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Article

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Digital inclusion or exclusion? Exploring the moderating role of governance in digitalization's impact on income inequality in developing countries

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Digitalization plays a critical role in economic development and ensuring social equity. The advancement of digitalization is expected to expand economic opportunities for previously underserved populations, thereby narrowing income disparities. However, it may also exacerbate inequality due to differences in access and skill levels. In this study, we utilize panel data from 45 developing countries over the period 2002–2023, employing the recently developed Method of Moments Quantile Regression (MMQR) by Machado & Santos Silva (2019) to examine the empirical relationship between digitalization and income inequality and to assess the role of governance quality in this relationship. Our findings reveal a strong negative impact of digitalization on income inequality across all specific and composite digitalization measures. Furthermore, we find that the relationship between digitalization and income inequality is contingent on governance quality and the type of digitalization adopted. Based on our research results, several governance implications are proposed to enhance the effectiveness of digitalization in reducing income inequality in developing countries.

1. Introduction

Income inequality has become an increasing concern for policymakers over the past few decades. Numerous studies have documented the rising trend of income inequality in many countries around the world during the 1990s, though at varying rates (Roine & Waldenström, 2015; Alvaredo et al., 2017). High levels of income inequality hinder skill accumulation and human development, thereby reducing economic growth (Tachibanaki, 2006; Sukiassyan, 2007). Income inequality also heightens uncertainty, vulnerability, and insecurity, undermines public trust in governance and government, increases social discord and tension, and leads to violence and conflict (United Nations, 2020). Therefore, in 2015, the United Nations established the Sustainable Development Goals (SDGs), with SDG10 aiming to "reduce inequality within and among countries" by 2030.

In the context of the Fourth Industrial Revolution, with the rapid development of digital technologies such as artificial intelligence, big data, cloud computing, and the Internet of Things, digitalization has increasingly been integrated into the economy and society, transforming the way we live, work, and communicate (Morrar et al., 2017; Autio et al., 2021). Digitalization is profoundly altering the relationships between people, technical systems, and the planet (Creutzig et al., 2022). It has changed how companies operate, improved the quality of life, and enhanced people's access to public services (Sabbagh et al., 2012). Innovative business models and the restructuring of value chains driven by the digital economy have increasingly become key drivers of economic growth (Hu et al., 2021). The COVID-19 pandemic in 2020 accelerated the digital transformation in business, education, services, and many other fields, but it also exacerbated the digital divide and socioeconomic inequality, particularly in low-income countries (Beaunoyer et al., 2020; Van Dorn et al., 2020; Song et al., 2021). The development of digitalization presents policy challenges related to addressing income inequality in nations. Digitalization could be an essential leveling tool through which people in different countries can enhance connectivity, financial inclusion, and access to commerce and public services more easily and conveniently (Noh & Yoo, 2008; Canh et al., 2020; Yin & Choi, 2023). However, from another perspective, due to the differences in initial human and financial capital, the extent to which people benefit from digitalization will vary (Zhang et al., 2020). Those who "have" are more likely to expand their opportunities, while those who "have not" gradually lose power and are excluded from the game (Tewathia et al., 2020). Consequently, this will increase income

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inequality within the economy. These arguments suggest that the impact of digitalization on national income inequality remains unclear. Studying the impact of digitalization on income inequality is crucial due to its significant effects on economic development and social equity in achieving sustainable development goals.

The relationship between digitalization and inequality depends on digital skills, technological, economic, and political forces, as well as the stage of development (Bauer, 2018; Consoli et al., 2023). Among various factors, governance quality plays a crucial role in shaping the impact of digitalization on income inequality. While digitalization can help mitigate income inequality, governance quality can either exacerbate or alleviate this impact (Adams & Akobeng, 2021). Some studies suggest that good governance can help minimize the negative effects of digitalization on income inequality, while also promoting a fairer distribution of benefits from technological advancements (Acemoglu & Robinson, 2012; Asongu & Odhiambo, 2019; Tchamyou et al., 2019). This is because good governance can ensure that public policies and legal regulations are established to manage the adoption of digital technology appropriately. It includes measures to protect workers' rights, prevent monopolies, and ensure that small businesses and vulnerable groups can participate in and benefit from the digitalization process. High-quality governance also ensures that the economic benefits of digitalization are distributed more equitably. For instance, investing in education and digital skill training for the workforce or implementing tax policies to redistribute income from sectors that benefit significantly from digitalization to sectors or groups negatively affected. Moreover, high governance quality also plays a role in mitigating risks of injustice and corruption, which can exacerbate income inequality. Good governance can ensure that policies are enforced transparently and fairly, preventing the concentration of digitalization benefits in the hands of a small, powerful group. Governance quality also plays a role in promoting financial inclusion, ensuring that everyone has access to financial services and economic opportunities created by digitalization, thereby reducing income inequality (Asongu & Odhiambo, 2019).

However, others argue that in a well-governed environment, more advanced entities, including highly educated and high-income individuals or large, technically proficient businesses, may be better positioned to exploit technological advantages to increase income, thereby widening the income gap with other groups (Acemoglu, 1998; Autor & Dorn, 2013; Piketty, 2014). Indeed, in a well-governed environment, governments may prioritize the development of high-tech industries to promote economic growth. However, if these policies are not accompanied by support measures for traditional industries or workers without digital skills, the gap between those working in high-tech industries and those left behind will grow, exacerbating inequality. Additionally, good governance often involves focusing on developing urban centers, where infrastructure and economic opportunities from digitalization are heavily invested. However, this can lead to regional inequality, as rural or less developed areas may not benefit from these policies, resulting in increasing income inequality between regions (Rodrik, 2018). Moreover, high governance quality can create a highly competitive labor market, where individuals with high skills, particularly in technology, receive superior wages and benefits. Meanwhile, those without access to quality education or digital skills, especially in traditional industries or manual labor, will struggle to find employment, leading to increased income inequality (Autor & Dorn, 2013). Even in environments with high governance quality, if social policies are not robust enough to support vulnerable groups or workers in industries susceptible to digitalization, inequality may rise. Good governance policies may focus on promoting economic and technological growth, but without balancing these with social protection measures, vulnerable groups may not benefit from this development (Acemoglu & Restrepo, 2018).

Thus, while high governance quality can help reduce inequality in many cases, if not appropriately adjusted to the challenges of the digital age, it may inadvertently exacerbate social division and increase inequality. Therefore, further research on the impact of digitalization and the regulatory role of governance quality is not only of theoretical significance but also of high practical value, guiding policy direction and interventions to mitigate income inequality in the digital age.

In developing countries, income inequality has risen over the past few decades. Some countries, particularly in Africa and Latin America, have witnessed a sharp divide between the rich and the poor (Palma, 2011). Additionally, the informal economy in developing countries often accounts for a significant portion, where workers are not legally protected and typically earn very low incomes (Petrova, 2019). The existence of this sector contributes to increased income inequality due to the lack of stable employment opportunities and social insurance. Globalization and digitalization have created new economic opportunities but have also deepened inequality. While some groups can leverage technology to improve their incomes, many others, especially those without digital skills, are left behind (Zhang et al., 2020). The pandemic accelerated digitalization across various sectors, from education to business and public services. However, this transition has also exacerbated the digital divide and income inequality, particularly in developing countries, where digital infrastructure is weak, and access to technology is lower than in developed countries (Nguyen, 2023). Therefore, in this study, we assess the impact of digitalization on income inequality and explore whether governance quality plays a moderating role in this impact in developing countries.

Our study makes several important contributions: First, we employ the Method of Moments Quantile Regression (MMQR), a novel estimation technique developed by Machado & Santos Silva (2019), to investigate the heterogeneous and distributional relationship between digitalization and inequality, while also examining the moderating role of governance quality in this relationship. MMQR allows for the accurate capture of the impact of digitalization on inequality across a global sample, including both the "haves" and the "have-nots," ensuring that the research question is addressed and appropriate policy recommendations are proposed to maximize welfare. According to (Ma et al., 2022; Wolde-Rufael & Mulat-Weldemeskel, 2022), MMQR overcomes several limitations of traditional regression models. Firstly, it provides precise and robust results even when the data distribution is non-parametric, contains outliers, exhibits minimal or no correlation, and is non-normalized. Secondly, this technique can identify distributional attributes unique to certain quantiles, thereby appropriately addressing issues of uneven distribution. Furthermore, MMQR allows for individual fixed effects across the entire conditional distribution, making predictors consistent with location and scale functions. By distinguishing the heterogeneous conditional covariate effects of digitalization, governance quality, and other control variables on income inequality, MMQR addresses unobserved heterogeneity. Additionally, it accommodates location-based asymmetry, as parameters may depend on the position of the dependent variable—income inequality—while generating reliable estimates under various conditions, including non-linear models. MMQR is described as a practice-oriented approach that simultaneously handles heterogeneity and endogeneity through moment restrictions, making it attractive for both asymmetric and non-linear estimations. A unique aspect of MMQR is its ability to handle non-crossing estimates without producing invalid responses. We also conduct robustness checks on the MMQR estimates using the System GMM average estimator.

Second, across multiple measures of digitalization, our first major finding is that the dominant impact of digitalization on income inequality is negative, implying that digitalization development reduces income inequality in developing countries. However, the magnitude of the effect varies significantly depending on the specific type of digitalization. Greater use of landline phones and the internet is associated with a larger reduction in income inequality compared to mobile phone usage.

Third, our study provides an intriguing finding regarding the role of governance quality in the impact of digitalization on inequality. The conventional view that good governance quality can enhance the role of digitalization in reducing inequality is challenged by our research. Instead, we provide strong evidence of the exacerbating effect of digitalization on income inequality in a good governance environment in developing countries. Those with higher educational attainment and better digital skills can more easily adapt and leverage the opportunities from digitalization to widen the income gap. When examining the detailed impact of each component of digitalization in interaction with governance quality, the effects of mobile and internet usage are similar, but the impact of landline phone usage contrasts with the aggregate effect of digitalization. This reveals a novel perspective on the role of governance quality in developing countries.

The remainder of this study is structured as follows: Section 2 presents the literature review. The methodology, including data, models, and methods, is detailed in Section 3. Section 4 discusses the results derived from MMQR estimation and robustness checks across estimation methods, including S-GMM. Finally, we conclude and outline several policy implications in Section 5.

