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Digital Economy and Artificial Intelligence in Subsahara Industrialization

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abstract:

This article examines the effects of the digital economy and artificial intelligence on the industrialization of sub-Saharan African economies. Thus, from a sample of 47 countries observed over the period 2003 – 2021, we estimate a model in panel data by the GMM system method. Overall, our results show that the digital economy and artificial intelligence contribute significantly to improving industrialization. In addition, they keep their robustness against the use of competing estimators. We suggest more investment in technological infrastructure, better human capital formation for a better contribution of the digital economy and artificial intelligence to industrial development.

Keywords: Sub-Saharan Africa, GMM in system, digital economy, artificial intelligence, industrialization.Abstract :

1. Introduction

Industrialization continues to be a major concern for both development economists (Cadot et al., 2016; Nguimkeu and Zeufack, 2019; Diao and 2021; Mignamissi and Nguekeng, 2022; Gandjon Fankem and Feyom, 2023 and Nguekeng and Mignamissi, 2023) in general than for

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African development agencies in particular. As proof, at the 2008 African Union Summit, held on the theme "Industrialization of Africa", the Action Plan for the Accelerated Industrial Development of Africa was adopted and serves as the main framework for the industrialization of the continent. Similarly, industrialization and structural transformation have been at the heart of the Economic Commission for Africa's (ECA) mandate since 2013. At the same time, the African Union reaffirmed the continent's commitment to industrialization in its Agenda 2063.

What's more, Africa's industrialization is part of one of five accelerators.[1] (dubbed High 5) defined by the African Development Bank to ensure the economic transformation of the continent (AfDB et al., 2017).

The interest given to the industrialization of the African continent is justified by the positive effects it has on economies. In this regard, Cadot et al. (2016), AfDB et al. (2017), AfDB (2018) and Nguimkeu and Zeufack (2019) argue that industrialization is an impulsive driver of inclusive economic transformation. Similarly, Stiglitz et al. (2013), Szirmai and Verspagen (2015), Alexiou and Tsaliki (2017) and Haraguchi et al. (2017) specify that industrialization is a factor in increasing productivity, access to capital, learning and innovation. Similarly, the African Trade Policy Centre (ATPC, 2019) argues that being much less vulnerable than extractive products to fluctuations in world prices, manufactured goods can help build a more sustainable tax base. These products also play a critical role in supporting inclusion, youth job creation and poverty reduction (ACPC, 2019). Despite the positive effects of industrialization on economies as noted by these theoretical and empirical constants, the industrialization situation of Sub-Saharan African countries remains worrying. According to the World Bank (2022), sub-regions have experienced varying fortunes.

Specifically, Central and Southern Africa have experienced deindustrialization with industrialization rates increasing from 36.36% in 2010 to 28.69% in 2020 and 28.51% in 2010 and 25.86% in 2020, respectively. In contrast, West and East Africa saw their rates increase from 19.79% and 19.19% to 22.38% and 21.62% respectively between 2010 and 2020. Similarly, the World Bank (2013) states that while from 1980 to 2009, the contribution of manufacturing industries to GDP increased slightly in North Africa, from 12.6% to 13.6%, it declined in the rest of the continent, from 16.6% to 12.7%. Then experienced a slight increase

[1] Feed Africa; Light up and power Africa; Integrate Africa; and Improving the quality of life of people in Africa are the other four components

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to 13.28% in 2019 (World Bank, 2020). Despite this slight increase, the impact on job creation remains low in Sub-Saharan Africa (SSA) with an average of only 10.22% compared to 26.43% in North Africa, 26.05% in East Asia, 27.26% in the European Union (EU) and 20.88% in North America (UNCTAD, 2019).

This low level of industrialization for some sub-regions and the premature deindustrialization observed in other sub-regions are the implacable proof that the situation is quite worrying in Sub-Saharan Africa. It is therefore important that the reflections are carried out in order to see the situation improve. In this respect, the literature review shows that several factors are likely to influence the industrial level of a country, in particular, the dysfunction of credit markets (Rowthorn and Ramaswamy, 1997; Devarajan, 2013 and Rodrik, 2015), institutions (Rodrik, 1999; Acemoglu et al., 2005; Easterly, 2005; Sachs, 2003), the level of human capital (Page, 2012), infrastructure in quantity and quality (UNCTAD, 2019; Duy et al., 2019; Canh and Thanhb, 2020; Azolibe and Okonkwo, 2020) and technological evolution (Acemoglu and Restrepo, 2018; UNCTAD, 2018; Albrieu et al., 2019; Andreoni and Anzolin, 2019; Bogliacino and Codagnone, 2019; ACPC, 2019 and UNIDO, 2019).

The latter factor deserves special attention, especially since today's technological realities are totally different from the technological environment that prevailed when the Plan of Action for the Accelerated Industrial Development of Africa was adopted in 2008. Technological evolution has fostered the rise of the digital economy and artificial intelligence. According to The Australian Bureau of Statistics the digital economy is: the global network of economic and social activities that are enabled by platforms such as internet, mobile and sensor networks, including e-commerce. Artificial intelligence refers to the set of techniques that allow machines to perform tasks and solve problems normally reserved for humans and certain animals (Rodriguez, 2016 and Blons, 2019).

While the digital economy is truly being embraced by SSA countries, artificial intelligence is still lagging behind in this region.

More specifically, access to the internet, which is an indicator of the digital economy (OECD, 2014, World Bank, 2016 and UNCTAD, 2017), has undergone a strong evolution with an access rate that has increased from 23.1% in 2000 to 66.32% in 2021 (World Bank, 2022). Despite this significant performance, Sub-Saharan Africa is still lagging behind other regions

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of the world such as North America, Europe and Southeast Asia, whose values of this rate are close to 100%.

The emergence and spread of advanced digital production technologies (artificial intelligence, big data analytics, cloud computing, Internet of Things, advanced robotics, and additive manufacturing, among others) are radically changing the nature of manufacturing production and gradually blurring the line between physical and digital production systems. Under favourable conditions, the adoption of these technologies by developing countries can foster inclusive and sustainable industrial development (UNIDO, 2020). The digital economy is now seen as a real stimulus to industrialization. Indeed, there is the direct contribution through the increase of digital capital as a factor of production. And the indirect contribution generated by the fact that this increase in digital capital has a positive effect on the overall productivity gains of the economy (Lemoine et al., 2011; Haehnsen, 2013 and McKinsey 2014).

The direct effects of the digital economy on industrialization concern on the one hand the increase in productive investment by companies, investment in tangible goods: digital equipment and materials; or intangible: software, used in the production process. Another effect is related to the increase in employee productivity. Good training of employees in the use of digital technology in companies increases their productivity, in particular thanks to the possibility of automating tasks, which lead to time savings, process improvements, increased exchanges and optimization of the organization. This reorganization leads to the improvement of labor productivity, a major determinant of the strengthening of industrialization (Kupfer et al., 2019).

New technologies in general and the digital economy and artificial intelligence in particular are at the heart of successful industrial development (UNIDO, 2020). They allow the creation of new products and, consequently, the emergence of new industries. They also contribute to an improvement in the efficiency of production, which lowers prices and opens the market to mass consumption, or increases profits, with possible effects on investment.

These new technologies can lead to product innovations, leading to the emergence of new industries, and the jobs and incomes associated with them (Graetz and Michaels, 2018; Ghodsi et al., 2019). This supports industrialization and social inclusion.

