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HOW DO DIFFERENT FORMS OF DIGITALIZATION AFFECT INCOME INEQUALITY?

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Abstract. This article examines how different forms of digitalization affect inequality in Europe. Using a cross-national dataset of economic development and digitalization across a range of regression specifications including country and time fixed effects, this article explores the heterogeneous relationships of disparate forms of digitalization – human capital, broadband connectivity, integration of digital technology into small and medium enterprises, and digital public services – with income inequality. Fixed country and time effects models show that only the digitalization of human capital and integration of digital technology by SMEs are associated with decreases in income inequality. Causal mediation analysis reveals that tertiary education, despite its oft-cited connection to digital technology uptake, has no causal effect on the pathways through which digitalization of labour and SME operations lower inequality, which are direct. The findings tentatively suggest that there exist informal sources of digital skills training apart from formal tertiary education and point to SMEs as a potentially impactful area for investing in digitalization as pathways for income redistribution.

Keywords: digitalization, income inequality, human capital, broadband connectivity, small and medium enterprises, public services.

JEL Classification: O14, O15, O33, E24.

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1. Introduction

Digitalization and inequality are the two most profound economic developments of the past century (Au, 2023a; Matt et al., 2015; Piketty & Saez, 2014; Vial, 2021).

In 2017, global expenditures on digital transformation technologies and services reached US$960 billion. By 2022, expenditures reached US$1.8 trillion, and are projected to rise to US$2.8 trillion (Sava, 2022). Such investments have precipitated into increasing integration of digital technologies into the provision of services by organizations and governments alike. Promising stronger connectivity and transmission of data between consumers and institutional stakeholders, digitalization is oft-touted as a vehicle for improving wellbeing, such as through smart city designs with improved traffic controls and crime-preventing surveillance measures (Silva et al., 2018; Yin et al., 2015), jumpstarting new circuits of sharing economies

(Kraus et al., 2019), and improving firm productivity and household consumption of goods (Bouncken et al., 2020; Matt et al., 2015).

During the same period, inequality has risen to galvanize nations worldwide (Colciago et al., 2019; Tomaskovic-Devey et al., 2015). Alvaredo et al. (2018) trace widening patterns of income disparities across major economies. The top 10% of income share has increased nearly everywhere since 1980, but most of all in the largest economies worldwide, namely, China (top decile income share standing at 41%), North America (accounting for 47%), Russia (46%), and India (56%). Conversely, the bottom 10% income share has decreased in these economies and held stagnant, at best, in other nations (see also Berman et al., 2016; Shin, 2020).

Indeed, while the link between digitalization and economic growth is well-understood, the coincidence of unprecedented technological innovation – and its attendant effects on the level of economic integration in the world economy – and rising levels of income inequality – soaring past predictions of the Kuznets hypothesis for developed nations at this level of prosperity – invites scrutiny of the connections between digitalization and inequality.

A technological shift on the order of digitalization at the national-level might instead aggravate the concentration of profits (economic rents) into the hands of a smaller group in a liberal market economy (Horii et al., 2013; Ni et al., 2022). Recent research has gone further to cast doubt on the ameliorative effects of digitalization on inequality, finding that it is confined to nations where the unequal concentration of wealth was higher, to begin with (Afzal et al., 2022; Antonelli & Gehringer, 2017; De Vita & Luo, 2021).

Understanding their connections is an urgent matter of theoretical as much as practical salience. Preliminary research on the long-term effects of inequality by the International Monetary Fund and economists shows that it incites protectionism, reverses globalization and economic development, and ultimately limits household participation in multiple sectors of the economy and, by extension, access to digital services and technologies (Colciago et al., 2019; Dabla-Norris et al., 2015; Jaumotte & Osorio Buitron, 2015; Mohd Daud et al., 2021; Tchamyou et al., 2019).

Building on this work, this article offers an exploratory analysis of digitalization and inequality in European nations, where the unequal concentration of wealth is comparatively lower than the U.S. Using a cross-national dataset of economic development and digitalization in Europe across a range of regression specifications and causal mediation analysis, this article explores the heterogeneous effects of disparate forms of digitalization (labour, connectivity in households, integration of digital technology into small and medium enterprises, and digital public services) on income inequality, while accounting for the potential mediating effects of tertiary education.

2. Existing literature

In light of economic evidence that the link between technology adoption and income discrepancies is heterogeneous (Demir et al., 2022; Jaumotte et al., 2013), the unequal distributional effects of digitalization for economic prosperity are theorized to be connected to household access to digital skills, technology, and public services in a given nation. Differences in uptake rates of digital technology use offer further evidence of its links to inequality, such as rural-urban or class discrepancies in Internet access (Bacher-Hicks et al., 2021; Gui & Büchi, 2021; Van Deursen et al., 2017).

Digitalization may affect inequality through several channels.