2. Literature review

2.1. Digitalization and income inequality

2.1.1. Theoretical framework

Income inequality refers to the uneven distribution of income across individuals or groups within an economy. The primary drivers of income inequality include globalization, education, technological change, labor market institutions, and government policies (Piketty, 2014). It remains a central issue in economic research, with ongoing debates regarding its causes and consequences. Recent technological advancements, particularly digitalization, have introduced new dimensions to this discourse. Defined as the integration of digital technologies into economic and social processes, digitalization has reshaped production structures and labor market dynamics. It serves as a powerful tool for addressing macroeconomic imbalances by enhancing economic integration, information sharing, and efficiency (Xu & Zhong, 2023). However, its impact on income inequality varies, depending on the degree of digital adoption, policy frameworks, and labor market conditions.

The skill-biased technological change (SBTC) theory suggests that digital advancements predominantly benefit highly skilled workers, exacerbating wage disparities (Autor, 2014). Berman et al. (1998) highlight the declining demand for low-skilled labor as industries shift toward skill-intensive production, reducing earnings for workers without digital competencies. This pattern is particularly pronounced in developed economies, where rapid technological progress intensifies labor market inequalities. Litvinenko (2020) underscores the role of research and education centers in equipping workers with digital skills, further reinforcing the advantage of high-skilled labor. Conversely, low-skilled workers face wage stagnation and job displacement due to their limited adaptability to technological change (Butler et al., 2020).

Despite these concerns, digitalization also holds the potential to promote economic inclusion. By expanding access to information, financial services, and remote work opportunities, digital technologies can lower economic barriers for marginalized groups (Goldfarb & Tucker, 2019). However, the extent to which digitalization mitigates or exacerbates inequality depends on the effectiveness of policies ensuring equal access to digital resources and workforce upskilling initiatives.

The relationship between digitalization and income inequality operates through three key mechanisms: labor market transformations, access to digital resources, and financial and entrepreneurial inclusion. First, digitalization has intensified wage polarization by increasing demand for high-skilled labor while automating routine-based jobs, particularly in manufacturing and clerical sectors (Goos et al., 2014). Workers proficient in digital technologies benefit from higher wages and employment opportunities, while those lacking these skills experience job displacement or wage suppression, deepening labor market inequalities.

Second, disparities in digital access create economic inequalities. The digital divide—marked by variations in internet access, technological literacy, and digital infrastructure—limits lower-income individuals' ability to benefit from online education, remote work, and digital entrepreneurship (van Dijk, 2020). Without adequate digital access, these individuals struggle to secure well-paying jobs in the digital economy, reinforcing income disparities. Policies promoting universal digital inclusion, digital literacy programs, and affordable connectivity are crucial for mitigating these effects.

Finally, digitalization fosters financial and entrepreneurial inclusion by broadening access to financial services. Fintech innovations, mobile banking, and digital platforms have reduced barriers to entrepreneurship and facilitated microfinance solutions, particularly in developing economies (Demirguc-Kunt et al., 2018). These advancements can support income redistribution by providing economic opportunities to lower-income groups. However, their effectiveness depends on regulatory frameworks, digital infrastructure, and financial literacy levels.

In summary, while digitalization presents both challenges and opportunities regarding income inequality, its overall impact is contingent on how societies navigate labor market transitions, bridge the digital divide, and leverage financial inclusion mechanisms. Effective policy interventions are essential to ensuring that digitalization fosters inclusive economic growth.

2.1.2. Empirical evidence

Empirical studies present divergent findings on the relationship between digitalization and income inequality. Digitalization may exacerbate disparities by creating digital divides, wherein individuals with greater access to and proficiency in digital technologies benefit disproportionately, leading to increased productivity and income concentration among those with higher initial human and financial capital (Zhang et al., 2020). In contexts marked by disparities in gender, education, and income, digitalization can further widen income inequality. Acemoglu (2002) argues that disadvantaged groups often lack the requisite skills or financial resources to capitalize on digital advancements, whereas individuals in higher socio-economic strata have greater access to information technology, reinforcing existing income disparities. Richmond & Triplett (2018) emphasize that information and communication technology (ICT) represents a skill-biased technological change that intensifies wage disparities and deepens economic inequalities. Supporting this perspective, Law et al. (2020) and Mohd Daud et al. (2021) employ panel data methods across various national contexts and conclude that digitalization amplifies income inequality. Law et al. (2020), using the panel mean group (PMG) estimator for 23 developed countries from 1990 to 2015, and Mohd Daud et al. (2021), employing system-GMM one-step estimation for 54 countries between 2010 and 2015, both find a positive correlation between digitalization and income inequality. Similarly, Zhang et al. (2020), analyzing 155 districts in China from 2010 to 2016 using fixed effects and 2SLS regression, report that internet penetration exacerbates consumption inequality, particularly in regions with higher educational attainment. If ICT-driven technological progress is skill-biased, its benefits may primarily accrue to individuals capable of leveraging these opportunities (Acemoglu, 1998; Goldin & Katz, 2009). More recently, Nguyen (2023), using balanced panel data from developed and developing economies between 2002 and 2020, finds that digitalization reduces inequality in developed economies but exacerbates it in developing countries when applying both GMM and PMG estimations.

Conversely, several studies suggest that digitalization fosters income generation and poverty reduction, ultimately mitigating income inequality and promoting inclusive economic growth (Ahmed & Al-Roubaie, 2013; Faizah et al., 2021). Digitalization contributes to economic expansion through three principal mechanisms: lowering production costs, increasing income, and generating employment opportunities (Untari et al., 2019; Loh & Chib, 2019). According to the

World Bank (2016), information technology enhances business efficiency, expands consumer choice, and promotes broader economic participation. Additionally, digitalization facilitates inclusion, innovation, and accessibility, providing economic opportunities for disadvantaged groups. The dissemination of information through digital platforms improves cost efficiency, making technology an essential tool for economic advancement (Noh & Yoo, 2008). Increased labor productivity resulting from digitalization may also contribute to reducing income inequality (Lloyd-Ellis, 1999). Mushtaq & Bruneau (2019) argue that digitalization enhances the welfare of rural populations by improving market access, strengthening farmers' bargaining power, and fostering income growth, which in turn alleviates poverty and income inequality. Similarly, Mora-Rivera and García-Mora (2021) find that expanding internet access in rural Mexico reduces poverty and narrows the income gap between urban and rural areas. Faizah et al. (2021) report that greater investment in ICT infrastructure diminishes income inequality in Indonesia, with the effect being more pronounced in lower-income regions. Using a multi-country sample, Canh et al. (2020) apply the system-GMM two-step method to analyze data from 87 countries between 2002 and 2014, concluding that advancements in digital and communication technologies help bridge income disparities, particularly through mobile phone and internet adoption. Adams & Akobeng (2021), examining panel data from 46 African countries between 1984 and 2018, demonstrate that ICT utilization—measured by internet access, fixed broadband, and mobile subscriptions—reduces income inequality. Yin & Choi (2023) further illustrate that in G20 countries between 2002 and 2018, digital technology adoption in production processes contributes to decreasing income disparities, with a stronger effect observed in middle-income nations compared to high-income ones. Wang & Shen (2024) provide additional evidence, showing that digital economy development mitigates income inequality in 97 countries, particularly benefiting lower-middle-income and low-income nations while exerting a lesser influence in wealthier economies.

2.2. The moderating role of governance quality in the relationship between digitalization and income inequality

According to Acemoglu and Robinson (2008), governance plays a crucial and fundamental role in determining the stages of economic growth and development across countries. As a result, many scholars have explored the impact of governance quality on wealth and income inequality.

Studies such as those by Nadia and Teheni (2014), which analyzed 39 countries from 1996 to 2009 using non-parametric correlation tests, and Kunawotor et al. (2020), which used D-GMM two-step estimation for 40 African countries from 1990 to 2017, consistently show that improvements in governance quality help reduce income inequality. Similarly, Blancheton and Chhorn (2021), examining Asia-Pacific countries from 1988 to 2014 through a combination of modified ordinary least squares (FMOLS) and panel dynamic ordinary least squares (DOLS) methods with Granger causality tests, found that better governance quality contributes to decreased income inequality.

In contrast, Perera and Lee (2013) found that governance quality can actually increase inequality, based on their study of nine developing Asian countries from 1985 to 2009 using system-GMM one-step estimation. They suggest that governance improvement measures in developing countries in East and South Asia should focus more on income distribution and poverty alleviation. Notably, Asamoah (2021), studying 24 developed and 52 developing countries from 1996 to 2017, discovered a negative impact of governance quality on wealth and income inequality. Specifically, while improved governance tends to increase income inequality in developing economies, it generally reduces inequality in developed economies.

Recognizing that integrating digitalization into the economy can enhance governance quality is crucial (Meijers, 2014). While some research directly examines digitalization's impact on income inequality, others explore the mechanisms through which it operates. These studies show that country-specific characteristics, such as economic-political factors (Richmond & Triplett, 2018), trade openness, foreign direct investment (Yin & Choi, 2023), and governance quality (Hope & Martelli, 2019; Adams & Akobeng, 2021), moderate the relationship between digitalization and income inequality.

Advancements in information and communication technology (ICT) have transformed lives by saving time, spreading knowledge, enhancing access to information, and automating processes with artificial intelligence. Digitalization boosts productivity and fosters transparency and governance (Maiti & Awasthi, 2020). Hope and Martelli (2019) examined the transition to a knowledge economy and its effects on income inequality in 18 OECD countries from 1970 to 2007, finding that this transition increases income inequality, though strong labor market governance moderates this effect. Similarly, Adams and Akobeng (2021) demonstrated that effective governance can strengthen the relationship between ICT and income inequality.

Previous research has underscored the controversial relationship between digitalization and income inequality across nations. Scholars have made efforts to address this debate by exploring various aspects of digitalization, such as different forms of digital technologies (Richmond & Triplett, 2018; Au, 2024), income-based country classifications (Nguyen, 2023; Wang & Shen, 2024), alternative measures of inequality (Richmond & Triplett, 2018), and employing diverse methodological approaches, including Propensity Score Matching (PSM) (Mora-Rivera and García-Mora, 2021), Generalized Method of Moments (GMM) (Canh et al., 2020; Adams & Akobeng, 2021; Mohd Daud et al., 2021), Panel Mean Group (PMG) (Law et al., 2020), and Two-Stage Least Squares (2SLS) (Faizah et al., 2021; Zhang et al., 2020).

However, there remains a significant gap in the literature regarding how varying levels of digitalization impact income inequality and the role of governance quality in moderating this relationship. To address this gap, the authors propose to employ the Method of Moments Quantile Regression (MMQR) to provide a more nuanced understanding of these dynamics.