Digitalization offers new opportunities for trade and industrial leaping. The digital economy can reduce barriers to entry and help connect micro, small and medium-sized enterprises to global markets and value chains, providing them with the necessary support services to

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facilitate their exports, including simplified payments and logistics. Digital applications are already being harnessed to promote innovation and entrepreneurship, including the empowerment of women as traders, and mobile and digital solutions are helping to address credit gaps.

Similarly, the gains from industrialization are not automatic, and the digital economy also presents enormous challenges to the continent in the context of the digital divide – only 23% of Africa's population uses the Internet, compared to the global average of 52%, and in the Central African Republic, Eritrea, Guinea-Bissau, Niger and Somalia, less than 5% of the population uses the Internet.1 Due to the concentration of digital technologies in advanced and advanced countries. From the skills-enhancing nature of digitalisation, the main beneficiaries of the digital economy are the most developed countries. Such a situation may limit Africa's ability to address its unemployment problem and lead it to take the traditional path of industrialization based on a high intensity of ………………………………………….

Regarding the indirect contribution, it is the high use of digital technologies that leads to an improvement in total factor productivity (TFP). This improvement in TFP is partly attributed to sectors producing digital equipment but also to sectors using digital innovations. These high productivity gains lead to lower production prices and sales of digital goods and services, which has an effect on price dynamics and therefore on inflation. The lower the prices, the more user sectors will be encouraged to invest in digital products in order to increase their productivity. Total factor productivity also depends on the wide diffusion of digital innovations throughout the economy. Indeed, digital innovation has "network" externalities, the more widely disseminated and adopted digital innovations, the greater the benefits will be (learning effect, economies of scale).

Given the above, the central question of this reflection is what is the contribution of the digital economy and artificial intelligence in the industrial development of Sub-Saharan African countries? The objective here is to assess the effects of these different dimensions of technological change on the industrialization of SSA countries.

The interest of this study is twofold. First, on the positive side, it proposes to consider a multidimensional approach to the notions of industrialization, digital economy and artificial intelligence. It aims to enrich the literature on this issue by conducting a specific reflection on the countries of Sub-Saharan Africa. Second, the study adopts a three-step methodological approach. First, we understand industrialization through the composite industrialization index

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(Sama, 2008; Nguekeng and Mignamissi, 2023) and use as complementary indicators manufacturing value added as a percentage of GDP, manufacturing employment in total employment for robustness analysis. Second, the digital economy is measured by internet penetration. Sensitivity analysis is done using the other dimensions of the digital economy and artificial intelligence. Finally, with regard to the technique of estimating our industrialization equation, we take into account the endogeneity bias which remains very likely either because of the omission of relevant variables or the reverse causality between industrialization and its determinants. To remedy this bias, we mainly apply, on a dynamic panel of 46 SSA countries observed between 2001 and 2021, the GMM estimator in system as developed by Blundell and Bond (1998). According to the literature, robustness is sought by the application of competing estimators, namely difference GMMs and fixed-effect and random-effect estimators.
After this introduction, four additional sections structure the rest of this article. The second presents the different approaches used to measure industrialization; The digital economy and artificial intelligence before highlighting some stylized facts. The third section is devoted to empirical strategy. The fourth section discusses the results. The fifth section concludes by noting some economic policy recommendations.

2. Industrialization, digital economy and artificial intelligence: measures and some stylized facts

2.1. Industrialization: Measurement and Stylized Facts in Sub-Saharan Africa

2.1.1 Measuring industrialization

Industrialization is the process of transforming primary products to obtain higher value-added products (Chandra, 2003, Nguekeng and Mignamissi, 2023). It is measured in the literature by several indicators including (i) consumption expenditure in the industrial sector or value added consumed in the industrial sector (Herrendorf et al., 2013); (ii) the share of industrial sector employment in total employment (UNCTAD, 2016); (iii) the share of industrial sector value added in GDP (Lectard, 2017 and Neuss, 2019); (iv) the share of manufacturing value added in GDP (Gui-Diby and Renard, 2018; Haraguchi et al, 2019 and Gandjon Fankem and Feyom, 2023) and (v) the composite industrialization index (Sama, 2008 and Nguekeng and Mignamissi, 2023).

The relevance of this index can be understood at several levels: - it makes it possible to federate certain factors capable of explaining the state of industrialization in Africa; - it also integrates industrial policies that are not homogeneous in Africa. The form chosen by Sama (2008) for

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the calculation of this composite index of industrialization (ICIndus) of Africa is that of a geometric mean according to the following formula:

$$\boldsymbol{ICIndus_i = 1 - \frac{\sqrt{(1-f_{1t})^2+(1-f_{2t})^2+\cdots+(1-f_{nt})^2}}{\sqrt{n}}} \qquad \textbf{(1)}$$

Where f_{it} represents the factor i associated with time t. There are six components of the index (the f_{it}): (i) the value added of industry in GDP; (ii) employment of the industrial sector in total employment; (iii) human capital as described by secondary school enrolment; (iv) the consumption of electricity captured by the number of kilowatts consumed per 1000 inhabitants; (v) the ratio of tractors per 100 km2 and (vi) the value added of agriculture to GDP. In general, these are ratios that can be interpreted as percentages.

But one of the limitations of this index is the fact that the variables that compose it are considered for all countries, implying that these countries all have the same economic structure. For example, taking into account agricultural value added, some countries may rank well than others since agricultural activity is not highly developed in all countries. Similarly, the index is calculated by the geometric mean, which is not very suitable here because it is based on theoretical weights. Given these limitations and with reference to Nguekeng and Mignamissi (2023), we adopt in this work the calculation of the composite index by the principal component analysis (PCA) method, which has the advantage of using non-uniform weights that take into account the variability of the data. It is based on empirical weightings that result from the internal phenomenon of the data that governs the overall movement of the data. Knowing that the variables used for the calculation come from various domains and therefore present a heterogeneity of the units of measurement, it is preferable to make a standardized PCA (Baccini, 2010).

2.1.2 Stylized facts of industrialization in SSA

Figure 1 below shows the evolution of the rate of industrialization (measured by the share of secondary sector value added in GDP) of three groups of countries. We note that the first group (whose industrialization rate is above 40% of GDP) is experiencing a downward trend ranging from 53.62% in 2003 to 46.24% in 2021. The second group, whose industrialization rate varies from 31.9% in 1991 to 26.95 in 2021, is experiencing premature deindustrialization. The third group, although with the lowest average rate, is trending upwards.