(1) Human capital. Governments, policymakers, and tertiary education institutes have embraced a turn to emphasizing the development of digital skills in the general population, particularly so in Europe (Donoso et al., 2020; Kiener et al., 2019; Non et al., 2021; Spada et al., 2022). Digital skills have come to account for significant discrepancies in educational attainment, social participation, and labour market outcomes. Those with digital skills command greater salaries, are more competitive on the job market, and receive more opportunities for promotion (Pagani et al., 2016). Additionally, empirical research finds that the income distributional effects of digital skills have knock-on effects on a macro-level. Inflows of foreign direct investment (FDI) in technological progress result in higher premiums placed on higher (digital) skills and higher returns to capital – coming to aggravate income disparities at an aggregate level (Jaumotte et al., 2013; Lim & McNelis, 2016; Mohd Daud et al., 2021; Ni et al., 2022).

Shang (2023) argues that digitalization can alleviate inequality by improving educational equity, that is, access to education by greater parts of the population. Using provincial data from China, he finds that digitalization improves coverage of digital financial products, lowers transaction costs, and improves access to credit for poor provinces, especially for less developed areas. The result of these improvements to digital finance is the alleviation of credit constraints for (residents of) poor provinces, which enable them to increase investment in education and human skills development. This research is in line with extant research that shows endowment effects on educational disparities and, as a result, broader income inequality (Mahdzan et al., 2023).

(2) Greater connectivity among households. The rise of e-commerce technology use by residents may enhance inter-city and inter-region trade, which reduces the effect of geographical distance on trade costs. This ultimately lowers prices and enhances access to goods and services, reducing inequality by optimizing household expenditures (Fan et al., 2018). Bauer (2018) goes further to identify links between income inequality and access to information and communication technologies, which he sources to discrepancies in labour outcomes. Indeed, digital technology access in households permits participation in e-commerce and captures an informal form of digital skills training that is useful for career development, a key source of inequality among European countries (Lucendo-Monedero et al., 2019).

Complementing this research, Skare and Porada-Rochoń (2022) analyse panel data in the U.S. to find that digital technology adoption on a macro-level as in the present study significantly increases social equality (reducing the Gini Index). Most saliently, they identify that technology adoption in households as a key form through which digitalization improves equality. This assertion is in line with economic evidence about the importance of digital infrastructure, such as broadband connectivity and Internet cables for cellular networks, for individual digital literacy (Shang, 2023; Van Dijk, 2006). Having this digital literacy, in turn, enables individuals to gain access to digital financial products, participate in higher-paying jobs with greater job complexity, and assist their employer organizations with improving firm efficiency (Bejaković & Mrnjavac, 2020; Li et al., 2023; Seo et al., 2019).

(3) Integration of digital technology by small and medium enterprises (SMEs). The uptake of digital technology by SMEs is associated with "optimizing internal processes [and] incorporating new technology" to the effect of improving efficiency in SMEs' business models (Loebbecke & Picot, 2015). In a study of 321 European SMEs, Bouwman, Nikou, and de Reuver (2019) find that SMEs that undertake digital transformation tend to allocate more resources to experimenting with their business models and ultimately improve business performance. Coupled with evidence that shows SMEs grow faster and promote aggregate job creation, contributing over 65% and 70% of total employment in high- and low-income countries respectively (Hall, 1987; Martin et al., 2017; Neumark et al., 2011), the inference emerges that encouraging digitalization among SMEs has knock-on benefits for income redistribution.

Li et al. (2023) recently demonstrate in a micro-study of Chinese firms, for instance, that digitalization affects the labour share (the proportion of labour available to the workforce and, by extension, the share of income they receive). As they point out, if labour share declines, that signals a trend of income distribution (higher inequality) that is unfavorable to workers and threatens economic growth and social stability (see also Clarke, 1995). Examining digitalization of firms on a micro-scale, Li et al. (2023) find that digitalization ultimately increases labour share by improving production capacity, enterprise profits, and enterprise efficiency. Additionally, digitalization indirectly increases labour share by easing financial constraints through reducing barriers to access for financial products and increasing financial efficiency (see also Lu et al., 2022). Finally, Li et al. (2023) find that digitalization increases labour share most in firms that are labour-intensive, a category of firms that also extends to SMEs in the present study. They credit this effect to a higher intrinsic motivation for digitalization by labour-intensive firms seeking to replace physical parts of the workflow with digital solutions, as well as digitalization's ability to ease financing constraints that disproportionately burden labour-intensive firms that allocate more funds to labour.

(4) Digitalization of public services. The integration of public services with digital technology by state institutions also works to reverse inequality as households gain more efficient access to a wider reach of services, participate in government decision-making, and service providers gain superior insight into household needs to personalize services (Bertot et al., 2016). In addition to reducing financial constraints for labour-intensive firms, digitalization reduces such constraints and improves cost-savings for state-owned enterprises (SOEs), which precipitate into greater labour share and lower inequality (Li et al., 2023).