2.3. Hypothesis development

The skill bias theory of Berman et al. (1998) implies a negative impact of technological change on income inequality, however, concentrated in developed countries. Meanwhile, according to the core-periphery theory, from a macroeconomic perspective, developing countries often lack the conditions for balanced growth. These nations typically have to concentrate their limited resources on a few advantageous sectors and regions to establish economies of scale, which can then drive economic development in less developed areas. However, digitalization has the potential to exponentially amplify economic momentum from developed regions to less developed ones, thereby improving resource allocation and narrowing income gaps. Additionally, digitalization can foster the creation of new industries, business models, and supplementary job opportunities for low-skilled workers. The increase in job opportunities and the expansion of employment can help alleviate poverty and reduce income inequality (Marmot & Wilkinson, 2001).

From a microeconomic perspective, when digitalization is integrated with education, it facilitates innovative teaching methods, provides access to a wider range of learning materials, and offers more valuable courses to countries with limited educational resources (Psacharopoulos et al., 2017). By accessing advanced educational resources, workers in less developed regions can acquire skills and update their knowledge, thereby laying a foundation for higher income.

Leng et al. (2020) demonstrated in their study of China that the application of information technology benefits the poor by promoting income diversification. Moreover, their research indicated that improvements in education and rural infrastructure, such as roads and broadband facilities, can enhance the adoption of IT in rural households, thus increasing income diversification and reducing income inequality. Based on the theoretical framework and previous empirical evidence, the research team proposes the following hypothesis:

Hypothesis H1: Digitalization reduces income inequality in developing countries.

Previous research has highlighted the critical role of governance quality in determining the redistribution of wealth within nations (Muller, 1988; Shen & Yao, 2008). These studies argue that democratic practices and electoral competition ensure that economic policies are implemented effectively, thereby improving income for poorer segments of society and promoting a more equitable distribution of wealth, which helps reduce income inequality. Supporting this argument, in the context of digitalization, research by Njangang et al. (2022) demonstrates that enhancing democratic processes in both developed and developing countries serves as an effective mechanism, positively moderating the relationship between information and communication technology (ICT) and income inequality. Other studies also suggest that good governance can mitigate the negative impacts of digitalization on income inequality, while promoting a fairer distribution of benefits derived from technological advancements, especially in developing countries (Acemoglu & Robinson, 2012; Asongu & Odhiambo, 2019; Tchamyou et al., 2019). Therefore, we hypothesize the following regarding the moderating role of governance quality:

Hypothesis H2: Governance quality enhances the impact of digitalization on income inequality.

3. Methodology

3.1. Data

This study uses a balanced dataset from 2002 to 2023 for 45 developing countries. These countries were selected based on the availability of data on key variables used in the study. A list of the countries used is presented in Appendix 1.

The Gini index is a widely used measure of income inequality between countries (Solt, 2020). The Standardized World Income Inequality Database (SWIID) offers a larger and more frequently updated sample than the World Bank, making it a more complete and reliable resource. SWIID employs a multi-effect algorithm that combines and standardizes inequality data from various sources, generating 100 calculations for each observation (Solt, 2016). Compared to other cross-country inequality databases, SWIID covers the widest range of countries and years (Richmond & Triplett, 2018). Thus, this study utilizes the Gini index based on pre-tax, pre-transfer household income from SWIID, following recommendations from previous research (Akpa et al., 2024; Kaulihowa & Adjasi, 2018; Law & Soon, 2020; Richmond & Triplett, 2018).

Digitalization, on the one hand, enhances and broadens access to resources, information, and markets, thereby helping to reduce income disparities. Conversely, the technology-driven shift towards skills-intensive environments in highly digitized contexts increases the costs associated with acquiring these skills, potentially worsening wage inequalities. In this study, we treat digitalization as the primary independent variable affecting income inequality. Drawing on recent research that represents digitalization (DIG) (Adams & Akobeng, 2021; Nguyen, 2022, 2023; Njangang et al., 2022), we employ a composite index generated through Principal Component Analysis (PCA). This index combines three indicators of digitalization: Mobile Cellular Subscriptions (per 100 people), Individuals Using the Internet (% of the population), and Fixed Telephone Subscriptions (per 100 people). These indicators are obtained from the World Development Indicators (WDI).

Political and legal environments play a crucial role in influencing economic growth, development, and inequality (Feld et al., 2010). Governance quality (GOV) is assessed using Principal Component Analysis (PCA) based on six indicators: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Rule of Law, Voice and Accountability, and Regulatory Quality. These indicators, derived from the Worldwide Governance Indicators (WGI), are rated on a scale from −2.5 (weakest governance) to + 2.5 (strongest governance).

We included several control variables in our research model: Economic Growth (GDP), Government Expenditure (GovExp), Education (EDU), Unemployment Rate (Unemploy), and Urbanization (URB). Building on Kuznets's (1955) foundational work, we model income inequality as a function of average income, represented by GDP per capita. Fan and Zhang (2004) show that government spending and investments in public infrastructure promote economic growth and reduce inequality. However, Chatterjee and Turnovsky (2012) argue that such investments can increase wealth inequality over time, necessitating a balance between average welfare and its distribution. Following Richmond and Triplett (2018b), we also include education, defined as school enrollment, primary (% gross), along with unemployment rate, trade openness, and inflation as economic control variables. Descriptive information and measurements for these variables are presented in Table 1.

3.2. Model

Building on relevant arguments and previous research, we propose a model to examine the impact of digitization, governance quality, and their interaction on income inequality. Additionally, control variables are incorporated into the research model. The inclusion of these control variables is grounded in evidence from prior studies (Abbas et al., 2022; Ajide et al., 2024; Baffour Gyau et al., 2025), which have demonstrated their significant influence on income inequality, thereby enhancing the comprehensiveness and accuracy of the analysis. Our proposed research model is outlined as follows:

Table 1
Variables definitions and sources.

Variables	Code	Measures	Sources
Income inequality	Gini	Gini index using pre-tax, pre-transfer household income	SWIID
Digitalization	DIG	DIG is obtained by applying Principal Component Analysis (PCA) to three component indicators: Mobile Cellular Subscriptions (per 100 people), Individuals Using the Internet (% of the population), and Fixed Telephone Subscriptions (per 100 people).	Author's calculations
Governance quality	GOV	GOV is derived using Principal Component Analysis (PCA) on six indicators: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Rule of Law, Voice and Accountability, and Regulatory Quality, which range from −2.5 to +2.5.	Author's calculations
Economic Growth	GDP	GDP per capita (constant 2015 US$)	WDI
Government Expenditure	GovExp	General government final consumption expenditure (% of GDP)	WDI
Education	EDU	School enrollment, primary (% gross)	WDI
Unemployment	Unemploy	Unemployment, total (% of total labor force)	WDI
Trade openness	TRADE	Trade (% of GDP)	WDI
Inflation	INF	Inflation, GDP deflator (annual %)	WDI

Source: Author's compilation.

$$Gini_{it} = \gamma_0 + \gamma_1 DIG_{it} + \gamma_2 GOV_{it} + \gamma_3 (DIG_{it} \times GOV_{it}) + \delta_j X'_{it} + (\mu_i + \varepsilon_{it}) \quad (1)$$

Here, $\gamma_1, \gamma_2, \gamma_2$ and δ_j represent the corresponding regression coefficients, with i and t denoting country and time, respectively. $DIG_{it} \times GOV_{it}$ represents the interaction term between digitalization and the governance quality index for country iii at time ttt. X'_{it} represents the control variables used in the model, including Economic Growth (GDP), Government Expenditure (GovExp), Education (EDU), Unemployment Rate (Unemploy), Trade Openness (TRADE), and Inflation (INF). Finally, μ denotes the fixed effect of the model, and ε represents the estimation error, assumed to be independently and identically distributed with a mean of 0 and constant variance $\sigma^2(\varepsilon_{it} \sim i.i.d(0, \sigma_\varepsilon))$.

3.3. Method

3.3.1. Cross-sectional dependence (CD) test

A key characteristic of panel data is cross-sectional dependence, which arises when a common factor makes units (countries) interdependent. Identifying this dependence is vital for panel data analysis (Wang et al., 2023). Neglecting cross-sectional dependence can result in biased and unpredictable outcomes (Chudik & Pesaran, 2022), undermining the reliability of the findings (Wang et al., 2023). To evaluate cross-sectional dependence among the variables, the Pesaran (2007) test was utilized. The formulation of the Pesaran (2007) test is as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{p=i+1}^{N} \rho_{pi} \quad (2)$$

In the equation above, T denotes the time dimension, N represents the panel size, and ρ_{pi} is the correlation coefficient. The null hypotheses for this test are no cross-sectional dependence. To further ensure the robustness of our analysis, we also employed the Friedman test to corroborate the presence of cross-sectional dependence.

3.3.2. Slope heterogeneity test

The countries studied display diverse characteristics in the research data, indicating that each cross-section is heterogeneous. The slope homogeneity or heterogeneity is crucial for the accuracy of estimation results. Consequently, this study utilizes the slope heterogeneity test proposed by Pesaran and Yamagata (2008), specified as follows:

$$\widetilde{\Delta_{SH}} = (\mathrm{N})^{\frac{1}{2}}(2K)^{-\frac{1}{2}}\left(\frac{1}{N}\widetilde{S} - k\right) \quad (3)$$

$$\widetilde{\Delta_{ASH}} = (\mathrm{N})^{\frac{1}{2}}\left(\frac{2k(T-k-1)}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}\widetilde{S} - k\right) \quad (4)$$

Among them, the adjusted delta tilde is $\widetilde{\Delta_{ASH}}$ and delta tilde is $\widetilde{\Delta_{SH}}$.

3.3.3. Stationary test

After assessing cross-sectional dependence in the panel data, we conduct unit root tests to determine if a variable is I(0) or I(1). If the CD test indicates cross-sectional dependence among countries, we use second-generation unit root tests, namely the CADF and CIPS tests developed by Pesaran (2007). The CADF test accounts for cross-sectional dependence, ensuring valid regression estimates. Equation (5) presents the CADF model.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \overline{y}_{t-1} + \sum_{j=0}^{k} \delta_{ik} \Delta \overline{y}_{t-j} + \sum_{j=1}^{k} \delta_{ik} \Delta y_{i,t-j} + \varepsilon_{it} \quad (5)$$

Where $\Delta y_{i,t-j}$ và $\overline{y}_{t-1}$ characterize the differenced and lags of the variable being tested. After calculating CADF, CIPS is calculated by averaging CADF and introduced by Pesaran (2007) as follows:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF \quad (6)$$

If cross-sectional dependence is absent, we employ first-generation unit root tests, specifically the Levin-Lin-Chu (LLC) test (Levin et al., 2002).