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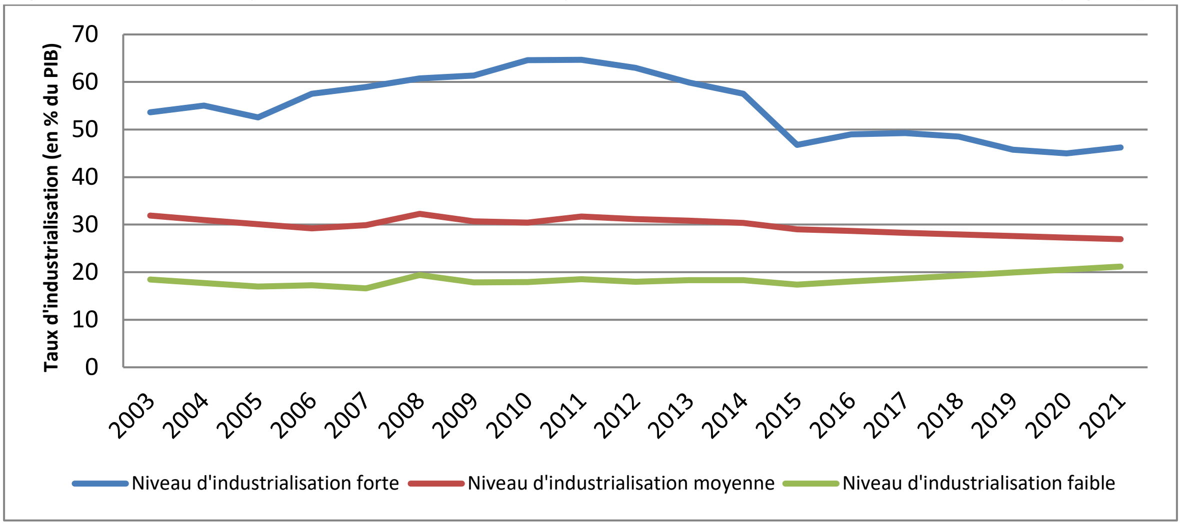
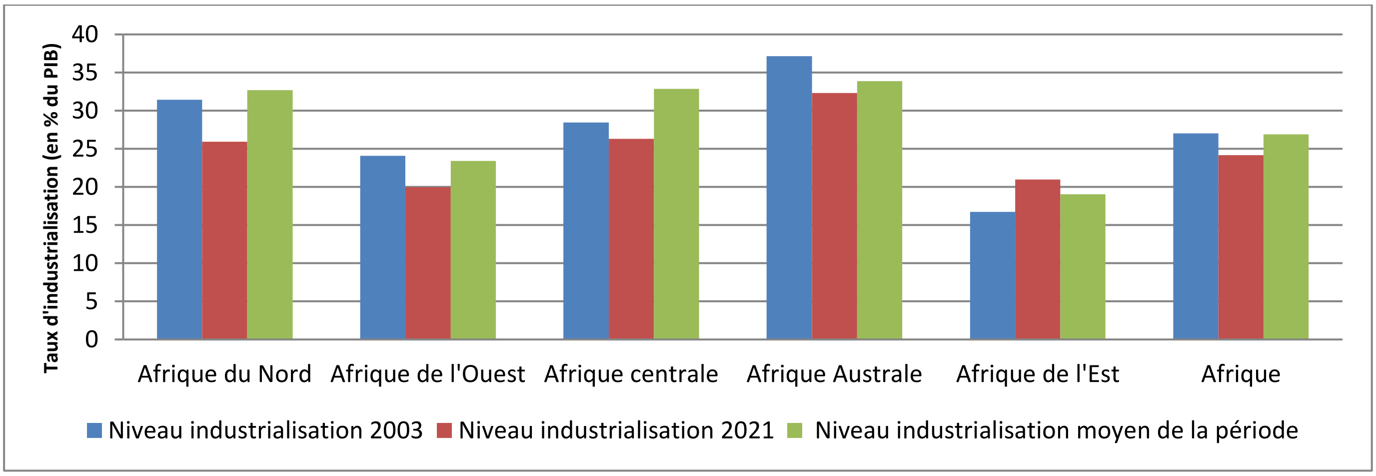
Figure 1: Evolution of industrialization (share of secondary sector value added in GDP) by group



Source: authors

The diagram below compares the evolution of the level of industrialization (percentage of secondary sector value added in GDP) between the subregions of Africa at the beginning of the study period (1991), at the end of this period (2021) and the average value over the entire period. Several readings can be done. First, we find that the overall average level of industrialization in Africa is relatively low (specifically 25.38%). For most of these subregions, the trend is downward, i.e. the level of industrialization declined between 1991 and 2017, except for East Africa, which experienced an upward trend (ranging from 16.32% to 20.98%). Southern Africa is the most industrialized subregion, this can be justified by the presence of South Africa, which is the locomotive not only in this subregion, but also in the greater African region.

Figure 2: Levels of industrialization among subregions of Africa



Source: authors

2.2 *Digital Economy and Artificial Intelligence: Measurement and Stylized Facts in Sub-Saharan Africa*

2.2.1 Measuring the digital economy and artificial intelligence

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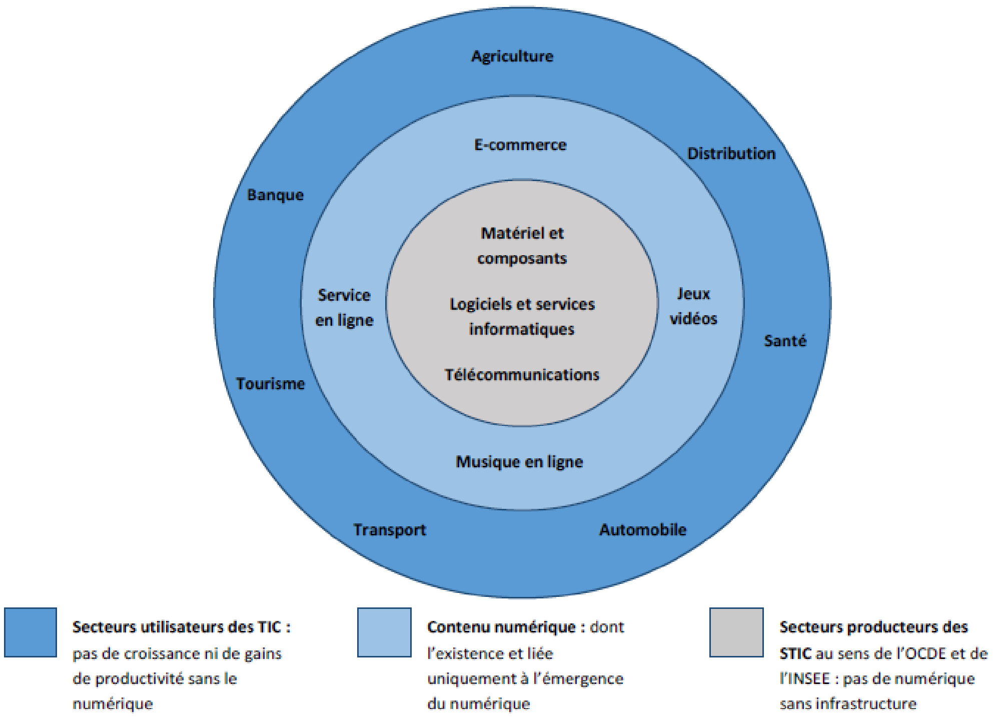
Even if the literature is varied and rich, there is no unanimous definition of the digital economy. Indeed, it is not limited to a particular sector of activity and encompasses very different concepts. According to The Australian Bureau of Statistics the digital economy is: the global network of economic and social activities that are enabled by platforms such as internet, mobile and sensor networks, including e-commerce. Activated also by efforts to achieve efficiency and productivity in production processes, inventories and knowledge management.

INSEE equates the digital economy with ICT-producing sectors. The ICT sector includes companies that produce goods and services that support the process of digitization of the economy, i.e. the transformation of information used or provided into digital information (IT, telecommunications, electronics). The transversal nature of the digital economy impacts all sectors of activity, it is at the origin of new innovative sectors and has made the existence of other sectors dependent on it. It brings together the ICT sector, user sectors and sectors with high digital content, the latter of which could not exist without these technologies.

Figure 1. Composition of the digital economy



Source: "The impact of the digital economy", Societal Review n°71 (1st quarter 2011).