Recent research on e-government, defined as the digital availability of research information, service forms, information about policies, licensing details (Lin et al., 2011), finds that it has the potential to ameliorate inequality. Digitalizing these public services is found to increase trust in institutions (Tolbert & Mossberger, 2006), but more importantly, increase transparency and participation in government-offered social services (Rosenberg, 2019). Part of this effect of reversing inequality stems from the fact that many disadvantaged parts of the population, such as racial and ethnic minorities, are disincentivized to access public services when they are in-person, often due to cultural and linguistic barriers.

This resonates with and provides empirical support for what Nobel Prize-winning economist Richard Thaler (2018) coins "sludge". Defined as excessive bureaucratic frictions, sludge might assume forms such as,

"unnecessarily complicated and cumbersome paperwork and form-filling requirements, hidden add-on fees, long and confusing fine print, unfavorable default settings, inconvenient cashback and refund conditions, messages that induce… costs in the form of… subscription traps, and bureaucratic red tape" (Shahab & Lades, 2021, p. 2)

Digitalizing public services thus helps improve the availability of information and lower barriers to access for essential services to reduce costs (such as eligible tax credits) and to bolster income (such as welfare, Matheus et al., 2021; Rosenberg, 2021).

3. Estimation framework

This article opts for a causal mediation approach, rather than an instrumental variable approach. We recognize that there are important differences that set apart instrumental variable approach from causal mediation analysis, and we believe the latter is better suited to this study.

An instrumental variable approach requires a number of instrumental variables equal to or greater than the number of explanatory variables tested, but given that there are four explanatory variables of interest in the present article to properly parse out the effects of digitalization, it would not be parsimonious to include so many instrumental variables. With four instruments and a sample lower than 200, the efficiency risks declining rapidly as the excess of observations over instruments becomes smaller and the risk of overestimating instrumented estimates grows (see Dippel et al., 2020). The instrumental variable approach only efficiently eliminates the simultaneous equation bias in samples much larger than those of the present study.

Using Monte Carlo simulations of 1309 instrumental variables regressions, Young (2022) recently finds that instrumental variables "has little power as, despite producing substantively different estimates, it rarely rejects the OLS point estimate or the null that OLS is unbiased, while the statistical significance of excluded instruments is exaggerated" (p. 1). This concern about the overstatement of the benefits of instrumental variables for reducing bias versus uninstrumented estimates or even simple regressions that are biased is not new.

Echoing this concern, Jiang (2017) identifies in a survey of 255 papers using the instrumental variable approach an overestimation of instrumental variable estimates compared to uninstrumented estimates by nine times, even when economic theory does not imply a downward bias in the uninstrumented estimates. As such, despite the ubiquity of instrumental variables, it is "difficult to argue that instrumental variable estimates… on the whole, are closer to the true (and unknown) parameters than the simple regression estimates that are potentially tainted by endogeneity" (p. 128).

One plausible explanation for this overestimation, he argues, lies in an overstatement of affirmative endogeneity or "adopt[ing] instruments because [of the] concern that in not doing so the uninstrumented estimates would likely overestimate the true effect", a risk that is aggravated in the inclusion of an excessive number of instruments (especially for too modest a sample).

Indeed, even acknowledging the possibility of endogeneity bias, there is "no reason to expect that the causal effects in close to 85% of all the cases studied by researchers should be predominantly higher than the simple correlational effect" (Jiang, 2017, p. 131).

Moreover, an instrumental variable approach assumes full mediation (only direct effects from a mediator) *a priori*, which is linked to why Jiang (2017) finds that instrumental variable estimates are so often and so exaggerated compared to uninstrumented estimates.

Thus, to keep our estimation models parsimonious, we focus on a causal mediation analysis approach instead. By contrast, causal mediation analysis estimates both direct and indirect effects of a mediator to estimate a total causal effect, in so doing capturing the possible cancellation of different pathways. Moreover, this approach is more flexible in permitting a small number of mediators that lend well for parsing out variations in multiple explanatory variables on a single outcome, as is the case in this study.

Causal mediation analysis converts counterfactual frameworks into precise effects (Pearl & Mackenzie, 2018). The objective is to decompose the total treatment effect into direct and indirect (mediating) effects. The mediating effect is one possible pathway through which a treatment (digitalization) affects a chosen outcome (inequality). It is infeasible to identify all indirect influences of digitalization on inequality, though we focus on variation in tertiary education (from Eurostat) as a mediator for the four DESI measures of digitalization, in order to estimate the impact of digitalization on inequality. Education is a plausible mediator for encouraging the development of digital skills, willingness to purchase internet services, uptake of e-commerce technologies by residents and SMEs, and digitalization of public services in a country.