3.3.4. Method of Moments quantile regression (MMQR)

This study employs the MMQR method proposed by Machado and Santos Silva (2019), which has the advantage of not only capturing the heterogeneity of variables at different levels but also effectively addressing issues such as extreme values and heteroscedasticity. We believe that the latent heterogeneous relationship between digitalization and income inequality across different quantiles of the income distribution is best captured by the panel data quantile regression framework. Consequently, we use MMQR as an available method that allows us to provide evidence on how income inequality varies across different quantiles with higher levels of digitalization (Berisha et al., 2023).

Moreover, existing panel data approaches have been reported to struggle with heterogeneity and cross-sectional dependence (Musa et al., 2024), whereas MMQR can effectively observe conditionally heterogeneous covariance effects (Awan et al., 2022). According to Ramzan et al. (2023), this method can account for asymmetric and nonlinear relationships to address endogeneity concerns. While MMQR may not completely eliminate endogeneity issues, it can mitigate their impact by estimating across the quantile distribution rather than relying solely on the conditional mean (Awan et al., 2022; Ramzan et al., 2023). MMQR provides reliable results for nonlinear models and allows for asymmetry based on location (Awan et al., 2022; Machado & Santos Silva, 2019). This method can produce heterogeneous estimates across the entire distribution.

Additionally, although methods such as FMOLS and DOLS can address correlation and endogeneity, they primarily focus on conditional mean estimation and fail to capture heterogeneous effects across the entire distribution of the dependent variable (Musa et al., 2024). In the context of this study, where the relationship between digitalization and income inequality may vary across different income levels, applying MMQR becomes essential to comprehensively reflect potential effects. The choice of MMQR is not solely based on its ability to handle nonlinearity and asymmetry but also on its capacity to provide more detailed insights that simpler approaches cannot achieve (Berisha et al., 2023; Dada et al., 2023). The robustness of the MMQR method has been confirmed in recent studies, and it can yield reliable results despite data abnormalities (Berisha et al., 2023; Dada et al., 2023; Musa et al., 2024; Ramzan et al., 2023).

Equation (7) presents a straightforward formula for predicting the conditional quantile location scale $\mathcal{Q}_y(\tau|R)$ variant:

$$Y_{it} = \alpha_i + X'_{it}\beta + \left(\delta_i + Z'_{it}\gamma\right)U_{it} \quad (7)$$

Here, the probability $P\{\delta_1 + Z'_{it} > 0\} = 1$ must be estimated, where $(\alpha, \beta', \delta, \gamma')'$ denotes the parameter vector. The terms $(\alpha_i, \delta_i), i = 1, \cdots, n$, represent the fixed effects of the i unit, and Z denotes a vector of K known factors of X. These are distinguishable transformations, and the elements l are as follows:

$$Z_l = Z_l(X), l = 1, \cdots, k \quad (8)$$

For each fixed l, X'_{it} is uniformly and independently distributed across all time periods T. U_{it} is uniformly distributed across individuals i and time t in the same manner and is orthogonal to X_{it}. The remaining variables do not need to be entirely exogenous, and equation (9) can be expressed as follows:

$$\mathcal{Q}_y(\tau|X_{it}) = (\alpha_i + \delta_i(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \quad (9)$$

Here, the vector of explanatory variables is denoted by X_{it}, $\mathscr{Q}_y(\tau|X_{it})$ represents the vector of the explained variables. $X_{it}^{\prime} - \alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ indicates a scalar coefficient, showing that quantile fixed effects τ differ from conventional least squares fixed effects in that individual effects do not shift the intercept. These parameters are independent of time variation, and their heterogeneous effects are influenced by changes in quantiles and different conditional distributions. The quantile sample τ, denoted as $q(\tau)$, is estimated by solving the obtained optimization problem.

$$min_q \sum_i \sum_t \rho\tau\left(R_{it} - \left(\delta_i + \mathscr{z}_{it}^{\prime}\gamma\right)q\right) \tag{10}$$

Where the check function is denoted as $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$.

Next, based on the model proposed in Equation (1), we reconstruct the model using the MMQR method by incorporating the variables from our research model. The details are presented in Equation (11).

$$\mathscr{Q}_{Gini}(\tau|X_{it}) = \alpha_{it} + \beta_{1\tau}DIG_{it} + \beta_{2\tau}GOV_{it} + \beta_{3\tau}(DIG_{it} \times GOV_{it}) + \beta_{4\tau}GDP_{it} + \beta_{5\tau}GovExp_{it} + \beta_{6\tau}EDU_{it} + \beta_{7\tau}Unemploy_{it} + \beta_{8\tau}TRADE_{it} + \beta_{9\tau}INF_{it} + \varepsilon_{it} \tag{11}$$

3.3.5. *Robustness test with two-step system Generalized method of Moments (S-GMM)*

To ensure robust findings, we employ the Two-Step System Generalized Method of Moments (S-GMM), a dynamic panel data estimation technique advanced by Blundell and Bond (1998) and Arellano and Bover (1995). This method helps mitigate unnecessary data loss and provides more reliable and consistent estimates for the coefficients in balanced panel datasets (Arellano & Bover, 1995). S-GMM is particularly well-suited for studies with large N, and it is especially appropriate when N > T. In this study, we analyze data from 45 countries (N = 45) over the period 2002–2023 (T = 22).

Moreover, the predictor variables are assumed to be not fully exogenous, suggesting that lagged values of income inequality may be correlated with past and current errors, which could introduce endogeneity issues. The S-GMM technique provides robust explanatory power compared to ordinary least squares (OLS), fixed effects (FE), and random effects (RE) models. It effectively addresses endogeneity and multicollinearity problems associated with predictor variables, particularly in the presence of endogenous factors. The S-GMM estimation method is robust to reverse causality and measurement error (Hauk & Wacziarg, 2009), as confirmed by the Hansen test.

To validate the robustness of the instruments used in the regression model, we compare the p-values from the Hansen and Sargan tests against a 5 % significance threshold to ensure there is no over-identification issue. Both tests are essential for establishing the reliability of the instrument variable estimates in econometric analysis (Canh et al., 2019; Sani et al., 2019). Additionally, the p-value from the AR(2) test is compared to the 5 % significance level to test for autocorrelation, with the null hypothesis (H_0) being that there is no autocorrelation. The null hypothesis is rejected if the p-value is below 0.05, while no autocorrelation is concluded if the p-value is above 0.05.

Based on Equation (1), the empirical specification for the study using the S-GMM method is expressed as follows:

$$Gini_{it} = \alpha_0 + \varphi Gini_{i,t-1} + \alpha_1 DIG_{it} + \alpha_2 GOV_{it} + \alpha_3(DIG_{it} \times GOV_{it}) + \delta_{it}X_{it} + (\mu_i + \varepsilon_{it}) \tag{12}$$

4. Results

4.1. *Descriptive statistics*

Descriptive statistics for the variables are presented in Table 2. The average Gini coefficient, a measure of income inequality, for developing countries during the period from 2002 to 2023 is 46.1659, with a standard deviation of 6.6408. The lowest recorded income inequality is 34.2 in Pakistan, while the highest is 72.3 in South Africa. The mean level of digitization (DIG) is 42.8952, with a standard deviation of 23.5519, ranging from 0.2290 to 90.1288, indicating a rapid increase in digitization across the studied countries. Governance quality (GOV) in developing countries is relatively low, with an average value of −0.2272 on a scale from −2.5 to 2.5, as reported by the Worldwide Governance Indicators developed by the World Bank since 2002.

The average GDP per capita is $4,800.65, with the minimum value recorded at $262.17 per capita in Burundi for the year 2023, and the maximum at $17,269.99 per capita in Poland for the same year. Government expenditure (GovExp) averages 14.50 % of GDP, indicating relatively low government spending. Education, as measured by the gross primary enrollment rate (EDU), has a high average of 99.31 %. The average unemployment rate (Unemploy) is 6.70 %. Trade openness (TRADE), represented by the ratio of total exports and imports to GDP, averages 76.56 %. Inflation across the developing countries in the study period averages 6.08 %. The correlation coefficients between the Gini coefficient and other variables are statistically significant at the 1 % level, highlighting a significant relationship between income inequality and these factors within the countries examined during the study period.

4.2. *Cross-section dependence tests and panel unit root tests results*

As outlined in the Methodology section, we conducted a cross-dependence test to assess the interdependence among research variables and select a suitable test for stationarity. Table 3 displays the results from both Pesaran's CD-test and Friedman's CD-test. The variables Gini, DIG, GDP, GovExp, EDU, Unemployment, TRADE, and INF show statistically significant cross-dependence at the 1 % level in both tests, while the GOV variable does not exhibit significant dependence. These results suggest that most research variables demonstrate considerable cross-dependence among the sample countries, except for GOV, which aligns with the expectation that trade and globalization foster interdependencies in global economies.

Table 2
Descriptive statistics and correlation analysis.

Variable	Obs	Mean	Std.Dev.	Min	Max	Correlation
Gini	990	46.1659	6.6408	34.2000	72.3000	1.0000
DIG	990	42.8952	23.5519	0.2290	90.1288	0.1621***
GOV	990	−0.2272	0.5504	−1.5900	1.2331	0.2512***
GDP	990	4800.6470	3804.668	262.1657	17269.99	0.3343***
GovExp	990	14.5027	4.6614	3.5875	36.14305	0.3076***
EDU	990	99.3147	12.9906	38.6836	140.3722	0.2938***
Unemploy	990	6.7040	5.1701	0.249	28.838	0.5751***
TRADE	990	76.5570	35.2377	21.6738	210.3743	−0.1132***
INF	990	6.0754	6.3388	−9.5588	84.6835	−0.0076

Note: *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

Table 3
Result of cross-sectional dependence.

Variables	Pesaran's CD-test		Freidman CD-test	
	Statistics	p-value	Statistics	p-value
Gini	11.333***	0.0000	96.847***	0.0000
DIG	137.377***	0.0000	849.691***	0.0000
GOV	−0.158	0.8748	25.359	0.9891
GDP	103.460***	0.0000	662.594***	0.0000
GovExp	17.848***	0.0000	119.092***	0.0000
EDU	16.087***	0.0000	116.822***	0.0000
Unemploy	9.463***	0.0000	58.630***	0.0000
TRADE	21.434***	0.0000	157.513***	0.0000
INF	38.415***	0.0000	297.487***	0.0000

Note: *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

Next, we employ slope heterogeneity test. The results, as shown in Table 4, reveal that the Delta coefficient is 21.436, with a significance level of 1 % (p-value = 0.000), and the adjusted coefficient (Adj.) is 29.024, also significant at the 1 % level (p-value = 0.000). These results indicate significant variation in the regression slopes among the countries in the sample. This variation is primarily attributed to differences in income distribution structures and consumption patterns across the countries.