The Boston Consulting Group (2015) identifies nine indicators of the digital economy:

Figure 2: Digital Economy Indicators

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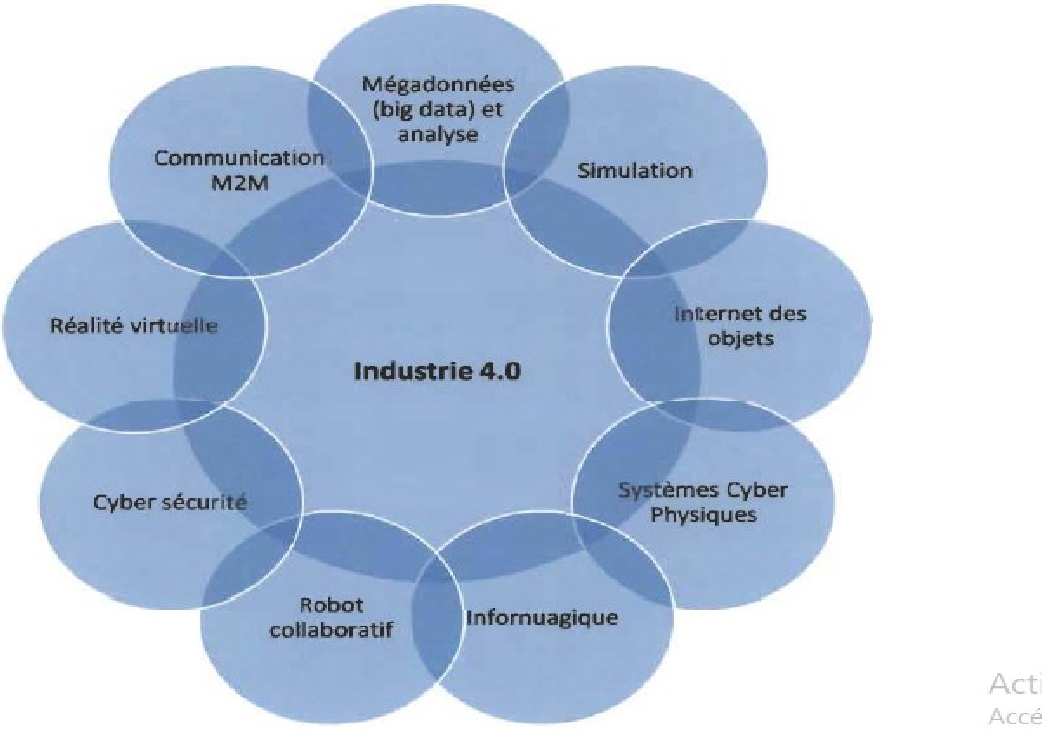

Source: Ruessman et al., 2015

The use of the internet, for example, has allowed the gathering of people and means by dematerializing physical distance to create, develop and share their ideas giving rise to new concepts, new content and consequently to the birth of a new generation of entrepreneurs and markets.

Artificial Intelligence has arrived in our lives recently under the conjuncture of 3 factors: the development of algorithms, accessibility to massive data and the increase in computing power that have allowed computers to equal or even surpass humans in very specific tasks. Yann LeCun defines Artificial Intelligence as *"A set of techniques that allow machines to perform tasks and solve problems normally reserved for humans and certain animals. AI tasks are sometimes very simple for humans, such as recognizing and locating objects in an image, planning a robot's movements to catch an object, or driving a car. They sometimes require complex planning, such as playing chess or go. The most complicated tasks require a lot of knowledge and common sense, for example to translate a text or conduct a dialogue."*
While definitions of artificial intelligence vary somewhat, it is customary to describe AI as automating tasks without the need to program them, thanks to machine learning, which gives them the ability to understand their environment, reason and interact with each other and with humans. AI would be for the American scientist and cognitive scientist Marvin Lee Minsky *"The construction of computer programs that perform tasks that are, for the moment,*

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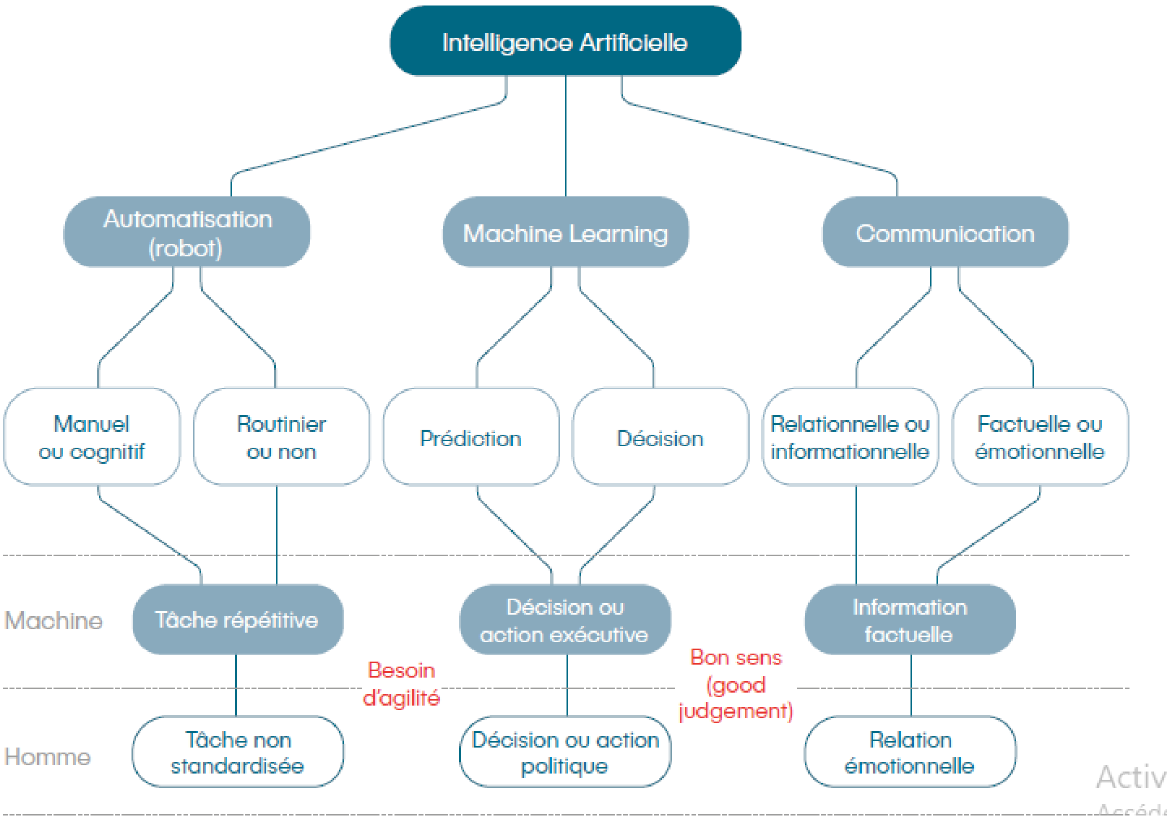
performed more satisfactorily by human beings because they require high-level mental processes such as: perceptual learning, memory organization and critical reasoning."

Beyond these concepts, AI is above all an interdisciplinary theoretical and practical field that aims to understand the mechanisms of cognition and reflection, and imitate them by a hardware and software device, for the purpose of assisting or replacing human activities.

