066 | 0.007 |
| INTU | -0.004 | 0.683 | INTU | 0.009 | 0.625 | INTU | 0.036 | 0.149 |
| CFTC | 0.054 | 0.280 | CFTC | -0.449 | 0.139 | CFTC | -5.799 | 0.004 |
| ACCE | 0.028 | 0.606 | ACCE | -0.050 | 0.338 | ACCE | 0-.037 | 0.000 |
| SCEN | -0.007 | 0.697 | SCEN | 0.034 | 0.000 | SCEN | 0.026 | 0.136 |
| ECT | -0.57 | 0.017 | ECT | -0.163 | 0.000 | ECT | -0.007 | 0.747 |
| Cons | 0.216 | 0.046 | Cons | 0.608 | 0.002 | Cons | -0.014 | 0.857 |
| **Country** | **Cote d'Ivoire** | | | **Ghana** | | | **Gambia** | |
| **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** |
| MOCS | -0.117 | 0.059 | MOCS | 0.136 | 0.082 | MOCS | 0.087 | 0.310 |
| INTU | 0.004 | 0.926 | INTU | 0.065 | 0.554 | INTU | 0.049 | 0.288 |
| CFTC | 0.921 | 0.092 | CFTC | -0.530 | 0.615 | CFTC | -0.773 | 0.091 |
| ACCE | -0.333 | 0.115 | ACCE | 0.025 | 0.946 | ACCE | -0.018 | 0.878 |
| SCEN | - | - | SCEN | 0.030 | 0.471 | SCEN | 0.014 | 0.432 |
| ECT | -0.259 | 0.000 | ECT | -0.045 | 0.557 | ECT | -0.074 | 0.419 |
| Cons | 0.839 | 0.007 | Cons | 0.004 | 0.990 | Cons | 0.182 | 0.500 |
| **Country** | **Guinea** | | | **Niger** | | | **Mali** | |
| **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** |
| MOCS | 0.037 | 0.216 | MOCS | -0.053 | 0.024 | MOCS | -0.011 | 0.514 |
| INTU | -0.038 | 0.505 | INTU | 0.010 | 0.753 | INTU | -0.005 | 0.872 |
| CFTC | -0.179 | 0.446 | CFTC | -0.403 | 0.000 | CFTC | -0.581 | 0.049 |
| ACCE | 0.048 | 0.341 | ACCE | -0.026 | 0.620 | ACCE | -0.041 | 0.707 |
| SCEN | 0.014 | 0.589 | SCEN | 0.011 | 0.402 | SCEN | 0.001 | 0.949 |
| ECT | 0.000 | 0.995 | ECT | -0.104 | 0.002 | ECT | 0.019 | 0.699 |
| Cons | -0.042 | 0.815 | Cons | 0.424 | 0.004 | Cons | -0.075 | 0.699 |
| **Country** | **Nigeria** | | | **Senegal** | | | **Togo** | |
| **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** | **Variable** | **Coff.** | **P. Val** |
| MOCS | -0.025 | 0.179 | MOCS | 0.046 | 0.901 | MOCS | 0.022 | 0.498 |
| INTU | -0.043 | 0.220 | INTU | 0.832 | 0.409 | INTU | -0.054 | 0.013 |
| CFTC | -0.190 | 0.053 | CFTC | -0.041 | 0.855 | CFTC | 0.297 | 0.003 |
| ACCE | -0.062 | 0.275 | ACCE | -0.030 | 0.459 | ACCE | 0.054 | 0.012 |
| SCEN | - | - | SCEN | -0.111 | 0.137 | SCEN | -0.191 | 0.235 |
| ECT | -0.078 | 0.306 | ECT | -0.305 | 0.000 | ECT | 0.106 | 0.083 |
| Cons | 0.362 | 0.302 | Cons | 1.188 | 0.004 | Cons | -0.501 | 0.073 |

The short-run country-specific outcomes are presented in Table 8. The findings indicate that technology adoption has had the greatest influence on household burdens in Cabo Verde. The three dimensions of technology—mobile and cellular subscribers (MOCS), clean fuel and technology for cooking (CFTC), and access to clean electricity (ACCE)—produced significant poverty-reducing effects exclusively in Cabo Verde. Among these dimensions, clean fuel and technology for cooking reduced poverty in nine countries, with significant effects observed in five of those countries (Cabo Verde, Ghana, Mali, Niger, and Nigeria) and insignificant effects in four (Senegal, Burkina Faso, Gambia, and Guinea).

Additionally, mobile and cellular subscriptions significantly impacted household burdens in Cabo Verde, Côte d'Ivoire, and Gambia. Conversely, access to electricity was found to have an insignificant influence on household burdens in Burkina Faso, Côte d'Ivoire, Ghana, Mali, Niger, and Nigeria. The results demonstrated strong evidence of the country-specific models returning to equilibrium, with the exception of Ghana, Guinea, Niger, Nigeria, and Togo. Notably, the adoption of mobile and cellular technology has exacerbated household burdens in six countries (Senegal, Burkina Faso, Ghana, Guinea, Gambia, and Togo). Furthermore, internet use has worsened poverty in Côte d'Ivoire, Gambia, Ghana, and Cabo Verde. As a result, Togo, Guinea, and Benin continue to experience insufficient access to electricity, contributing to an increasing number of individuals remaining below the poverty line.