In time series analysis, testing for unit roots is crucial for determining the stationarity of variables, which directly affects the analysis and modeling methods used. In this study, for variables exhibiting cross-sectional dependence, the second-generation CIPS test for unit roots was employed. Conversely, for variables without cross-sectional dependence, the first-generation Levin-Lin-Chu (LLC) test was applied.

The results of the CIPS test, as shown in Table 5, reveal that the variables DIG, EDU, and INF are stationary at level (I(0)) with 1 % significance. Conversely, the variables Gini, GDP, GovExp, Unemploy, and TRADE are integrated of order one (I(1)), indicating that they are stationary at first differences. Similarly, the LLC test results in Table 6 indicate that the GOV variable is stationary at level (I(0)) with 5 % significance. This classification is critical for selecting the appropriate method for further analysis, ensuring the accuracy and reliability of the models and research outcomes.

4.3. Results of method of moments quantile regression

Table 7 presents estimates of the impact of various variables on income inequality across different quantiles. The results indicate that digitization (DIG) has a statistically significant negative effect on income inequality, confirming our hypothesis H1. Notably, at lower quantiles (Q20), the impact of digitization on inequality is positive and weakly significant (at the 10 % level), suggesting that early-stage digital adoption may disproportionately benefit high-skilled workers, in line with the skill-biased technological change (SBTC) theory (Autor, 2014; Berman et al., 1998). In contrast, at higher quantiles (Q60, Q70, Q80, Q90), digitization exerts a clear negative effect, progressively reducing inequality, with the absolute value of the coefficient increasing. This pattern supports the notion that digitalization facilitates financial and entrepreneurial inclusion (Demirguc-Kunt et al., 2018) and enhances access to economic opportunities, particularly for lower-income groups

Table 4
Result of slope heterogeneity test.

Slope heterogeneity		
Delta	21.436***	0.000
Adj.	29.024***	0.000

Note: *** represent statistical significance at 1 %.
Source: Author's calculation.

Table 5
Results of the unit root test with CIPS.

Variables	Level	First difference	Decision
Gini	−1.551	−2.454***	I(1)
DIG	−2.416***	–	I(0)
GDP	−1.855	−3.441***	I(1)
GovExp	−1.964	−4.309***	I(1)
EDU	−2.467***	–	I(0)
Unemploy	−1.398	−3.889***	I(1)
TRADE	−1.589	−3.907***	I(1)
INF	−3.480***	–	I(0)

Note: *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.
Source: Author's calculation.

Table 6
Results of the unit root test for GOV variable.

Methods	Level		First difference	
	Statistics	p-value	Statistics	p-value
Levin-Lin-Chu (LLC) test	−2.3042**	0.0106	−12.0025***	0.0000

Note: **, *** represent statistical significance at 5 % and 1 %, respectively.
Source: Author's calculation.

at advanced digital adoption stages. These findings align with theoretical expectations and previous empirical research (Aker, 2010; Antonelli & Gehringer, 2017; Qureshi, 2011; Yin & Choi, 2023).

A key mechanism behind this trend is digitalization's role in reshaping labor market structures. In the early stages, digitalization increases demand for high-skilled workers, leading to wage polarization (Goos et al., 2014). However, as digital access expands and digital literacy improves, the technology becomes a tool for economic inclusion, allowing previously marginalized groups to engage in digital entrepreneurship and remote work (Goldfarb & Tucker, 2019). To the extent that digitization contributes to economic growth, it offers a multidimensional approach to combating poverty and enhancing economic development, positively impacting both social and human capital (Röller & Waverman, 2001). Given the significant fixed transaction costs faced by households in rural and isolated areas, digitization is particularly beneficial in improving access to resources, information, and markets, enabling businesses to increase productivity and profits, and facilitating higher labor productivity and incomes for poor individuals and households (Aker, 2010; Qureshi, 2011). Moreover, digitalization mitigates geographic disadvantages by reducing information asymmetries and transaction costs, allowing low-income individuals to integrate into the global economy more effectively (Demirguc-Kunt et al., 2018). Additionally, digitization demonstrates notably strong network effects and rapid technological change, as illustrated by its role in enhancing competitiveness, reducing rent-seeking behavior, and disrupting existing wealth concentration (Antonelli & Gehringer, 2017).

Interestingly, our analysis of the interaction between digitization and governance quality (DIGxGOV) on income inequality revealed a positive and statistically significant effect across most quantiles. This indicates that high governance quality may exacerbate the income gap among different population groups, increasing income inequality. Contrary to the expectation that governance would enhance digitization's potential to reduce inequality in developing countries, our findings suggest it hinders equitable income effects. This challenges Hypothesis H2 and contradicts earlier studies that reported strong negative effects of these factors on inequality (Richmond & Triplett, 2018). This result aligns with van Dijk's (2020) argument that disparities in digital access and literacy can reinforce existing economic stratification, even in well-governed environments. In well-governed countries, digitization appears less influential on income distribution equity. This may stem from specific groups reaping disproportionate benefits from technology, leaving others behind. A favorable governance environment tends to

Table 7
Results of MMQR estimation.

Variables	Location	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
DIG	−0.0413***	−0.0279***	0.00357	−0.00952	−0.0273*	−0.0387***	−0.0470***	−0.0537***	−0.0607***	−0.0722***	−0.0843***
	[0.0126]	[0.00816]	[0.0204]	[0.0175]	[0.0144]	[0.0128]	[0.0122]	[0.0121]	[0.0123]	[0.0134]	[0.0153]
GOV	−3.707***	−0.210	−3.370***	−3.469***	−3.602***	−3.688***	−3.750***	−3.801***	−3.853***	−3.939***	−4.030***
	[0.612]	[0.398]	[0.994]	[0.852]	[0.692]	[0.623]	[0.596]	[0.591]	[0.602]	[0.653]	[0.743]
DIGxGOV	0.0625***	−0.00696	0.0737***	0.0704***	0.0660***	0.0632***	0.0611***	0.0594***	0.0577***	0.0548***	0.0518***
	[0.0108]	[0.00701]	[0.0175]	[0.0150]	[0.0122]	[0.0110]	[0.0105]	[0.0104]	[0.0106]	[0.0115]	[0.0131]
GDP	2.592***	0.143	2.364***	2.430***	2.521***	2.579***	2.621***	2.656***	2.692***	2.750***	2.812***
	[0.290]	[0.189]	[0.472]	[0.404]	[0.328]	[0.296]	[0.283]	[0.280]	[0.286]	[0.310]	[0.353]
GovExp	0.231***	0.114***	0.0485	0.102	0.174***	0.221***	0.254***	0.282***	0.311***	0.357***	0.407***
	[0.0494]	[0.0321]	[0.0801]	[0.0691]	[0.0567]	[0.0504]	[0.0480]	[0.0475]	[0.0486]	[0.0529]	[0.0603]
EDU	0.0731***	−0.0166**	0.0997***	0.0920***	0.0814***	0.0746***	0.0697***	0.0656***	0.0615***	0.0547***	0.0475***
	[0.0127]	[0.00825]	[0.0206]	[0.0177]	[0.0144]	[0.0129]	[0.0123]	[0.0122]	[0.0125]	[0.0135]	[0.0154]
Unemploy	0.537***	0.299***	0.0573	0.197**	0.387***	0.509***	0.598***	0.670***	0.745***	0.867***	0.997***
	[0.0602]	[0.0392]	[0.0968]	[0.0860]	[0.0730]	[0.0623]	[0.0581]	[0.0570]	[0.0592]	[0.0653]	[0.0751]
TRADE	−0.0315***	0.00845***	−0.0451***	−0.0411***	−0.0358***	−0.0323***	−0.0298***	−0.0277***	−0.0256***	−0.0222***	−0.0185***
	[0.00503]	[0.00327]	[0.00816]	[0.00701]	[0.00573]	[0.00512]	[0.00489]	[0.00484]	[0.00494]	[0.00537]	[0.00612]
INF	0.0322	0.0306	−0.0169	−0.00255	0.0169	0.0294	0.0384	0.0459	0.0535*	0.0660**	0.0793**
	[0.0289]	[0.0188]	[0.0470]	[0.0403]	[0.0328]	[0.0295]	[0.0282]	[0.0279]	[0.0285]	[0.0309]	[0.0352]
Constant	14.17***	0.822	12.85***	13.24***	13.76***	14.10***	14.34***	14.54***	14.75***	15.08***	15.44***
	[2.230]	[1.450]	[3.623]	[3.103]	[2.521]	[2.269]	[2.171]	[2.152]	[2.192]	[2.379]	[2.707]

Note: Standard errors in [ ]; *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

advantage large enterprises and investors who can effectively leverage digitization, concentrating benefits among a small, powerful elite. While good governance usually fosters economic and political stability, it can also amplify the power of special interest groups, ultimately increasing inequality (Van Reenen, 2011).

Van Reenen (2011) emphasizes that advanced technology boosts productivity and income for highly skilled individuals while exacerbating income inequality, as these individuals benefit more than those with lower skills. This finding is consistent with the SBTC framework, which argues that technological change disproportionately benefits those with existing digital competencies, thereby widening income disparities (Autor, 2014; Berman et al., 1998). Downes (2009) points out that disparities in technological advancement and governance quality may increase inequality. As technology evolves rapidly, social, economic, and legal systems lag, allowing progressive workers to exploit technological opportunities, which may widen income gaps. Unequal access further suggests that digitization could reinforce existing economic stratification. Carte et al. (2011) observe that, despite strong regulations and policies, the benefits of online education in Sri Lanka are limited by a lack of relevant skills, high illiteracy rates, and weak information infrastructure. This is supported by Samoilenko and Osei-Bryson (2011), who found that economic strength and infrastructure availability significantly affect the impact of digitization and contribute to growing inequality in 18 transition economies.

Furthermore, the impact of digitization on income inequality varies depending on the type of digital access, reinforcing the digital divide hypothesis (van Dijk, 2020). In an environment with strong governance, increased digitization is associated with lower levels of income inequality; however, this effect is notably dependent on the type of access. Mobile-based digitalization, which requires higher upfront costs and more advanced technological literacy, may primarily benefit wealthier individuals with strong human capital, exacerbating wage gaps. In contrast, affordable and widely available digital infrastructure, such as fixed broadband and public internet access points, facilitates economic inclusion and mitigates inequality (Goldfarb & Tucker, 2019). Therefore, in the following section, we analyze the impact of each digitization component and its interaction with governance quality on income inequality to provide a more detailed explanation.