Figure 3: Areas of action of artificial intelligence



Source : Yann LECUN

2.2.2 Digital economy and artificial intelligence: some stylized facts in SSA

Figure 4: Evolution of the Internet access rate in Sub-Saharan Africa

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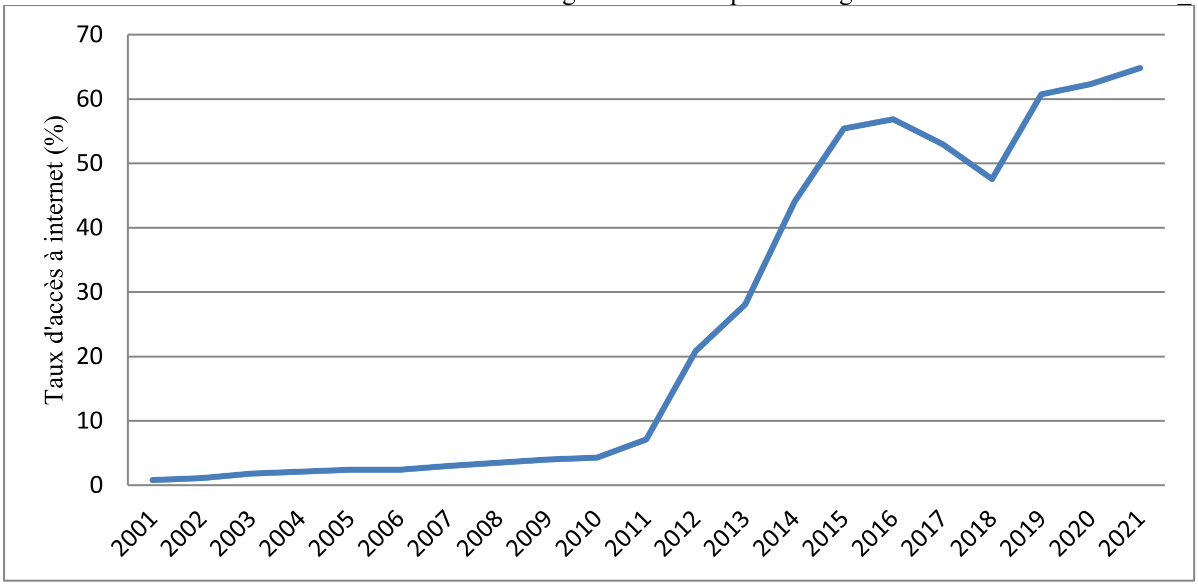

Source: authors based on World Bank data

It appears from the graph above that internet access in SSA is increasing over the period 2001 – 2021. The challenges ahead are many. One example is the extension of sub-regional interconnection to all populations. Indeed, fibre-optic broadband infrastructure capacity is still low, the backbone to link countries has yet to be established, and the prices of electronic communications, compared to other regions of the world and the level of income, are very high.

Another priority is the continuous improvement of the quality of service and consumer experience of electronic communications in order to guarantee the availability of services 24 hours a day, 7 days a week, in environments where the fibre-optic network is sometimes cut off while its redundancy is not always ensured, Or even the electricity grid is not very stable, all this without obscuring the questions of the proper quality of communication.

However, the creation and diffusion of NAP technologies remains concentrated globally, with low development in most emerging economies. According to the Industrial Development Report 2020, 10 economies (the pioneers) are responsible for 90% of global patents and 70% of exports directly associated with these technologies. Next are 40 other economies (the followers) that are adopting these technologies, but in a much more moderate way. The remaining economies either have low activity (laggards) or are not involved at all in the creation and use of these technologies (lagging economies).

Figure 5: Correlations between industrialisation and the digital economy in SSA

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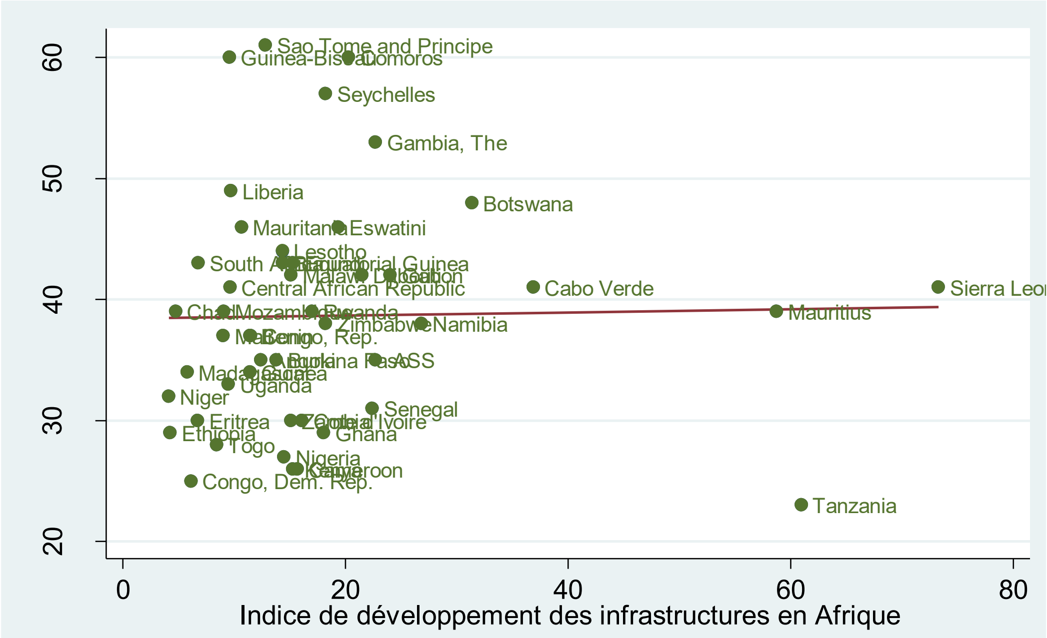

Source: authors

3. Study methodology

3.1 Study Design Specification

3.1.1 Theoretical model

We start from the approach of Rowthorn and Wells (1987), who propose a theoretical model whose industrialization or deindustrialization could be observed without links to infrastructure. The main stylized facts require that the income elasticity of demand for goods be inelastic, real demand for services increases with national income, and labour productivity be higher in the manufactured (industrial) sector than in the service sector. On the basis of these proposals, it is explained how in the development phase there is an increasing importance of industrial production, which induces a transition to a service economy that foresees the future decline in industrial employment (Rowthorn and Ramaswamy, 1997).

The model states that the overall product (Y) comes from three sources, namely agriculture (Y_a), industry (Y_i) and services (Y_s):

$$Y = Y_a + Y_i + Y_s \qquad (2)$$

Per capita consumption of agricultural products is considered to be fixed. On the other hand, the population is also constant and equal to L, and the economy is assumed to be at full employment. Following these assumptions, it can be noted that Y_a=bY (0<b<1) and Y_s=cY (0<c<1), b and c being constants. It is assumed that productivity in each sector grows at a constant rate over time. Productivity in the agricultural and industrial sectors is equal ($y_a = y_i$), but higher than that of the service sector (y_s) :

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$$y_a = y^0 e^{\lambda\alpha t}$$
$$y_i = y^0 e^{\lambda\alpha t} \tag{3}$$
$$y_s = y^0 e^{\alpha t}$$

y_a, y_i and y_s represent products per capita[2] and $\lambda > 1$, $y^0 > 0$ et $\alpha > 0$, constants. From these details, the total employment is written :

$$L = \frac{Y}{y^0}\left[ce^{-\alpha t} + (1-c)e^{-\lambda\alpha t}\right] \tag{4}$$

Therefore,

$$y = \frac{y^0 e^{\alpha t}}{c + \ (1-c)e^{-\alpha(\lambda-1)t}} = \frac{y_s}{c + \ (1-c)e^{-\alpha(\lambda-1)t}} \tag{5}$$

$y = Y/L$ is defined as the total productivity of the economy (in all three sectors).

