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Digitalization and pollution: Evidence from South Africa

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ABSTRACT

Drawing on OECD Inter-Country Input-Output Database and Carbon Dioxide Emissions Embodied in International Trade Database from 2000 to 2018, this study measures the level of industrial digitalization of 44 industries in South Africa from the input side and empirically analyzes the effect of industrial digitalization on CO2 emissions. The results show that industrial digitalization significantly reduces the intensity of CO2 emissions in production. The effect of industrial digitalization on CO2 emissions exhibits more prominent for the tertiary industry and those industries with high digital skills. The digital inputs from foreign countries have a greater impact on CO2 emissions than domestic digital inputs. Industrial digitalization reduces CO2 emissions through two mechanisms: increasing productivity and optimizing the factor input structure. Furthermore, we compare South Africa with other four BRICS countries and find that significant emission reduction effects are observed through industrial digitalization in Brazil, South Africa and China. These findings carry important practical implications for industrial digital transformation and sustainable development in developing countries, particularly in promoting eco-friendly production and enhancing the quality of economic development in African nations.

1. Introduction

The world economy is undergoing a period of transformation driven by the rapid digitalization of economic activities. Since the fourth industrial revolution, with the continuous acceleration of global integration, trade and economic exchanges among countries have become increasingly frequent, and the digital economy has emerged as a novel catalyst for economic growth.

Driven by the trend of economic globalization, the digital economy in Africa has developed rapidly, gradually forming a new economic form based on digital devices and technology, with widespread participation of digital enterprises and internet platforms (Abendin & Duan, 2021). Africa holds substantial potential for digital economic growth. According to the *State of the Industry Report On Mobile Money (2023)*, Africa has the largest number of mobile currency accounts in the world. By the end of 2022, the number of registered mobile currency accounts in Africa reached 781 million, accounting for 48.8 % of the total global mobile currency accounts. African governments recognize the digital economy as a strategic enabler to achieve their aspirations of high-quality economic development. *The Digital Transformation Strategy for Africa (2020–2030)* outlines the goal and plan for digital development in Africa, with the construction of "Digital Africa" has become a consensus among African countries. In 2021, South African Minister of Communications and Digital Technologies published the *Draft National Policy on Data and Cloud,* which aims to transform South Africa's economy into a digital economy that is both data-intensive and data-driven.

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With the rapid development of the world economy, humanity faces are facing unprecedented challenges and increasingly recognize the importance of protecting the environment. Green development is the key to a high-quality economy and lies at the core of a sustainable society. According to the report of *CO2 Emissions in 2022* issued by International Energy Agency (IEA), the global energy-related carbon dioxide emissions grew by 1.1 % in 2023, increasing 410 million tonnes to reach a new record high of 37.4 billion tonnes. OECD shows that approximately 80 % of the energy supply in OECD countries still relies on fossil fuels, which are related to the use of coal, oil, natural gas and petroleum products. Especially the manufacturing and transportation, which produce most greenhouse gases, undermining the global efforts to mitigate climate change. Positioned at the lower end of the value chain, South Africa's industry largely consists of low-tech manufacturing characterized by high energy consumption and pollution. Developing countries like South Africa not only emit pollutants from domestic production but also receive carbon emissions transferred from countries higher up the value chain (Gibbon, Bair, & Ponte, 2008; Zhang, Jiang, Tong, et al., 2017).

Against this backdrop, the present paper aims to examine the relationship between industrial digitalization and carbon dioxide emissions in South Africa's industry, providing theoretical support for its sustainable development. There is no universally agreed-upon definition of the digital industry. According to the *Roadmap toward a Common Framework for Measuring the Digital Economy* released by OECD in 2020, the Information and Communications Technology (ICT) industry is generally considered a digital enabling industry and is considered a core digital economy measure in the proposed DETF definition. It provides infrastructure, digital goods, and services so that other producers can use it for their own interests. US Bureau of Economic Analysis (BEA) defines the digital economy as the sum of digital enabling infrastructure, e-commerce activities, priced digital services and federal nondefense digital services. *The Statistical classification of Digital Economy and Core Industries (2021)* issued by National Bureau of Statistics of China also defines the accounting framework and criteria for the digital industry.