The ubiquity of digital technologies has formalized the training of digital skills in education. Indeed, education in the twenty-first century is an important source of digital skills on account of the integration of digital technology in schools itself as a medium of instruction (Akçayır & Akçayır, 2017; Au, 2023b; Williams, 2022; Zhou, 2018). In an authoritative systematic review of all the determinants of digital skills training, Van Laar et al. (2020) further find that education is among the most significant predictors of digital skills and, by extension, desire to use digital technologies.

Furthermore, there is convincing evidence that tertiary education is an important source of skills education and its adherent wage premium in explaining widening inequality (Autor, 2014). In addition to being a source of additional financial resources, tertiary education has also been associated with higher financial literacy and skills to manage financial resources (Bandelj & Grigoryeva, 2021). Figure 1 is a directed acyclic graph (DAG) that illustrates the relationship between the DESI measures of digitalization (D), tertiary education (M), and inequality (Y).

Let *HiD* denote high level of digitalization, and *LoD* denote low digitalization. Let the potential outcome $Y_{it}(HiD)$ indicate the Gini Index of country i at time t if they have a high

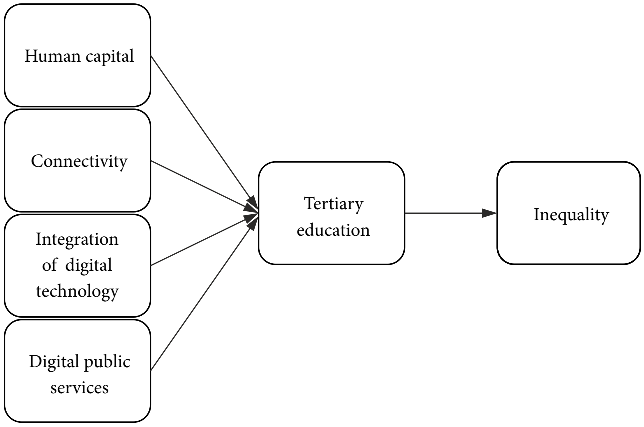

Figure 1. Framework based on a DAG. Explanatory variables – digital human capital, broadband connectivity, integration of digital technology, digital public services. Mediator – tertiary education. Outcome – inequality

level of digitalization, and $Y_{it}(LoD)$ the Gini Index of country i at time t if they have a low level of digitalization. Accordingly, let $M_{it}(HiD)$ and $M_{it}(LoD)$ represent the level of tertiary education that country i achieves at time t should it have high and low levels of digitalization, respectively.

We estimate that:

$$Y_{it}\left(HiD\right) = Y_{it}(HiD, M_{it}\left(HiD\right)$$

and,

$$Y_{it}\left(LoD\right) = Y_{it}(LoD, M_{it}\left(LoD\right)$$

indicate the potential outcomes $Y_{it}(HiD)$ and $Y_{it}(LoD)$ as functions of the values of both digitalization and tertiary education. In this counterfactual framework, each country has a potential set of outcomes based on possible values of digitalization (high, low) and differences between these outcomes inform causal effects of interest (Brand et al., 2019; Kratz et al., 2022).

We can incorporate these notations into calculations of the direct and indirect effects of digitalization. In terms of direct effect, we can define TE_{it} as the total effect or the expected difference in Gini Index at time t had country i had high rather than low digitalization:

$$TE_{it} = Y_{it}\left(HiD, M_{it}\left(HiD\right)\right) - Y_{it}\left(LoD, M_{it}\left(LoD\right)\right). \tag{1}$$

Through Eq. (1), we ask whether a country that has high digitalization has a different outcome of inequality than if it had low digitalization. Macro-level data offers an advantage for this kind of analysis, as countries do have the benefit of having both treated (high digitalization) and untreated (low digitalization) outcomes, if they choose to invest more in digitalization over time.

Eq. (1) can be decomposed into direct and indirect effects (pathways through which the independent variable affects the dependent variable, while accounting for the mediator). We can estimate a natural direct effect (NDE) through:

$$NDE_{it} = Y_{it}\left(HiD, M_{it}\left(LoD\right)\right) - Y_{it}\left(LoD, M_{it}\left(LoD\right)\right). \tag{2}$$

Eq. (2) denotes the expected difference in inequality for country *i* at time *t* if each country had a higher versus lower level of digitalization, if they each started out with a low level of digitalization (holding the treatment *D* constant).

Similarly, we can estimate a natural indirect effect (NIE), which is the causal mediation effect of the treatment on the outcome through the mediating variable for country *i*:

$$NIE_{it} = Y_{it}\left(HiD, M_{it}\left(HiD\right)\right) - Y_{it}\left(HiD, M_{it}\left(LoD\right)\right). \tag{3}$$

Eq. (3) indicates what changes would happen to the outcome if tertiary education changed from what is observed when countries have higher versus lower levels of digitalization, if they started out with a high level of digitalization. For instance, $Y_{it}\left(HiD, M_{it}\left(HiD\right)\right)$ indicates the level of inequality for country *i* at time *t* with high level of digitalization and level of tertiary education for high level of digitalization, and $Y_{it}\left(LoD\right) = Y_{it}\left(LoD, M_{it}\left(LoD\right)\right)$ indicates the level of inequality for the same country *i* with the same level of digitalization *but* with the level of tertiary education if it had a low level of digitalization (a counterfactual). The mediating effect here explains the degree to which digitalization impacts inequality through tertiary education.