Due to the fact that $\alpha > 0$ et $\lambda > 1$, The asymptotic attitude of the relation (4) results in:

$$\frac{y}{y_s} = \frac{1}{c} \tag{6}$$

This equality is consistent with the principle of Baumol et al. (1989) that the average rate of productivity growth decreases in compensation with growth in the services sector. This is an illustration of the theory of asymptotic stagnation, because aggregate growth is constrained by what happens in the dominant economic sector.

By defining by $P_a = \frac{L_a}{L}$, $P_i = \frac{L_i}{L}$ and $P_s = \frac{L_s}{L}$ the relative shares of employment in agriculture, industry and services, it can be established that :

$$P_a = \frac{b}{y^0} e^{-\lambda\alpha t}$$
$$P_s = \frac{c}{c + \ (1-c)e^{-\alpha(\lambda-1)t}} \tag{7}$$

Giving that $P_i = 1 - (P_a + P_s)$, it follows that :

$$P_i = 1 - \left[\frac{b}{y^0} e^{-\lambda\alpha t}\right] - \left[\frac{c}{c + \ (1-c)e^{-\alpha(\lambda-1)t}}\right] \tag{8}$$

---

[2]Output per capita in each sector is defined as follows:: $y_a = \frac{Y_a}{L_a}$, $y_i = \frac{Y_i}{L_i}$ et $y_s = \frac{Y_s}{L_s}$, avec L_a, L_i et L_s employment in sectors, such as $L = L_a + L_i + L_s$.

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So when $t \to \infty$, $P_i \to 0$, since $P_a \to 0$ et $P_s \to 1$. In other words, the share of agricultural employment tends to cancel out while that of services tends towards 1. But what about the share of industrial employment?

Based on the fact that $P_i = 1 - (P_a + P_s)$, The following differential is obtained:

$$\frac{dP_i}{dt} = -\frac{dP_a}{dt} - \frac{dP_s}{dt} = \lambda\alpha P_a - (\lambda - 1)\alpha P_s(1 - P_s) \tag{9}$$

Thus, $\frac{dP_i}{dt} > 0$ if and only if $\lambda\alpha P_a > (\lambda - 1)\alpha P_s(1 - P_s)$, that is, when the rate of decline of the agricultural labour force is greater than the rate of growth of employment in the services sector. In poor or developing countries, this condition is easily met since P_a is high. With this in mind, an increase in the share of industrial employment is expected..

Finally, the share of industry in the real product (industrialization rate) is as follows::

$$\frac{Y_i}{Y} = 1 - \frac{Y_s}{Y} - \frac{Y_a}{Y} = 1 - c - \frac{b}{y^0} e^{-\alpha t} c + (1 - c) e^{-\alpha(\lambda - 1)t} \tag{10}$$

This share grows rapidly in the initial stage of development, but converges towards an upper limit over time. In a mature economy, the rate of industrialization stabilizes while employment in the sector tends to decline, due to increasing productivity.

3.1.2 Empirical model

The industrialization process has been studied by Hossein and Weiss (1999) in absolute and relative terms. In the absolute version, the analysis of the industrialization process is based on the value added of the secondary sector, while the relative version focuses on the rate of industrialization, i.e. the share of the absolute value of the secondary sector in GDP. Hossein and Weiss (1999) explain industrialization by internal factors such as GDP, urbanization, natural resources and external factors, including trade openness. But knowing that today, the level of industrialization is the consequence of several other new factors, it becomes imperative to integrate them into the equation. These include the digitalization of the economy and governance. To that end, the model adopted in that article is as follows:

$$\begin{aligned} \ln(Indust_{it}) = \beta_0 + \beta_1 \ln(Indust_{it}) + \beta_2 In(EcoNumt_{it}) + \beta_3 \ln(PIB_{it}) \\ + \beta_4 \ln(CapHum_{it}) + \beta_5 \ln(Urb_{it}) + \beta_6 \ln(IDE_{it}) + \beta_7 \ln(Infrast_{it}) \\ + \beta_8 \ln(OuvCom_{it}) + \beta_9 \ln(Gouv_{it}) + +\mu_i + \lambda_i + \nu_{it} \end{aligned} \tag{11}$$

$Indust$is the measure of industrialization. First, we apprehend it by the composite index of industrialization whose calculation technique is presented above. We then use as

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complementary indicators, the share of employment in the industrial sector and the value added of manufacturing output as a percentage of GDP for the analysis of robustness. $Indust_{it-1}$ represents the level of delayed industrialization. It makes it possible to capture the memory of the phenomenon of industrialization.

$EcoNumt_{it}$ represents the level of digital economy in country i in year t. This is our variable of interest. With reference to the work of Kodongo and Ojah (2016) and Azolibe and Okonkwo (2020), we retain the African Infrastructure Development Index developed by the African Development Bank.

PIB is real gross domestic product per capita. It will be modelled in level and squared, with a view to testing the non-linearity postulated by Clark (1957) between GDP and industrialization. Moreover, the choice of this variable is justified to test the big push theory of industrialization (Murphy et al., 1989a, 1989b). $CapHum_{it}$ refers to the human capital captured by the enrolment rate (secondary cycle) in the country concerned. It facilitates the absorption of new technologies needed by industry (Alaya et al., 2009 and Anand et al. (2013). u*rb* represents the level of urbanization of the country, approximated by the proportion of the population living in urban areas. It captures the demand capacity of manufactured products. IDE_{it} measures the effect of net capital flows on the industrialization process. This variable measures whether the FDI balance has contributed to the industrialization of the African continent. *OuvCom* refers to trade openness, understood as the share of total trade in GDP. This variable generalizes the model of Rowthorn and Wells (1987) in open economy.

$Infrast_{it}$ represents the level of infrastructure in country i in year t. This is our variable of in terest. With reference to the work of Kodongo and Ojah (2016) and Azolibe and Okonkwo (2 020), we retain the African Infrastructure Development Index developed by the African Deve lopment Bank. It is a composite indicator whose construction is done in four stages[3] (AfDB, 2 018). $Gouv_{it}$is a governance index constructed using the World Bank's six governance indica tors (Kaufmann et al., 2010): citizen voice and accountability, political stability and freedom f rom violence, government effectiveness, quality of regulation, rule of law, and control of corr uption. All the above indicators range from -2.5 (poor quality of governance) to +2.5 (good q

[3] (i) la sélection des indicateurs pertinents ;(ii) le traitement des données manquantes ; (iii) la normalisation des indicateurs si les unités de mesure sont différentes ; (iv) la pondération des indicateurs et (v) enfin l'agrégation des indicateurs

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uality of governance). The β are parameters to be estimated. μ_i is the country-specific effect, λ_t the temporal effect and ν_{it} the rest of the hazard.

3.2 Presentation of the sample, the data and their processing

Due to data availability, the study covers the period 2003-2021 and the sample consists of 47 countries in sub-Saharan Africa (see list in Annex 2). Data for these countries are extracted from the databases of several agencies (see sources in annex 3)..