Most studies use ICT to represent the digital economy, which does not scientifically reflect the development of the digital economy and will lead to biased empirical results of the study (Meng & Zhao, 2022). It is worth emphasizing that the application of digital technology in industry may have spillover effects and intangible impacts, so industries containing digital elements now far exceed those originally classified as ICT. If the digital industry includes all sectors using digital elements like data and the internet, most industries would soon fall under this concept, blurring the scope of the digital industry. In addition, the purpose of defining the digital industry in this paper is to measure the level of industrial digitalization, therefore, we focus on industries with the capacity to drive digital transformation, rather than those merely containing digital elements.

From the above documents and studies, we define the OECD narrow caliber digital industries based on the *International Standard Industrial Classification of All Economic Activities (ISIC Rev4.0)*, as shown in Table 1.

This study empirically analyzes the effect of industrial digitalization on CO2 emissions reduction based on OECD *Inter-Country Input-Output Database* and *Carbon Dioxide Emissions Embodied in International Trade* from 2000 to 2018. We define the range of digital products to measure the level of industrial digitalization. Next, we analyze the emission reduction mechanism of industrial digitalization. As for empirical analysis, we conduct a series of robustness tests and adopt several IVs in order to ensure the unbiasedness of the results. We also compare the emission reduction effects of industrial digitalization across different industries and BRICs countries. The results of the research show that 1) Industrial digitalization significantly reduces the intensity of CO2 emissions in production. 2) The effect of industrial digitalization on CO2 emissions is more pronounced in the tertiary industry and those industries with high digital skills. 3) Digital inputs from foreign countries have a greater impact on CO2 emissions than domestic digital inputs. 4) Industrial digitalization reduces CO2 emissions through two mechanisms: increasing productivity and optimizing factor input structure. 5) Compared with BRICS countries, Brazil exhibits the most significant emission reduction effects through industrial digitalization, followed by South Africa and China, while industrial digitalization shows no significant impact on CO2 emissions in Russia and India.

The present study contributes to the literature in the following ways. 1) We discuss the effects of industrial digitalization in reducing CO2 emissions from the input side, providing a complement to the research on the relationship between the digital economy and the environment. Most existing studies focus on the impact of digital technology on the environment and the economic benefits of industrial digitalization, there are few researchers have combined the level of industrial digitalization and pollution together. 2) In the extant literature, there is currently no unified standard for classifying digital products and digital industries. This paper identifies digital products in accordance with the documents issued by OECD, UNCTAD, etc., and proposes a method to measure the level of industrial digitalization. 3) Despite growing evidence of South Africa's unique advantages in developing a digital economy, as yet relatively few studies have focused on industrial digitalization in the country. This paper explores the emission reduction mechanisms of industrial digitalization in South Africa and compares the effects of different industries and input sources, providing theoretical support and viable pathways for developing countries like South Africa to promote industrial digitalization and achieve sustainable development.

The remainder of this paper is organized as follows. Section 2 discusses previous literature on industrial digitalization. Section 3 explains the theoretical mechanisms. Section 4 describes methods and data. Section 5 presents empirical results. Section 6 concludes

Table 1
OECD digital industries.

Classification	Industry code	Industry name
	C26	Computer, electronic and optical products
Digital Infrastructure	J61	Telecommunications
	J62_J63	IT and other information services
Digital Media Services	J58_J60	Publishing, audiovisual and broadcasting activities

the paper and provides policy implications.

2. Literature review

2.1. Industrial digitalization

According to existing research, there is no unified definition for industrial digitalization. Hirsch-Kreinsen (2016) argues that industrial digitalization is a process of social and economic changes caused by the application of digital technology based on the application system especially in the production network, and proposes that the process of digitalization can be divided into two stages: the first stage, economic departments use data and information to realize the invisibility of production, consumption and circulation, and in the second stage, economic entity change to a digital form. Coreynen, Matthyssens, and Van Bockhaven (2017) proposed that digitalization refers to the increasing use of digital technology to connect people, systems, companies, products, and services.