Having outlined the possible pathways through which direct and indirect effects may take shape, we estimate the total effect of the four forms of digitalization on education. To do so, we estimate a set of regressions predicting the mediator tertiary education (*M*) that includes the treatment (*D*) digitalization on all four DESI measures (let *D* be substituted by the digitalization of human capital D_{HC}, connectivity D_{Con}, integration of technology by SMEs D_{SME}, and digitalization of public services D_{Pub}) in country *i* at time *t*, using the following form:

$$M_{it} = a_i + bD + \varepsilon_i. \tag{4}$$

For the treatment, digitalization was considered high (*HiD*) if the value of each DESI in country *i* was equal to or greater than that of the European Union in time *t*, and conversely, digitalization was considered low (*LoD*) if it fell below the European Union benchmark.

Additionally, we estimate a full outcome regression model (Eq. (5)) that also includes the mediator (tertiary education). This allows us to test for the correlations between the four forms of digitalization and variations in inequality *Y* in country *i* in year *t* according to World Bank and Eurostat data. Tertiary education, captured in M_{it}, is used to mediate for measures of digitalization of human capital D_{HC}, connectivity D_{Con}, integration of technology by SMEs D_{SME}, digitalization of public services D_{Pub}, while controlling for other country characteristics X'. Also included in some specifications are country fixed effects (c_i)) in to account for time-invariant country characteristics possibly related to inequality, as well as country-specific time trends (year *t*) to capture additional variation.

Following Li et al. (2023) and Skare and Porada-Rochoń (2022), who assert that modifying the country- and time- fixed effects for regression analyses across multiple model specifications is a form of robustness check, we note that conducting our regressions with multiple model specifications that vary the time- and country-specific fixed effects additionally has the benefit of serving as robustness checks.

$$Y_{it} = a_i + bD_{HC} + cD_{Con} + dD_{SME} + eD_{Pub} + fM_{it} + gX' + c_i + t + \varepsilon_i. \tag{5}$$

Variance Inflation Factor (VIF) tests determined the variables to non-multicollinear. Model fit statistics are used to compare distinctions between model specifications. We report three model fit statistics, the Root Mean Square Error (RMSE), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). The BIC is more commonly used with its ability to "weigh costs of model complexity against increasing accuracy", where a general decline indicates improved model fit (Scarborough et al., 2021, p. 831).

4. Data and methods

4.1. Data on digitalization

This study uses pooled data between 2017 and 2021 from the European Commission's Digital Economy and Society Index (DESI) and macroeconomic data from Eurostat and the World Bank across 27 nations and a final sample of n = 135 (Table 1), which is reasonably robust with sufficient degrees of freedom for a study of inequality at the national-level (Maas & Hox, 2005): Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

Created in 2017, the DESI summarizes indicators about digital transformations in constituent member nations of the European Union (European Commission, 2022). Assesses the overall penetration of digital transformation in a given nation, the DESI has a composite measure that is, in turn, the sum of four constituent DESI measures of digitalization: human capital, connectivity, integration of digital technology, and digital public services. Each is calibrated on a scale from 0 to 100, with 100 being the most digitalized and 0 not digitalized at all.

(1) Human capital refers to the proportion of the working population that has digital skills or digital content creation skills, as well as the employment of workers in Internet and Communication Technology (ICT) enterprises.

(2) Connectivity refers to the provision of fixed broadband coverage, the available latency of this coverage, mobile broadband (availability of 4G or 5G, whichever was the latest generation at the time of the DESI data's update), and broadband prices.

(3) Integration of digital technology is calculated by assessing the extent of digital technology use by SMEs, the types of technologies used (e.g. Cloud, social media, Big Data, artificial intelligence, e-Invoices, etc.), and the use of technology in facilitating e-commerce (selling online, turnover, and cross-border services).

(4) Digital public services as a category are calculated by assessing the extent to which state-issued forms are pre-filled, the number of e-Government users, the availability of digital public services for citizens and businesses, and the extent to which government data is openly available (online).

For illustrative purposes, Figure 2 presents the rate of overall digitalization in all EU nations based on their composite DESI from 2017 to 2022. The general uptrend across all nations sensitizes us to the consistent pace of digitalization in the EU overall.