Tableau 1 : Descriptive statistics of study variables

Variables	Observations	Moyenne	Ecart type	Minimum	Maximum
Industrial Composite Index	848	0.32540	0.70109	-1.2260	1.0156
Manufacturing added value	851	26.8927	13.8362	1.882058	84.28298
Industrial employment	851	12.63315	8.76131	1.8	41.6
Internet access rate (in %)	851	39,250	19,258	12,947	79,258
Transportation Index	851	8,931581	9,441964	0,915	52,651
Electricity index	851	7,432974	15,15251	0	93,559
Water and sanitation index	851	4,893791	9,043326	0	76,93782
ICT index	851	46,71999	19,91946	6,044	97,55667
Real GDP	851	3.23e+10	4.85e+10	1.18e+08	4.64e+11
Schooling rate (secondary)	851	37.94428	24.93011	5.21677	85.971
Urban population	851	39.59261	18.06029	5.416	67.366
Foreign Direct Investments	845	5.34e+08	1.32e+09	-7.12e+09	1.16e+10
Commercial opening	845	31,349	22,344	9,722	66,353
Africa Infrastructure Development Index (IDIA)	851	17,57814	15,01458	0,369	94,32366
Governance	815	2,285	0,977	-2,300	1,801

Source: authors based on UNCTAD, WDI, WGI databases

Tables 1 and 2 respectively present the descriptive statistics and the correlations between the variables of the study, It appears from Table 2 that the correlations between the majority of the explanatory variables are not high to cause serious problems of multi-collinearity, We note a priori the existence of a positive relationship between industrialization and Internet access. This means that industrialization in SSA is a growing function of the digital economy. This justifies the use of more advanced econometric estimates to clarify the type of relationship.

Table 2: correlation matrix between study variables

	1	2	3	4	5	6	7	8
1	1,000							
2	0,204	1,000						
3	0,301	-0,526	1,000					
4	-0,068	-0,222	0,309	1,000				
5	0,132	-0,160	0,280	-0,014	1,000			
6	0,281	0,288	-0,166	-0,280	0,029	1,000		
7	-0,081	0,205	-0,381	-0,029	-0,049	0,040	1,000	
8	-0,217	-0,029	0,170	-0,087	-0,074	-0,153	-0,017	1,000

1. Composite Industrialization Index; 2, internet access; 3, real GDP: 4, enrolment ratio; 5, urban population; 6, foreign direct investment; 7, Trade Openness; 8, Governance.

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Source: authors

3.3 Estimation strategy

This reflection is conducted on the countries of Sub-Saharan Africa observed from 1991 to 2021. Both inter-individual and inter-temporal dimensions are considered and the appropriate model here is a panel. However, conventional estimation methods are silent on controlling for endogeneity bias, which remains highly likely, because the causality between economic vulnerability and each of the explanatory variables can work in both directions, which justifies the specification of our dynamic panel model.

Indeed, in a dynamic panel model, the effects specific to unobservable countries are correlated with the delayed dependent variable, which provides inconsistent estimators. Using the lagged values of the first difference of the endogenous variable as instruments, Arellano and Bond (1991) developed the GMM difference estimator. However, Arellano and Bover (1995) and Blundell and Bond (1998) demonstrated that when the dependent variable is persistent over time, the lagging values are very poor instruments. Using additional moment conditions, these authors manage to develop the GMM into a system, which is a more robust alternative estimator. The GMM system estimator is therefore retained as part of this work. It combines equations in difference with those in level. These two equations are estimated simultaneously. Variables are instrumented by their primary differences and delayed value. Their validity is tested by the Sargan and Hansen test.

Finally, we perform four robustness tests of our results. The first test focuses on the sensitivity of our results compared to indicators competing with the composite industrialization index. The second test focuses on the robustness of our results to competing indicators of the digital economy and artificial intelligence. In the third test, we test the robustness of our results compared to competing estimators, especially those of least squares on stacked data, static panels (fixed effects and random effects). The fourth robustness test incorporates fixed effects into the overall model, relative to different groups of countries in terms of their level of industrialization or deindustrialization.

4. Results of the study

We begin this section with a discussion of the results. And subsequently, we test these results in various robustness tests.

4.1 *Results of estimates and discussions*

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Table 3 below presents the results of the GMM system estimates of our industrialization equation for the entire sample. His observation shows that our specification is significant overall. Indeed, the null hypothesis of Wald's global significance tests is rejected (p-value is equal to 0.000). In addition, Sargan's over-identification test confirms the validity of the variables lagged in level and difference as instruments used. Moreover, Arellano and Bond's second-order autocorrelation test does not reject the hypothesis of the absence of second-order autocorrelation in our specification.

The traditional variables of the model have in most cases the expected signs with however variable statistical significances. The significance of the coefficient of the lagging dependent variable (composite industrialization index L1) reveals that the level of industrialization of the previous period has a positive and significant effect (at 1%) on the current level. The estimated coefficient indicates that an increase in industrialization in the previous year of 10% leads to an increase in that of the current year of 3.02%, taking into account the influence of other variables.

The coefficient of internet access has a positive and significant sign at 1%. This means that the digital economy is improving the level of industrialization in Sub-Saharan Africa. These results are consistent with those found by Blons (2019) and UNCTAD (2018). More specifically, a 10% increase in Internet access leads to an improvement in industrialization of 0.254% on average. The low value of the coefficient is synonymous with a very limited effect of the Internet on industrialization. This result is explained by the realities encountered in these African countries. Although remarkable increases have been observed in recent years, the level of Internet access is still far from sufficient. As proof, companies established in several African countries face difficulties in connecting to the Internet and especially at a very low speed. This is mainly the case for countries such as the Central African Republic, Madagascar, Cameroon, Chad, the Democratic Republic of Congo, Ethiopia, Eritrea, Niger and Somalia, which continue to occupy the last positions despite considerable progress (UNCTAD, 2020).

Similarly, the results of our regressions show that income remains a fundamental explanatory factor for industrialization. Indeed, at first, income has a positive impact on industrialization. This fundamental result is consistent with those established by Rowthorn and Ramaswamy (1997, 1999), Kaya (2010), Kang and Lee (2011), and Dong et al. (2011). However, there is a threshold effect. Since Clark (1957), a consensus has been established on the non-linearity of the relationship between GDP and industrialization: this is the theory of the inverted U of

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industrialization. However, it is understandable why deindustrialization is generally coupled with the development process, as there is therefore a shift in the workforce from the industrial sector to the service sector. We derive this result in accordance with those of Rowthorn and Ramaswamy (1997), Kang and Lee (2011) in the case of OECD countries, Kaya (2010) in the case of developing countries in general, Gui-Diby and Renard (2015) in the case of African countries in particular. Overall, the results confirm a positive link between industrialization and growth (Atesoglu, 1993). While industrialization is now considered one of the most important drivers of economic growth, this is not the case in Africa, where very poor industrialization performance has been detrimental to high growth (AfDB et al., 2017).

The level of human capital, as measured here by the secondary school enrolment rate, seems to be negatively linked to industrialization in Africa. Indeed, Africa is the continent that is experiencing the phenomenon of brain drain the most. The best-educated Africans are attracted to foreign multinationals at the expense of their home countries, which fail to absorb a highly skilled workforce. This creates a vicious circle of deindustrialization, i.e. low levels of industrialization cause and amplify deindustrialization. However, this result is contrasted by the Japanese data. According to Ogasawara (2018), Japan benefited from increasing industrialization due to a high accumulation of human capital in education and health in the early 20th century..

The urban population plays an ambiguous role in determining the level of industrialization. Integrated into the model to assess the potential effect of market size as an engine of industrialization, it would rather, in the case of African countries, have a perverse effect. Indeed, population growth in urban areas would be harmful to industrialization in Africa, particularly because of the low contribution of the population to the development of countries. The population in most African countries is characterized by poverty and inequality, a low level of human capital, factors that do not contribute to the dynamism of the economy, and therefore to industrialization. In this context, a population unable to contribute to the transformation of the economy and without real purchasing power is specialized in small trades of rescue and subsistence as can be seen in most large African cities.