Regarding the impact of control variables, economic growth (GDP) positively impacts income inequality at higher quantiles (Q70, Q80, Q90), suggesting it exacerbates inequality, particularly in wealthier countries. Although economic growth is generally seen as a way to improve living standards, it can also increase income disparity for several reasons. The benefits of growth are often unevenly shared, with higher-income groups and individuals possessing advanced education or specialized skills typically reaping more rewards. Moreover, as the economy expands, wages in high-skill industries often rise faster than those in low-skill jobs, amplifying income gaps (Piketty, 2014). Additionally, lower-income groups have limited access to quality education and technology, further widening the income divide. Economic growth tends to thrive in urban and developed areas, leaving rural and less developed regions behind. It often shifts the workforce from agriculture to manufacturing and high-skill services, requiring advanced qualifications that skilled workers acquire, while those in traditional sectors experience stagnant incomes. Thus, while economic growth can offer significant advantages, without equitable distribution policies and support for lower-income groups, it can lead to increased income inequality, often referred to as the "dark side of growth."

Government expenditure (GovExp) has a positive and statistically significant impact on income inequality across most quantiles. Generally, government spending is expected to aid in income redistribution and reduce inequality. However, in environments characterized by inefficient governance, a common issue in developing countries, government expenditure may be squandered due to corruption or poor management. When resources are misallocated or wasted, lower-income groups may not receive the necessary services or support, leading to increased inequality. Additionally, if spending is not monitored and transparent, funds may not reach the intended recipients, resulting in benefits being concentrated among a small segment of society.

In contrast, the quality of governance (GOV) has a negative and statistically significant effect on income inequality across all quantiles, with the estimated coefficient decreasing from lower to higher quantiles. This reflects that higher governance quality can help reduce income inequality across the entire distribution by more effectively implementing public spending policies, taxation, and social insurance programs, as well as distributing resources more equitably. These results are consistent with the findings of Richmond and Triplett (2018).

Education (EDU) and unemployment (Unemploy) exhibit a positive and statistically significant impact on income inequality across most quantiles, indicating that education and unemployment rates contribute to a comprehensive increase in income inequality. Education can exacerbate income inequality if there are no measures to ensure fairness and equal access for all individuals. Disparities in the quality of education, education costs, uneven benefits from education, and social factors can all contribute to rising inequality. Duncan and Murnane (2011) analyze that differences in educational investment between wealthy and impoverished families are a major driver of income inequality. Bourdieu (1986) argues that education is not only a means of enhancing human capital but also a tool for reinforcing social structures and social stratification. Similarly, unemployment is a significant factor contributing to increased income inequality. Unemployment not only directly reduces income, widening the income gap between the employed and unemployed, but also negatively impacts disadvantaged groups, affecting their psychological and social well-being and leading to labor market polarization. Prolonged unemployment can result in skill and experience loss, diminishing job search capabilities and future advancement opportunities (Autor & Dorn, 2013; Nichols et al., 2013).

Trade openness (TRADE) negatively impacts inequality across all quantiles, indicating that trade liberalization reduces income stratification within countries. It lowers income inequality by creating job and income opportunities, improving the quality of goods and services, and fostering investment and development (Goldberg & Pavcnik, 2007). Conversely, inflation (INF) increases inequality at higher quantiles by eroding the real value of income, raising living costs, limiting access to financial opportunities, and distorting economic incentives. Research by Agénor (2004), Albanesi (2007), Doepke and Schneider (2006), and Easterly and Fischer (2001) highlight that inflation adversely affects low-income individuals, broadening the income gap and worsening social inequality.

Fig. 1 presents a graphical representation of the relationship described above. Notably, while the interaction effect between digitization and governance quality on inequality is positive, in environments with high governance quality, the impact of digitization on increasing inequality diminishes from lower to higher quantiles. This may be because, at higher levels of governance quality, a higher level of public literacy can more effectively leverage digitization to narrow the income gap between different segments of the population. We interpret these results to suggest that a minimum level of governance quality is necessary to ensure that the proliferation of digitization helps reduce income inequality and that countries with better governance have less room to exploit income disparities.

Next, we evaluate the impact of each component of digitization, including mobile cellular subscriptions, individuals using the internet, and fixed telephone subscriptions, on income inequality to provide a

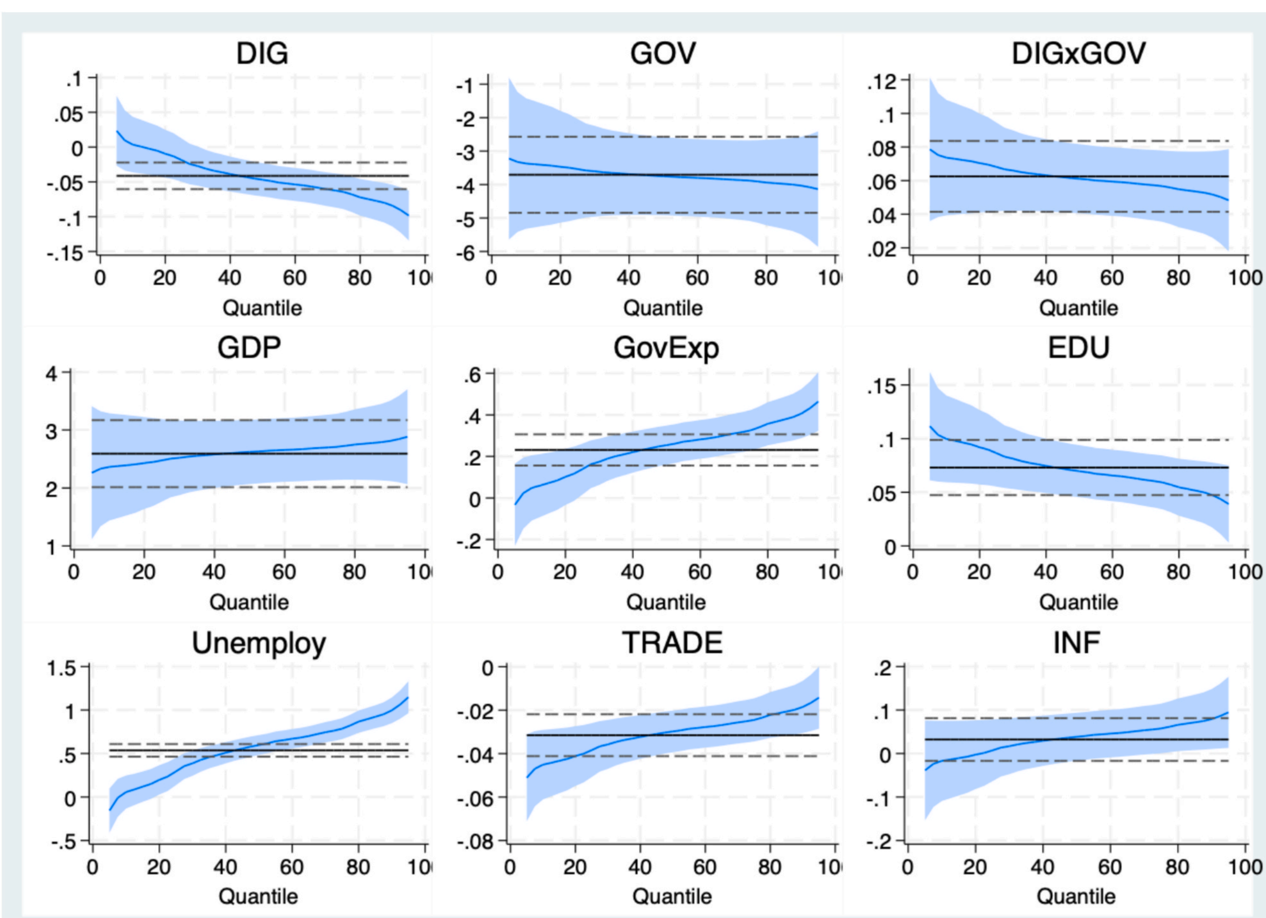

Fig. 1. Graphs the coefficients of a quantile regression. *Source: Author's calculation.*

more comprehensive view of how digitization affects income inequality in developing countries. The results are presented sequentially in Tables 8, 9, and 10.

The results once again affirm the role of digitization in reducing income inequality, with negative coefficients found for all three main components of digitization. Statistical evidence is notably stronger for the two mobile measures (Table 8) and internet usage (Table 9) across most quantiles, whereas the impact on income inequality reduction for fixed telephone usage (Table 10) is primarily observed at the median quantiles. When considering the magnitude of the effects, it appears that the coefficients for fixed telephone and internet usage are stronger compared to mobile phones and tend to increase at higher quantiles. Fixed telephone and internet services are generally less expensive, easier to use, more widely available, and have established infrastructure for both individuals and networks. As such, these forms of digitization may be more accessible to low-income individuals, allowing them to gain the greatest benefits. Consequently, their impact on reducing inequality is higher than that of other forms. In contrast, mobile phones seem to be more expensive and difficult to use compared to fixed telephones and the internet in developing countries, particularly for low-income households and individuals with limited education. Thus, progressive individuals may be better able to exploit these technologies to enhance their income. Therefore, the impact of mobile phone usage on narrowing income gaps is smaller compared to the other two forms.

As noted by previous studies, such as Andonova and Diaz-Serrano (2009), the development and proliferation of digitization are highly sensitive to governance quality, though the effects vary by technology—mobile technology is less constrained by governance quality and political risks. Roztocki and Weistroffer (2011) also argue that differences in the economic and business environment, such as economic conditions, labor force characteristics, legal and regulatory frameworks, and customer characteristics, influence the effectiveness of digitization. Similarly, Samoilenko and Osei-Bryson (2011) suggest that some countries may derive greater benefits from digitization than others due to differences in governance effectiveness. We assess the role of governance quality in the impact of digitization components on inequality in developing countries by examining the interaction of each component. Results in Tables 8, 9, and 10 show that the interaction between governance quality and digitization measures, including mobile usage (Table 8) and internet usage (Table 9), exhibits positive effects, whereas the interaction between fixed telephone usage and governance quality (Table 10) has a negative effect on inequality.