Table 1. Descriptive statistics of variables

	Mean	Standard Deviation	Observations
A. Digitalization measures			
Human capital	11.3	2.3	135
Connectivity	8.46	2.47	135
Integration of digital technology	6.99	2.37	135
Digital public services	13.8	3.99	135
B. Inequality			
Gini Index	29.6	4.06	135
C. Country characteristics			
GDP per capita	31,173	20,873	135
Change in GDP per capita	4.36	5.39	135
Employment rate	54.8	4.89	135
Change in employment rate	1.03	2.1	135
Inflation	1.76	1.23	135
D. Education			
Tertiary education	30.3	7.26	135

All nations classify as high-income nations, according to the World Bank's standard of a GDP per capita of above USD$12,535 with the sole exception of Bulgaria, and with a reasonably low mean Gini Index of 29.63, so the sample speaks to developed nations whose concentration of wealth is not severe.

4.2. Inequality data

Data on inequality was retrieved from the World Bank. To measure the extent of inequality in a given nation, the Gini Index was the outcome variable. Despite configurations of the Gini Index that have been devised over the years, such as to adjust its properties of continuity, additivity, linear homogeneity, translation invariance, symmetry, or anonymity (Ceriani & Verme, 2012), the basic form of its expression is consistently premised on measuring distances of individual wealth from some standard (mean, median, geometric mean, etc.) of population wealth (Anand, 1983; Sen, 1973; Yitzhaki, 1979). The Gini Index used in this study (for Europe) is thus based on comparing individual wealth to median population wealth. A Gini Index of 100 represents perfect inequality in a nation and 0 represents perfect equality.

4.3. Other country characteristics

A nation's level of economic development has been found to have an enduring correlation with its level of income inequality (Dion & Birchfield, 2010; Kuznets, 1955, 1963; Muller, 1988; Weede, 1980; World Bank, 2021). The most advanced capitalist economies report the highest levels of inequality (Piketty & Saez, 2006), prompting explanations in sociology and

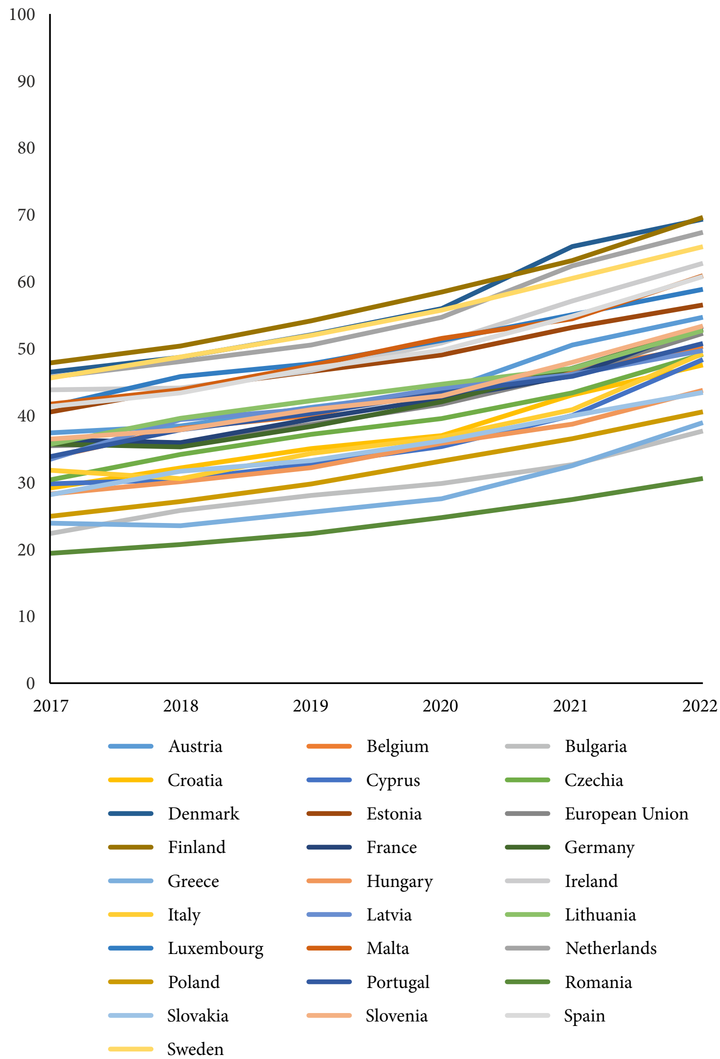

Figure 2. Rate of digitalization (composite DESI) in all EU nations

economics that point to the effects of the changing distributions of jobs, employment rates, and occupational pay among nations in an age of digitalization (Beckfield, 2006; McCall & Percheski, 2010; Myles, 2003). Yin and Choi (2023) recently show that digitalization has different intensities of effect on income inequality depending on changes in GDP per capita within and across countries. As such, the main country control variables *X′* include change in GDP per capita, employment rate, and core inflation. Each indicator was recorded on an annualized basis and recorded from the World Bank and Eurostat.