Foreign direct investment (FDI) appears to be negatively linked to industrialization, although there is generally no linkage. This finding supports that of Pamukçu and Cincera (2001) in the case of developing economies, particularly in Turkey. In sum, investment (especially foreign investment) seems to confirm the thesis of deindustrialization generally observed in developing

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countries (Kudina and Pitelis, 2014). On the contrary, the work of Rowthorn and Ramaswamy (1997), Kaya (2010), and Kang and Lee (2011) attests to the existence of a positive link in developing countries and the OECD. Their result is later confirmed by Qiong and Minyu (2013) in the case of the Chinese economy. This is because investment leads to increased demand for manufactured goods (Rowthorn and Ramaswamy, 1997), but also the return on domestic investment can be reinvested in the local economy (Kaya, 2010). Other results show a lack of significant link between FDI and industrialization in the case of African countries (Gui-Diby and Renard, 2015). The result is a lack of consensus on the nature of the link between investment (domestic and foreign) and the level of industrialization.

Trade openness is a catalyst for industrialization in African economies. However, when considering imports and exports separately, there is a negative sign for the former (Rowthorn and Ramaswamy, 1997) and a positive sign for the latter (Kaya, 2010). By retaining the rate of openness, which is a variable combining the two dimensions of trade, the expected sign would be uncertain, and would depend on the importance of one or the other dimension, but much more on the correlation between these dimensions and macroeconomic performance indicators. By finding a positive and significant sign at 1% in this work, it appears that trade openness as perceived in Africa promotes the import of manufactured goods that would strengthen local consumption. In the end, according to Mukherjee and Chanda (2017), while trade liberalization appears to be a driver of industrialization, particularly to the benefit of large companies, protectionism, on the other hand, is harmful to the development of industrial companies. This result contradicts the thesis of the protection of the infant industry.

Overall, the good quality of institutions seems to be positively linked to industrialization, even if the link between institutions and industrialization is variously appreciated in the literature. Taking the particular case of corruption and Moran (1998), it can be noted that the debate has swung from one position to another over the decades. During the 1960s, the school of thought associated with modernization theory held that corruption was often positively correlated with economic growth (Huntington, 1968, Leff, 1964). Subsequently, corruption was perceived as hostile to growth by undermining the basis of stable and rational public policies and market allocation (Rose-Ackerman, 1978; Theobald, 1990). The latter thesis is still widely perceived today, especially following the "eruption of corruption" of the 1990s (Alam, 1989; Leiken, 1997; Naim, 1995). Moran (1998) further argues that East Asian countries are important case studies on the role of corruption in industrialization. By focusing specifically on the case of

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South Korea, it establishes two main results: (i) first, corruption coexists with development; (ii) second, corruption in South Korea is plural, i.e. it can take many forms: functional, harmful, irrelevant and relevant, but always present during rapid industrialization. This is not, of course, to argue that corruption has fuelled growth or to recommend it as a plausible policy option for developing or transition economies. However, and contrary to Sachs (2003), it is clear that in many cases poor governance is detrimental to growth because it generates political instability (Easterly and Levine, 2003) and reinforces the choice of bad policies (Acemoglu et al., 2003). Taking into account the case of Africa, the institutional dimensions related to citizen voice and accountability, political stability, absence of violence and the fight against terrorism, the rule of law are the most relevant in terms of industrialization, even if, in general, good governance is conducive to industrialization.

Table 3: Results of estimates with GMM in system of the industrialization equation of SSA countries, 2003 - 2021

VARIABLES	Variable dépendante : indice composite d'industrialisation coefficients
L1. Composite industrialization index	0.302***
	(0.0128)
Internet access	0.0254***
	(0.00794)
Real GDP	0.113***
	(0.00799)
Real GDP squared	-0.082***
	(0.0179)
Secondary school enrollment rate	-0.114***
	(0.0212)
Urban population (as % of total population)	-0.00818***
	(0.00242)
Foreign direct investment	-0.129***
	(0.00330)
Trade openness (% of GDP)	0.0486***
	(0.00699)
Governance	-0.0515***
	(0.00333)
IDIA* CapHum	-0.0821***
	(0.035)
IDIA* Governance	-0.0450***
	(0.00242)
Constant	3.900***
	(0.0585)
Observations	845
Nomber of countries	47
Wald chi2	908.41
Prob > chi2	0.000
Temporal effect	Non
Country fixed effect	Non
Group fixed effect	Non
Sargan test	49.92
Prob > z	0.397

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AR(1) test	2.66
Prob > z	0.008
AR(2) test	0.54
Prob > z	0.586

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: authors

4.2 Analyses of sensitivity and robustness of results

The sensitivity of the results is analysed in relation to the components of the Africa Infrastructure Development Index and the robustness assessment is made in relation to competing industrialization indicators and competing estimation techniques.

4.2.1 Analysis of the robustness of results

- *Robustness of results compared to competing industrialization indicators*

Table 4 below tests the robustness of the results to competing industrialization indicators of the share of secondary sector value added in GDP and the share of manufacturing value added in GDP. The results confirm the strength of the positive relationship between the digital economy and industrialization in SSA. The effects of the digital economy are higher on the share of manufacturing value added than on the share of value added of the secondary sector.

Table 4: Sensitivity to complementary components of the composite industrialization index

VARIABLES	Industrialization composite index	Dependent variable: Share of secondary sector value added in GDP	Share of manufacturing value added in GDP
Africa Infrastructure Development Index (IDIA)	**0.0317*** (0.00884)**	**0.0660** (0.0403)**	**0.168** (0.0247)**
Control variables	Oui	Oui	Oui
Constante	Oui	Oui	Oui
Observations	845	838	836
Number of dumpays	47	47	47
Wald chi2	908.41	575.71	46.83
Prob > chi2	0.000	0.000	0.000
Temporal fixed effect	Non	Non	Non
Country fixed effect	Non	Non	Non
Group fixed effect	Non	Non	Non
Sargan test	49.92	12.79	45.64
Prob > z	0.397	1.000	0.570
AR(1) test	2.66	0.36	1.34
Prob > z	0.008	0.003	0.009
AR(2) test	0.54	1.16	1.06
Prob > z	0.586	0.245	0.289

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: authors

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❖ *Robustness of results compared to competing estimator*

The robustness of the estimation technique used here is proven by competing technique such as GMM in difference.

Table 6: Robustness to Competing Estimators

VARIABLES	GMM en système	GMM en différence
GVC Participation Index	**0.0317*** (0.00884)**	**-0.0257 (0.0241)**
Control variables	yes	Yes
constant	Yes	Yes
Observations	845	838
Number of countries	47	47
Wald chi2	539.83	175,58
Prob>chi2	0.0000	0.0000
Time effect	No	No
Country effect	Yes	Yes

Note: Robust standard deviations in parentheses ***; ** and *: 1%, 5% and 10%

Source: Authors.

It emerges from the observation of this table that the use of the competing technique allows us to also have the result consistent with the economic intuition thus confirming the robustness of our results.

5. Conclusion and policy recommendations

The objective of this article was to analyze the effects of the digital economy and artificial intelligence on the industrialization of sub-Saharan African countries. To achieve this, we have specified an industrialization model (apprehended by the composite industrialization index) that considers the digital economy as one of the explanatory variables. Observing 47 SSA countries over the period 2003-2021 and taking into account the problem of endogeneity, we used the GMMs in the system to make the estimates. We find that the digital economy contributes significantly to improving industrialization. The results obtained remain broadly stable when controlled by the different components of industrialization. In addition, they keep their robustness against the use of competing estimator.

For an improvement in the contribution of the digital economy to industrialization, we suggest massive investments in technological infrastructure and better human capital formation.

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