## 5. Discussions

The insignificant effect of technology adoption in West Africa in the short run is anticipated, given the high costs associated with acquisition and operation, as reported by [10], [39], [12]. Consequently, the high cost of adoption may limit the number of adopters and the rate of penetration in the short term, adversely affecting household burdens. The long-run dominating impact of technology adoption (internet users, access to electricity and clean fuel, and technology for cooking) on household burdens in West Africa can be attributed to the necessary time required to adjust to long-term realities. This finding aligns with Muchdie's [12] observations in Indonesia. However, it contradicts the conclusions of Mirza et al. [13] and Njangang et al. [15], who posited that access to technology may exacerbate income inequality and push the most vulnerable members of society into poverty traps. Further, [61], [62], [63], [64] found Fintech and cyber activities relevant in improving welfare and sustainable development. Similarities and or differences in results may be a result of policy and stage of development, rate of technology penetration and level of acceptance, data-generating process, and method of analysis.

The persistent increase in poverty, despite the rise in the number of internet users and mobile subscribers in some countries, may be attributable to the underutilization of adopted technologies and the non-inclusiveness of users. Many internet users and mobile subscribers in both rural and urban areas primarily use their devices for basic functions, such as making calls and engaging in social media, which undermines the potential economic benefits. Regarding inclusiveness, potential adopters may be excluded from the technology ecosystem due to factors such as high acquisition and usage costs, illiteracy, and inadequate electricity supply. Insufficient energy production and the resultant inadequate supply from grid providers in some West African countries have negatively impacted economic activities that could enhance welfare and alleviate poverty. Furthermore, factors contributing to increased household burdens in certain West African countries, despite technology adoption, may include high costs of petroleum products, cooking appliances, and gadgets, as well as energy supply shortages.

The varying outcomes highlight differences in technology adoption rates, penetration levels, and overall development in West Africa. These disparities also reflect the unique circumstances of individual countries in the context of technological development. The implication is either an increase in poverty or an insignificant decrease in the region's poverty rate.

## 6. Contribution and research findings

The long-run findings show that technology adoption has no significant inhibitory impact on household burdens in West Africa, except for mobile and cellular subscribers. Accordingly, the null hypothesis of no significant effect is supported. Nevertheless, the three methods generated consistent estimates in the long run. The study rejects the null hypothesis of no significant effect, though two dimensions of technology from each method significantly reduced household burdens. Access to clean electricity was found to suppress household burdens; its effect, however, was considered insignificant, according to all estimating techniques. Additional findings include the efficacy of the household burden model in the region to significantly adjust to equilibrium at a speed of 8%.

### 6.1. Conclusion

Technology adoption is recognized as a critical factor for sustainable development; however, limited research has been conducted to explore its linkages with household burden in West Africa. This study aims to address this gap and contribute to the existing literature in this area. We hypothesize that mobile and cellular usage, internet access, clean fuel and cooking technologies, and access to electricity and school enrollment significantly impact household burden. To theorize the relationship between household burden and technology adoption, we employed the Schumpeterian model of endogenous innovation. The study generated both group-level and country-specific outcomes. The group findings revealed an insignificant effect of all dimensions of technology adoption on household burden in the short run, except for mobile and cellular subscriptions. However, we found that technology adoption can significantly reduce household burden in the long run. Additionally, the country-specific results demonstrated varying relationships between technology adoption and household burden, reflecting differences in penetration rates and levels of development. Thus, the study concludes that technology adoption has the potential to diminish household burden in West Africa, hence satisfying its objectives and answering the research question.

### Implications

Consequently, it is imperative for countries to develop tailored technology adoption policies that are suitable for their specific environments and levels of development. Practically, not all dimensions of technology adoption considered—such as mobile subscriptions, internet usage, clean fuel and cooking technology, and access to electricity—have significant contributions to reducing household burden within the countries studied. Therefore, we advocate for targeted policies aimed at enhancing penetration rates and inclusivity for those technological dimensions that have the potential to alleviate household burdens. Furthermore, we recommend the development and promotion of technology dimensions that have not significantly contributed to reducing household burdens. By implementing these measures, more households in the sub-region could escape the poverty trap and make significant contributions to national income.

### Limitations and future research

This study acknowledges the limitation of data availability, as only 12 out of 16 countries were analyzed. Other dimensions of technology, such as information and communication technology (ICT), transport, and locally fabricated technologies, could also relieve household burdens but were not captured in this study. We, therefore, recommend future research to explore these additional dimensions of technology and investigate other areas, such as technology's impact on health and well-being.

### Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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### Author contribution

All authors contributed to the study conception, design, Data curation, formal analysis, original draft and writing, Methodology, supervision, validation, Review, and editing. All authors read and approved the final manuscript and are accountable for all aspects of the work.

### Declaration of use of AI in the writing process

This study is not a product of AI. All statements are either original to the authors or from cited other authors.

### Acronyms

| | |
|---|---|
| ARDL | Autoregressive Distributed Lags |
| CADF | Cross-sectional Augmented Dickey-Fuller |
| CD | Cross-sectional Dependency |
| CIPS | Cross-sections Im, Pesaran and Shin |
| GMM | Generalized Method of Moments |
| ICT | Information and Communication Technologies |
| OLS | Ordinary Least Squares |
| OWID | Our World in Data |
| PMG | Pool Mean Group |
| SDGs | Sustainable Development Goals |
| UN | United Nations |
| WAMZ | West African Monetary Zone |
| WLS | Weak Least Squares |

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