It is worth noting the distinction between digitization and digitalization. Although the definitions of the two have been relatively clearly divided, there are still a large number of sources that use the two words interchangeably in papers (Bogner, Voelklein, & Schroedel, 2016; Skender & Ali, 2019), so judgment needs to be made based on the context. Digitization is the process of converting analog information into a digital format, in which the information is organized into binary digits. The result is the representation of an object, image, sound, document, or signal by generating a series of numbers that describe a discrete set of points or samples. For example, replacing hand-filled forms with an online version that goes directly into the database (Gobble, 2018). Digitalization refers to the use of digital technology and probably digitized information to improve and transform business processes and harvest value in new ways (Machado et al., 2019). Thus, our study focuses on the mechanism of digital inputs in production with the definition of this process as "industrial digitalization".

Most of the extant literature on industrial digitalization mainly focus on analyzing the impacts of the Internet, information and communication technology (ICT), and digital technology. There is a large and growing literature that documents a link between digitalization and productivity growth. Manufacturing digitization improves productivity through technological innovation, automated and intelligent control, lower human errors, implementation of the hybrid lean-agile manufacturing ecosystem, etc. (Ghobakhloo, 2020). Digitalization can not only improve manufacturing productivity but also impact other industries and individuals. Bitnet adoption increased academic productivity at middle-tier universities (Agrawal & Goldfarb, 2008). Cijan, Jenič, Lamovšek, and Stemberger (2019) prove that digitalization improves employees' job satisfaction and contributes to higher employee autonomy, which leads to more productivity. Moreover, the continuous updating of ICT and the first-mover advantage of digitalization have led to the diminishing effect of digitalization on productivity over time. Compared to engagement with the digital economy in later years, the adoption in the earlier years has a more substantial impact on future productivity (Tranos, Kitsos, & Ortega-Argilés, 2021).

In terms of information transmission, due to the application of digital technology, the industry can obtain and update market information promptly and feed it back to production, alleviating the production lag caused by information asymmetry and improving production efficiency (Zhong, Xu, Klotz, et al., 2017). Digital transformation helps to make available timely and relevant data to managers, employees, and external entities such that these individuals better understand the work situations being faced to carry out work more effectively (Dao, Langella, & Carbo, 2011).

With the integration and penetration of digital technology along the industrial network, technology and industry have formed an innovative development pattern of benign interaction (Basu & Fernald, 2007; Lipsey, Carlaw, & Bekar, 2005). ICT facilitates the emergence of new manufacturing technologies such as cloud manufacturing, and additive manufacturing (Alcácer, Cantwell, & Piscitello, 2016). These advanced technologies lead to cleaner production (Amjad, Rafique, & Khan, 2021). de Oliveira Neto, Correia, Silva, de Oliveira Sanches, and Lucato (2019) studied the Brazilian textile industry and found that technological innovation improvements in manufacturing processes, increasing the energetic efficiency to reduce energy consumption. Besides, the replacement of old equipment with advanced technology is environmentally friendly.

Overall, with the input of digital factors and the drive of digital technology, traditional industries innovate production technology, improve traditional production factors, transform management models, integrate digital services, and realize industrial digital transformation. It will increase productivity, improve resource utilization efficiency, and reduce waste, changing the traditional industrial value chain, and thereby promoting the upgrading of industrial structure (Edquist & Henrekson, 2017; Vial, 2019; Zhang, Zhang, Li, & Zhang, 2022).

2.2. Digitalization and environment

Closely related to our research is the impact of digitalization on the environment, and the academic community has not yet formed a common consensus. There is a complex and uncertain relationship between digitalization and the environment, which can be broadly categorized into the following three types:

First, digitalization has positive effects on the environment. The digital economy realizes a new round of energy technology innovation, improves energy efficiency, and reduces energy loss, thereby effectively suppressing carbon emissions. Liu, Yang, Li, and Zhong (2022) find that the digital economy can promote the upgrading of industrial structure and improve the urban green economy from three aspects: green and low-carbon development, value distribution transfer, and forced demand changes. Lei et al. (2024) find a significant positive association between digitalization and sustainable development, digitalization indirectly fosters green productivity through the promotion of technological innovation, the enhancement of human capital, and upgrades in the industrial framework. In Africa, ICT reduces CO2 emissions through network avenues of decreasing costs and constraints associated with economic activities

(Asongu, 2018).