One explanation for the differences in the role of governance quality on the impact of each digitization component on inequality is that individuals with higher education and better digital skills are more likely to adapt to and benefit from digitization, particularly with mobile and internet technologies. However, not everyone has access to modern technology and the internet, especially in rural or impoverished areas. Additionally, mobile and internet usage can create opportunities for accessing high-skill jobs that may displace many traditional jobs, particularly manual and low-skilled jobs. Those employed in these sectors face a higher risk of job loss and.

difficulty finding new employment, thereby exacerbating income gaps and increasing inequality. Governance quality, which encompasses aspects such as corruption control, government effectiveness, political stability, absence of violence or terrorism, regulatory quality, rule of law, voice, and accountability, plays a crucial regulatory role in the relationship between digitization and inequality. In practice, developing countries often deviate from the ideal of equitable distribution, as governance quality typically focuses on economic growth, which can sometimes harm income equality. In some cases, governance quality may inadvertently exacerbate inequality by enabling elites to manipulate social improvements for exclusive economic benefits. For example, in contexts of high governance quality, elites might exploit improvements in regulatory quality and government effectiveness to increase their income concentration (Acemoglu & Robinson, 2010). However,

Table 8
Results of MMQR estimation with DIG = Mobile.

Variables	Location	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
DIG	−0.0113*	−0.0130***	0.0109	0.00432	−0.00451	−0.00961	−0.0132**	−0.0167***	−0.0204***	−0.0254***	−0.0322***
	[0.00612]	[0.00391]	[0.0102]	[0.00866]	[0.00701]	[0.00628]	[0.00599]	[0.00591]	[0.00603]	[0.00650]	[0.00755]
GOV	−3.446***	−0.664	−2.314*	−2.649**	−3.099***	−3.358***	−3.541***	−3.717***	−3.906***	−4.161***	−4.510***
	[0.845]	[0.541]	[1.403]	[1.192]	[0.959]	[0.866]	[0.828]	[0.816]	[0.831]	[0.894]	[1.043]
DIGxGOV	0.0235***	0.00127	0.0213*	0.0220**	0.0228***	0.0233***	0.0237***	0.0240***	0.0244***	0.0249***	0.0255***
	[0.00758]	[0.00485]	[0.0126]	[0.0107]	[0.00859]	[0.00777]	[0.00743]	[0.00732]	[0.00746]	[0.00802]	[0.00935]
GDP	2.343***	−0.0430	2.416***	2.394***	2.365***	2.348***	2.336***	2.325***	2.313***	2.296***	2.274***
	[0.256]	[0.164]	[0.426]	[0.361]	[0.291]	[0.263]	[0.251]	[0.248]	[0.252]	[0.271]	[0.316]
GovExp	0.242***	0.0966***	0.0774	0.126*	0.192***	0.229***	0.256***	0.282***	0.309***	0.346***	0.397***
	[0.0477]	[0.0305]	[0.0792]	[0.0676]	[0.0548]	[0.0490]	[0.0467]	[0.0460]	[0.0470]	[0.0507]	[0.0589]
EDU	0.0739***	−0.0150*	0.0995***	0.0919***	0.0818***	0.0759***	0.0718***	0.0678***	0.0635***	0.0578***	0.0499***
	[0.0131]	[0.00835]	[0.0217]	[0.0184]	[0.0149]	[0.0134]	[0.0128]	[0.0126]	[0.0129]	[0.0138]	[0.0161]
Unemploy	0.542***	0.321***	−0.00541	0.157*	0.374***	0.499***	0.588***	0.673***	0.764***	0.888***	1.056***
	[0.0615]	[0.0393]	[0.101]	[0.0896]	[0.0755]	[0.0636]	[0.0596]	[0.0588]	[0.0611]	[0.0669]	[0.0758]
TRADE	−0.0352***	0.0122***	−0.0560***	−0.0498***	−0.0416***	−0.0368***	−0.0335***	−0.0302***	−0.0268***	−0.0221***	−0.0157**
	[0.00517]	[0.00330]	[0.00857]	[0.00733]	[0.00595]	[0.00531]	[0.00506]	[0.00498]	[0.00509]	[0.00549]	[0.00638]
INF	0.0387	0.0268	−0.00700	0.00655	0.0247	0.0351	0.0425	0.0496*	0.0572**	0.0675**	0.0816**
	[0.0289]	[0.0185]	[0.0479]	[0.0407]	[0.0328]	[0.0296]	[0.0283]	[0.0279]	[0.0284]	[0.0306]	[0.0356]
Constant	15.61***	1.846	12.46***	13.40***	14.65***	15.37***	15.88***	16.37***	16.89***	17.60***	18.57***
	[2.130]	[1.363]	[3.537]	[3.004]	[2.418]	[2.184]	[2.088]	[2.058]	[2.096]	[2.254]	[2.629]

Note: Standard errors in [ ]; *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

Table 9
Results of MMQR estimation with DIG = Internet.

Variables	Location	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
DIG	−0.0392***	−0.0241***	0.00196	−0.00907	−0.0263**	−0.0360***	−0.0422***	−0.0495***	−0.0557***	−0.0641***	−0.0772***
	[0.0106]	[0.00677]	[0.0169]	[0.0148]	[0.0119]	[0.0108]	[0.0105]	[0.0105]	[0.0109]	[0.0118]	[0.0138]
GOV	−2.542***	−1.069**	−0.715	−1.205	−1.971***	−2.400***	−2.679***	−3.000***	−3.277***	−3.651***	−4.233***
	[0.667]	[0.425]	[1.061]	[0.922]	[0.743]	[0.679]	[0.660]	[0.662]	[0.683]	[0.738]	[0.866]
DIGxGOV	0.0280**	0.00869	0.0131	0.0171	0.0234*	0.0268**	0.0291**	0.0317***	0.0340***	0.0370***	0.0417***
	[0.0121]	[0.00770]	[0.0193]	[0.0166]	[0.0134]	[0.0123]	[0.0120]	[0.0120]	[0.0124]	[0.0134]	[0.0157]
GDP	2.829***	0.288	2.336***	2.469***	2.675***	2.790***	2.865***	2.952***	3.027***	3.127***	3.284***
	[0.297]	[0.189]	[0.473]	[0.409]	[0.329]	[0.302]	[0.294]	[0.295]	[0.304]	[0.328]	[0.386]
GovExp	0.244***	0.0848***	0.0986	0.138**	0.198***	0.232***	0.254***	0.280***	0.302***	0.332***	0.378***
	[0.0492]	[0.0314]	[0.0782]	[0.0682]	[0.0550]	[0.0501]	[0.0487]	[0.0488]	[0.0503]	[0.0544]	[0.0639]
EDU	0.0638***	−0.0347***	0.123***	0.107***	0.0824***	0.0684***	0.0594***	0.0489***	0.0399***	0.0278*	0.00886
	[0.0129]	[0.00820]	[0.0204]	[0.0179]	[0.0145]	[0.0131]	[0.0127]	[0.0127]	[0.0131]	[0.0142]	[0.0167]
Unemploy	0.535***	0.324***	−0.0177	0.131	0.363***	0.492***	0.577***	0.674***	0.758***	0.871***	1.047***
	[0.0629]	[0.0401]	[0.0974]	[0.0918]	[0.0755]	[0.0648]	[0.0620]	[0.0618]	[0.0637]	[0.0701]	[0.0810]
TRADE	−0.0356***	0.0121***	−0.0563***	−0.0507***	−0.0420***	−0.0372***	−0.0340***	−0.0304***	−0.0272***	−0.0230***	−0.0164**
	[0.00518]	[0.00330]	[0.00822]	[0.00721]	[0.00583]	[0.00528]	[0.00512]	[0.00513]	[0.00529]	[0.00573]	[0.00672]
INF	0.0304	0.0371*	−0.0331	−0.0161	0.0106	0.0255	0.0351	0.0463	0.0559*	0.0689**	0.0892**
	[0.0305]	[0.0195]	[0.0487]	[0.0422]	[0.0340]	[0.0311]	[0.0302]	[0.0303]	[0.0313]	[0.0338]	[0.0397]
Constant	13.18***	0.863	11.70***	12.10***	12.72***	13.06***	13.29***	13.55***	13.77***	14.07***	14.54***
	[2.382]	[1.520]	[3.800]	[3.280]	[2.639]	[2.424]	[2.359]	[2.366]	[2.441]	[2.634]	[3.098]

Note: Standard errors in [ ]; *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

Table 10
Results of MMQR estimation with DIG = Telephone.

Variables	Location	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
DIG	−0.0475*	0.000847	−0.0489	−0.0485	−0.0480	−0.0476*	−0.0474*	−0.0472*	−0.0469	−0.0466	−0.0461
	[0.0270]	[0.0166]	[0.0406]	[0.0343]	[0.0294]	[0.0274]	[0.0270]	[0.0272]	[0.0286]	[0.0311]	[0.0368]
GOV	−0.180	−1.943***	3.168***	2.098**	0.995	0.213	−0.302	−0.865	−1.519**	−2.212***	−3.317***
	[0.657]	[0.403]	[0.990]	[0.841]	[0.729]	[0.669]	[0.655]	[0.665]	[0.698]	[0.761]	[0.902]
DIGxGOV	−0.0837***	0.0566***	−0.181***	−0.150***	−0.118***	−0.0952***	−0.0802**	−0.0638**	−0.0447	−0.0246	0.00761
	[0.0321]	[0.0197]	[0.0483]	[0.0409]	[0.0352]	[0.0326]	[0.0320]	[0.0324]	[0.0340]	[0.0371]	[0.0438]
GDP	2.000***	−0.0421	2.073***	2.049***	2.026***	2.009***	1.997***	1.985***	1.971***	1.956***	1.932***
	[0.283]	[0.174]	[0.425]	[0.359]	[0.308]	[0.287]	[0.282]	[0.285]	[0.300]	[0.326]	[0.385]
GovExp	0.259***	0.0340	0.200***	0.219***	0.238***	0.252***	0.261***	0.270***	0.282***	0.294***	0.313***
	[0.0481]	[0.0295]	[0.0722]	[0.0611]	[0.0524]	[0.0488]	[0.0480]	[0.0485]	[0.0510]	[0.0554]	[0.0655]
EDU	0.0740***	−0.0230***	0.114***	0.101***	0.0879***	0.0787***	0.0726***	0.0659***	0.0582***	0.0500***	0.0369**
	[0.0125]	[0.00769]	[0.0188]	[0.0160]	[0.0137]	[0.0127]	[0.0125]	[0.0127]	[0.0133]	[0.0145]	[0.0171]
Unemploy	0.501***	0.334***	−0.0750	0.109	0.299***	0.433***	0.522***	0.619***	0.732***	0.851***	1.041***
	[0.0585]	[0.0359]	[0.0888]	[0.0771]	[0.0689]	[0.0599]	[0.0580]	[0.0598]	[0.0626]	[0.0691]	[0.0828]
TRADE	−0.0349***	0.0174***	−0.0648***	−0.0553***	−0.0454***	−0.0384***	−0.0338***	−0.0288***	−0.0230***	−0.0168***	−0.00689
	[0.00520]	[0.00319]	[0.00784]	[0.00668]	[0.00581]	[0.00530]	[0.00518]	[0.00527]	[0.00553]	[0.00604]	[0.00717]
INF	0.0329	0.0324*	−0.0228	−0.005	0.0134	0.0264	0.0350	0.0443	0.0552*	0.0668**	0.0852**
	[0.0285]	[0.0175]	[0.0428]	[0.0362]	[0.0311]	[0.0290]	[0.0284]	[0.0288]	[0.0302]	[0.0329]	[0.0389]
Constant	18.58***	1.637	15.76***	16.66***	17.59***	18.25***	18.68***	19.16***	19.71***	20.29***	21.22***
	[2.456]	[1.508]	[3.690]	[3.118]	[2.675]	[2.495]	[2.452]	[2.479]	[2.604]	[2.831]	[3.344]