5. Main empirical results

Table 2 presents the full estimation results using Eq. (5). The regression models predict variations in the Gini Index against the four forms of digitalization, while holding constant other country characteristics, and including combinations of time- and country-specific fixed effects. As a form of robustness check, they show varying RMSE results, offering useful nuance into the most empirically salient models.

Digitalization of human capital is negatively associated with inequality in specifications with and without country and time fixed effects (Models 1, 2, 3). Connectivity is positively associated with inequality only in the time fixed effect specification (Model 2). Integration of digital technology by SMEs is negatively associated with inequality across all three specifications of fixed effects (Models 1, 2, 3). Digital public services are non-significantly associated with decreases in inequality in country (Model 1) and two-way fixed effects (Model 3), but significantly associated with increases in inequality in the time fixed effect specification (Model 2).

The time fixed effects model (Model 2) suggests that improving connectivity and digitalizing public services are associated with increases in inequality across countries within a given year, but we are careful not to overestimate the fit of this model given its high RMSE.

Table 2. Coefficient estimates (standard error) of the full model

Explanatory Variable	Model 1	Model 2	Model 3
Human Capital	–0.306* (0.137)	–0.692** (0.262)	–0.331* (0.161)
Connectivity	0.086 (0.061)	0.292 (0.196)	0.079 (0.073)
Integration of Digital Technology	–0.193* (0.086)	–0.779** (0.253)	–0.205* (0.106)
Digital Public Services	–0.103 (0.079)	0.305* (0.147)	–0.118 (0.110)
Change in GDP per Capita	0.036* (0.018)	0.208* (0.102)	0.046 (0.029)
Change in Employment	–0.063 (0.046)	–0.294 (0.186)	–0.057 (0.050)
Inflation	–0.069 (0.086)	–1.022** (0.341)	–0.051 (0.098)
Tertiary Education Rate	0.072 (0.065)	0.068 (0.058)	0.066 (0.069)
Constant	30.914*** (2.001)	35.518*** (2.086)	31.601*** (3.635)
Country fixed effects	Yes	No	Yes
Country-specific time trends	No	Yes	Yes
AIC	327	758	334
BIC	436	799	455
Root mean square error	0.597	3.28	0.596
Observations	135	135	135

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

More informatively, the RMSE of the country (Model 1, RMSE = 0.597) and two-way fixed effects (Model 3, RMSE = 0.596) models indicates they are much more promising. The results in both models are largely in line with one another. Including country controls (Model 1) yields notable, negative, and significant estimates of digitalizing human capital and integration of digital technology by SMEs. A one-point increase in digitalizing human capital predicts a –0.306 decrease (standard error 0.137) in the Gini Index and a one-point increase in integration of digital technology predicts a –0.193 decrease (standard error 0.086) in the Gini Index.

The size of the estimated impact of these two DESI measures on inequality grows even further after we include country and time controls (Model 3): a one-point increase in human capital predicts a –0.331 decrease (standard error 0.161) in the Gini Index and a one-point increase in integration of digital technology by SMEs predicts a –0.205 decrease (standard error 0.106) in the Gini Index. These results tentatively corroborate observations of optimizing household expenditures among low- and middle-income groups, as well as improvement of SME performance, as possible pathways through which digitalization helps to reverse inequality (Bouwman et al., 2019; Donoso et al., 2020; Kiener et al., 2019; Loebbecke & Picot, 2015; Non et al., 2021; Pagani et al., 2016; Spada et al., 2022).

Table 3. Mediation analyses of the mediating effect of tertiary education on the constituent DESI measures' associations with the Gini Index, with estimations of direct, indirect, and total effects. Estimates (standard error) are reported

Predicting Gini		Estimate	95% Confidence Interval	
Human Capital	Indirect	–0.023 (0.310)	–0.650	0.604
	Direct	–1.942* (0.722)	–3.412	–0.473
	Total effect	–1.965** (0.655)	–3.299	–0.632
Connectivity	Indirect	–0.206 (0.177)	–0.561	0.149
	Direct	0.054 (0.694)	–1.357	1.465
	Total effect	–0.153 (0.681)	–1.539	1.234
Integration of Digital Technology	Indirect	–0.111 (0.310)	–0.742	0.521
	Direct	–1.459 (0.729)	–2.941	0.022
	Total effect	–1.570* (0.662)	–2.916	–0.224
Digital Public Services	Indirect	–0.475 (0.453)	–1.404	0.455
	Direct	–0.062 (0.805)	–1.702	1.579
	Total effect	–0.536 (0.673)	–1.904	0.831

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

Table 3 presents results of regressions to test for the separate pathways (total effects decomposed into natural direct and natural indirect effects) on tertiary education, based on Eq. (4). The results visualize the mediating effects of tertiary education on DESI measures of digitalization when countries are digitalized compared to when not. It is worth noting that the indirect effects are not significant, suggesting that the influence of digitalization on inequality is direct. We observe that digitalization predicts lower inequality in every measure in its total effects, consistent with the direction of the full outcome model in Table 2. Comparing high digitalization with low digitalization in country i at time t, the effects of digitalization of human capital and integration of digital technology by SMEs are significant and substantial: human capital is associated with a –1.965 decrease in the Gini Index, whereas integration of digital technology is associated with a –1.57 decrease in the Gini Index.