Second, some studies have shown that the development of the digital economy has adverse effects on the environment. The use of digital technology not only directly increases electricity consumption but also gives rise to energy consumption through the production of equipment and the operation of infrastructure (Røpke & Christensen, 2012; Salahuddin & Alam, 2016). ICT agglomeration indirectly increases CO2 by improving economic scale (Hao, Li, Ren, Wu, & Hao, 2023). Danish, Baloch, Saud, and Fatima (2018) point out that ICT, financial development and economic growth worsen the environmental quality, and the moderating effect of ICT and financial development increases CO2 emissions.

Third, the impact of digitalization on the environment is uncertain and has different effects depending on specific circumstances. Berkhout and Hertin (2004) propose three ICT-environment links: direct effect, indirect effect, and structural or behavioral effect. This theory has been widely accepted and recognized (Danish et al., 2018; Shehzad, Xiaoxing, Sarfraz, & Zulfiqar, 2020). Higón, Gholami, and Shirazi (2017) hold that the relationship between ICT and CO2 emissions is an inverted U-shaped relationship. On one hand, ICT is among the sources contributing to the increasing levels of CO2 emissions in terms of the production of ICT machinery and devices. On the other hand, it is also expected to reduce CO2 emissions on a global scale by developing smarter cities, industrial processes, and energy-saving gains.

In conclusion, there is abundant research on industrial digitalization, and whether the digital economy has a positive or negative impact on the environment is uncertain. However, these literature reviews provide limited insights into its environmental effects. The previous literature typically related “industrial digitalization” to digital technologies such as ICT and explored their impacts on the environment, rather than the overall level of industrial digitalization; while empirical studies that have measured the level of industrial digitalization ignore the environmental effect. Among those limited studies on African industrial digitalization, scholars tend to focus on improving productivity and welfare, with the lack of studies on pollution.

In view of the above issues, based on input-output analysis, this paper first identifies digital industry to measure the level of industrial digitalization in South Africa, then empirically studies the emission reduction effect of industrial digitalization from the input side, enriches the existing research and explores the mechanism of digital emission reduction.

3. Theoretical hypothesis

3.1. Industrial digitalization can reduce CO2 emissions in production

Industrial digitalization mainly relies on the input of digitally enabled products and the advancement of digital technology. According to the industrial input-output theory, the performance and technical content of intermediate input will directly affect all aspects of the industrial production process, including not only the most basic production cost, output quantity, and quality but also energy loss, human capital, emissions, and industrial added value (Miller & Blair, 2009; Oberfield, 2018).

The application of digital technology is the key to industrial digital transformation. Digital technology helps to reduce error rates and remove processes that rely heavily on cheap labor. At the same time, it reduces misallocation of resources, enhances energy efficiency, and provides sustainable alternatives (Mondejar, Avtar, Diaz, et al., 2021). In addition, digitalization empowers traditional industries with intelligent production and management, reducing excessive resource consumption and pollutant emissions, and thereby promoting industrial emission reduction (Li, Dai, & Cui, 2020). Utilize terminal digital technology to digitally track and monitor all aspects of the product, enabling on-demand supply and efficient production, ultimately leading to high efficiency and energy savings (Meng & Zhao, 2022).

Hypothesis 1. Industrial digitalization can reduce CO2 emissions in production.

3.2. Industrial digitalization can enhance productivity, thereby reducing CO2 emissions

Industrial digitalization has a positive effect on reducing pollution emissions, but the specific mechanisms and ways of interaction are different. According to new classical economics, the development of industry is mainly affected by three factors: labor force, capital, and technology. Based on the perspective of production, this paper explores the mechanism of the impact of industrial digitalization on emission reduction from the perspective of technology effect and structural effect.

In the literature review section, it has been verified that digitalization improves productivity in various ways, such as technological innovation, improvement of labor quality, optimization of production processes and so on (Pan, Xie, Wang, & Ma, 2022). Due to the decrease in the defective rate and the productivity improvement, the energy consumption and waste generated per unit of product produced are reduced, thereby reducing the intensity of CO2 emissions. From another perspective, the primary objective of industry is profit maximization. In the initial stage, the industry focuses on enhancing productivity while overlooking environmental concerns. However, once productivity reaches a certain level, the industry tends to shift its focus from improving productivity to optimizing production processes, exploring ways to upgrade the industrial structure, and achieving sustainable development. At this stage, clean production receives considerable attention and the industry will allocate more capital and effort to pollution control.