Note: Standard errors in [ ]; *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

these arguments somewhat differ for fixed telephone usage, as fixed telephones are relatively inexpensive and preferred in rural and impoverished households due to their ease of use and existing infrastructure. Therefore, in a good governance environment, increased use of fixed telephones can enhance information access for poorer individuals, thereby creating opportunities for income growth and narrowing the income gap with higher-income individuals, thus reducing income inequality.

4.4. Robustness test with S-GMM

A common concern when estimating models with nonlinear terms and time-series data is the potential occurrence of endogeneity and multicollinearity. By using interaction variables in the model and noting that our dependent variable, inequality, often has past dynamics, we have identified that the interaction terms and the past dynamics of the dependent variable are causing multicollinearity issues with some other variables and potential endogeneity in the model. To address this concern and further assess the reliability of the results, we conduct a regression analysis using the System Generalized Method of Moments (S-GMM) approach. The results are presented in Table 11.

Diagnostic assessments, including the Hansen test and AR(2) autocorrelation test, which cannot be rejected at the 5 % significance level, indicate that the S-GMM estimates are valid. The results confirm that the negative impact of digitization on income inequality persists, with an effect size of −0.00165 at a 1 % statistical significance level. The S-GMM estimates also provide more robust results compared to MMQR in assessing the role of governance quality in the relationship between digitization and income inequality. We find that, overall, good governance enables progressive and skilled components of the economy to better leverage the benefits of digitization to increase income, while some traditional jobs are displaced, leading to reduced income for certain segments of the population and widening the income gap. Finally, the results regarding the impact of control variables are entirely consistent with previous findings.

Table 11
Robustness test results with S-GMM.

Dep. Var: Gini	DIG
Gini (t-1)	0.952***
	[0.00341]
DIG	−0.00165***
	[0.000591]
GOV	−0.137**
	[0.0558]
DIGxGOV	0.00410***
	[0.000801]
GDP	0.0662***
	[0.0226]
GovExp	0.00872**
	[0.00398]
EDU	0.00347*
	[0.00191]
Unemploy	0.0382***
	[0.00421]
TRADE	−0.00119**
	[0.000490]
INF	0.00349***
	[0.000874]
Constant	0.996***
	[0.172]
N	945
No. of IVs	42
No. of Countries	45
AR (2)	0.064
Hansen test	0.270

Note: Standard errors in [ ]; *, **, *** represent statistical significance at 10 %, 5 % and 1 %, respectively.
Source: Author's calculation.

5. Conclusion

Income inequality poses significant challenges to achieving sustainable development goals in countries, as it leads to various societal repercussions. Theory suggests that digitization can either promote or hinder poverty alleviation by increasing access to opportunities and markets or by encountering barriers due to skill disparities. With recent developments, governance quality is considered a crucial factor in harnessing the benefits of digitization within the economy. In this paper, we investigate the relationship between digitization and income inequality, along with the moderating role of governance quality, for a group of 45 developing countries using data from 2002 to 2023. Specifically, we examine how digitization affects income inequality both directly and indirectly under the influence of governance quality. We also explore whether these effects differ across countries with varying levels of income inequality using quantile regression analysis. To the best of our knowledge, this is the first study to explore the relationship between digitization and income inequality with the role of governance quality at the cross-national level using quantile regression.

Three main conclusions can be drawn from our findings. First, digitization reduces income inequality. This result is consistent across all four digitization measures, including the three component measures—mobile phone usage, internet access, and fixed telephone subscriptions—and the composite measure of these three factors. Second, governance quality diminishes the positive impact of digitization on narrowing the income gap, exacerbating inequality across all quantiles of the income distribution, with a more pronounced effect at higher quantiles. Lastly, and equally important, while we observe that governance quality appears to act as a catalyst in increasing inequality due to the combined effects of digitization, fixed telephone usage—characterized by its low cost, ease of use, and existing infrastructure—emerges as a solution to mitigating income inequality, in contrast to the other components, such as mobile phone usage and internet access.

Our study extends the Skill-Biased Technological Change (SBTC) Theory by demonstrating that while digitization generally reduces income inequality, its effects are uneven across different technological components. Unlike previous studies that focus primarily on advanced economies, our findings highlight that in developing countries, governance quality can exacerbate the skill bias by favoring individuals with higher digital literacy, thereby limiting the equalizing potential of digitization. This suggests that the traditional assumptions of SBTC—where technology primarily benefits skilled workers—should be revisited to account for governance structures that mediate these effects. Additionally, our findings contribute to the Institutional Theory of Economic Development by revealing that governance quality does not always act as a catalyst for reducing inequality through digitization. In contrast to prior assumptions that strong governance uniformly enhances digital benefits, we find that in highly unequal societies, governance mechanisms may disproportionately favor higher-income groups, thereby exacerbating digital divides and income inequality. This suggests a need to refine existing theoretical frameworks to account for governance-related disparities in digital access and benefits.

Furthermore, our study refines the Digital Divide Theory by highlighting that different forms of digital access—mobile phone usage, internet access, and fixed telephone subscriptions—have heterogeneous effects on income inequality. In particular, we demonstrate that fixed telephone subscriptions, as a low-cost and accessible form of digitization, are more effective in reducing income inequality than mobile and internet penetration. This challenges the dominant assumption that advanced digital technologies alone drive economic inclusivity and suggests that affordability and accessibility remain critical components of digital equity.

Finally, we expand the Financial and Entrepreneurial Inclusion Framework by illustrating that the distributional impact of digitization depends not only on access to financial technology but also on how governance facilitates or hinders equitable digital financial services. Our results indicate that while fintech and digital platforms can democratize economic opportunities, ineffective governance may prevent these tools from reaching marginalized populations, thereby limiting their role in reducing income inequality.

These findings contribute to a growing but still limited body of literature on the role of digitization and governance quality in reducing income inequality and promoting sustainable development globally. Consistent with recent studies, we find that digitization is a significant driver in mitigating inequality. However, we extend these findings by indicating that a certain level of income and governance quality is required to prevent gaps in leveraging skills related to more costly and advanced forms of digitization, thereby maximizing digitization's role in narrowing the income gap.

From a practical standpoint, our findings suggest several important policy implications. First, while digitization policies should aim to reduce income inequality, a targeted approach is necessary. Policymakers should prioritize digital inclusion strategies that cater to low-income populations, ensuring that digital tools and services are accessible to those who need them most. This includes investing in information technology infrastructure, high-speed internet, and providing digital skills training programs. Second, for digitization to most effectively reduce inequality, governments can create supportive policies for startups and innovation, facilitating access to capital, technology, and markets for small and medium-sized enterprises. This will help reduce income disparities by generating more job opportunities and economic growth.

Third, beyond traditional education, digital literacy initiatives should be expanded to ensure that workers can effectively participate in an increasingly digitized economy. Public-private partnerships can play a key role in bridging this skill gap. Fourth, our results suggest that good governance must ensure that the benefits of digitization are not concentrated in a small segment of society but are distributed widely. Policies need to ensure that digitization efforts do not create larger gaps between different population groups. In particular, regulatory frameworks should be strengthened to prevent digital monopolies and ensure fair competition in digital markets. Finally, collaboration between the public and private sectors is essential to maximize the benefits of digitization. Governments should promote public–private partnership projects to develop digital infrastructure and provide digital services, ensuring that all citizens have the opportunity to access and benefit from these services, with the aim of reducing income inequality and ensuring sustainable and inclusive economic development. Without such proactive measures, digitization may risk deepening, rather than alleviating, existing income disparities.

While this study provides important contributions to understanding the relationship between digitization, governance quality, and income inequality, several limitations remain, offering avenues for future research to provide deeper insights. Specifically, the analysis focuses on a group of 45 developing countries, which may limit the generalizability of the findings to developed economies or those with distinct structural characteristics. Future research could extend the analysis to developed economies or different regions to assess variations in the impact of digitization on inequality across institutional contexts, thereby yielding practical policy implications. Additionally, although this study employs four different measures of digitization, certain advanced aspects remain unexplored, such as the effects of artificial intelligence, blockchain technology, or digital financial platforms on income inequality. Future studies could examine these more advanced dimensions of digitization to offer a more comprehensive understanding of how digital transformation influences income distribution. Finally, further research could explore how the interplay between digitization and other factors, such as microfinance, social welfare policies, or vocational training programs, can more effectively mitigate income inequality. This could provide valuable policy insights into optimizing the benefits of digitization in achieving sustainable development goals.

CRediT authorship contribution statement

Thi Lam Ho: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Conceptualization. **Le Hong Ngoc:** Writing – original draft, Software, Methodology, Data curation. **Thu Hoai Ho:** Writing – original draft, Supervision, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix 1. Developing countries (45 countries).

Albania	Croatia	Kyrgyz Republic	Poland
Armenia	Dominican Republic	Malaysia	Romania
Botswana	Ecuador	Mali	Senegal
Brazil	Egypt, Arab Rep.	Mauritius	South Africa
Bulgaria	Ghana	Mexico	Tanzania
Burkina Faso	Honduras	Moldova	Thailand
Burundi	Hungary	Mongolia	Togo
Chad	India	Niger	Tunisia
Chile	Indonesia	Pakistan	Viet Nam
China	Jamaica	Paraguay	
Colombia	Jordan	Peru	
Costa Rica	Kenya	Philippines	

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