6. Conclusions

The march of digitalization as a model of development has been the subject of headlines and academic scrutiny by economists for the past decade, but little work has examined its relationship with the massive rise of inequality, especially in Europe.

This study explores this relationship by disaggregating digitalization across different forms and testing their effects on inequality across a range of regression specifications with country and time fixed effects. Regressing Gini Index on DESI measures of human capital, broadband connectivity, integration of digital technology into SMEs, and digital public services, we find that only digitalizing human capital and integration of digital technology into SMEs predict lower inequality in European countries.

The two relationships are strong, significant, and negative in the country fixed effects and two-way fixed effects specifications, the two models that displayed the greatest fit. A one-point increase in DESI human capital predicts a –0.367 decrease in the Gini Index and a one-point increase in DESI integration of digital technology by SMEs predicts a –0.228 decrease (standard error 0.106) in the Gini Index. Corroborating, while extending previous research on e-commerce and inequality in developing economies with higher concentrations of wealth, these findings show that the ameliorative association that the integration of digital technology into SMEs has on inequality is true in Europe as or developed economies which in aggregate have a lower concentration of wealth, to begin with.

Other variables that have gained prominence in recent literature – changes in GDP per capita, changes in employment, inflation – do not display a robust relationship with inequality compared to digitalization. Additionally, we test for the mediating influence of tertiary education, which is lauded as a significant predictor of digital development given its role in medium of instruction. Though tertiary education provides digital skills needed to access digital platforms, we rule out the influence of tertiary education as a mediator. The present findings show that it has no causal effect on the pathways through which digitalization of labour and SME operations lower inequality, which are direct. These findings help identify that tech-savviness (digital skills) in labour and SME business operations as a pathway to economic growth by extending their merits to income redistribution.

What are some barriers to the integration of digital technology? The time fixed effects model showed a positive correlation between digital public services and inequality. This suggests that, contrary to theoretical postulations that state digitalization will better distribute welfare outcomes, there is *wastage* in the provision of public services through digital means. This resonates with and provides empirical support for excessive and cumbersome bureaucratic frictions that disincentivize participation, including excessive paperwork, hidden fees, confusing language, and inconvenient refunds.

Whether the wastage of services identified in this study is institutional (the slowdown or outright loss of welfare meant for residents or added costs mounted by the digitalization of services that are passed unequally to tax-paying residents) or psychological (residents' refusal to participate in the digital formats of services), sludge is evident in the fundamental inhibition to the take-up rate of services as a consequence of their (digital) form.

In sum, this article contributes to the macroeconomic and developmental economic literature on which it draws by demonstrating new pathways for improving inequality through digitalization that are myriad and complex. Digitalization is an increasingly important area for capital allocation by national governments worldwide, especially as artificial intelligence technologies promise to revolutionize labour. However, this study casts scrutiny on the abuse of digitalization as a loanword for development with little empirical attention to the forms that digitalization can assume and their actual repercussions for wellbeing.

In effect, this study identifies heterogeneous elasticity in the conception of digitalization as a panacea for social good by disaggregating the pathways through which specific forms of digitalization (human capital, connectivity, integration of digital technology, and digital public services) come to shape income distributions to different degrees, even in developed economies like European nations with relatively low concentrations of wealth.

Not all forms of digitalization alleviate income inequality, with some forms of digitalization even found to problematize the issue of inequality in their present forms, such as ongoing efforts to digitalize public services. The problems with digitalizing public services thus merits more than additional investment, but further empirical research on the ways in which public services are delivered at present and ways to reduce their bureaucratic frictions.

Certain areas of digitalization, on the other hand, are found to play an understated role in reducing income inequality, such as digital human capital (skills training) and digital technology integration into SMEs, which merit significantly more investment. This study's findings tentatively suggest that there exist informal sources of digital skills training apart from formal tertiary education and point to SMEs as a potentially impactful area for investing in digitalization (such as to improve internal workflow) as pathways for income redistribution.

Our findings lend inspiration for future microeconomic research on the drivers that motivate uptake of digital technology among SMEs, as well as inspiration for policymaking in this direction by incorporating digitalization into business plan evaluations for the already-wide roster of business loan terms available to SMEs in Europe. Finally, given that this study was based on European nations, it stands to reason that the present findings may extend only to high-income nations. Future research is required to analyse whether similar effects hold true for digitalization and inequality in nations with lower levels of development.

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Author contributions

AA was responsible for conceiving the study, designing data collection, data analysis, and writing the entire article.

Disclosure statement

The author declares there are no conflicts of interest.

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