Hypothesis 2. Industrial digitalization can enhance productivity, thereby reducing carbon dioxide emissions.

3.3. Industrial digitalization can change the structure of input factors, thereby reducing CO2 emissions

The structure of input factors determines production, they are fluid with combinations and substitutions exist. Different input factors lead to varying levels of productivity and result in products of distinct characteristics (Acemoglu & Azar, 2020; Simpson & Tsukui, 1965). Factor endowment is the basis of industrial development and transformation, and the quantity, quality, and type of input factor endowment determine the direction, sustainability, and value of digital transformation.

Industrial CO2 emissions are affected by the industrial structure and increase or decrease with changes in resource input structure and energy utilization efficiency (Brannlund & Persson, 2012; Khuntia, Saldanha, Mithas, et al., 2018). Specifically in the following aspects: First, digital products have the characteristics of low pollution, using digital products as inputs directly increases the proportion of clean inputs in the industry. These digital inputs replace traditional raw materials, reducing the proportion of polluting inputs (Hirsch-Kreinsen, 2016). Second, at the same time, production factors exhibit combinability. With the increase of digital inputs, the industry will actively input more high-quality intermediate products, such as raw materials with high production rates and clean energy to match those digital inputs, to pursue the best factor utilization and adapt to digital production. Third, digital technology in inputs has a spillover effect, leading to changes in the original attributes of other production materials, such as transforming high-energy-consuming factors into low-energy-consuming factors (de Oliveira Neto et al., 2019).

Through the above methods, industrial digitalization can change the allocation structure of industrial input elements, increase the proportion of clean elements, reduce the redundancy of highly polluting elements, and thus inhibit the generation of industrial pollution.

Hypothesis 3. Industrial digitalization can change the structure of input factors, thereby reducing carbon dioxide emissions.

4. Empirical strategy

4.1. Model specification

To estimate the consequence of industrial digitalization on CO2 emission reduction, the specification of the baseline regression is as follows:

$$CO2int_{it} = \beta_0 + \beta_1 Dig_{it} + X_{it} + \delta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where i is industry, t is year; $CO2int_{it}$ is carbon dioxide emission intensity of industry i in year t; Dig_{it} is the level of industrial digitalization of industry i in year t; X_{it} is a set of time-varying control variables for industry characteristics; δ_i is the industry fixed effect, δ_t is the year fixed effect, the inclusion of industry fixed effects absorbs the unobserved heterogeneity in the industry-specific determinants of productivity, whereas the year dummies control for macro-economic shocks common to all industries; ε_{it} is the error term. Besides, we cluster the standard error at the industry level to address potential heteroskedasticity and correlation problems.

4.2. Variable

4.2.1. The level of industrial digitalization (dig)

The level of industrial digitalization is the core explanatory variable of this paper, measured by the proportion of digital intermediate input to total intermediate input in the industry. The data comes from the *Inter-Country Input-Output Tables (ICIO)* within the OECD's STAN database, covering input-output data from 2000 to 2018 for 45 sectors in South Africa. We drop the industry "T97_T98" due to missing data.[1] The following is the specific calculation method for industrial digitalization:

Firstly, work with the input-output tables. Direct input coefficient is defined as the input of another industry directly consumed by unit output in one industry, measured by:

$$A_{jit} = \frac{a_{jit}}{TTL_{it}} \quad (2)$$

where A_{jit} is direct input coefficient which refers to the intermediate inputs of industry j required to produce one unit of output in industry i year t; a_{jit} refers to the intermediate inputs from industry j to industry i in year t; TTL_{it} refers to total output of industry i in year t.

However, direct input coefficient has not covered the indirect economic connections between industries. Total input coefficient covers all the indirect connections among varying sectors (Leontief, 1970), the formula is:

$$E_{jit} = \left(I - A_{jit}\right)^{-1} - I \quad (3)$$

where E_{jit} refers to total input coefficient matrix which refers to the total intermediate inputs of industry j required to produce one unit of output in industry i year t; I refers to identity matrix; A_{jit} refers to direct input coefficient matrix; $\left(I - A_{jit}\right)^{-1}$ is the Leontief inverse matrix.

Secondly, the digital input consumed per unit output of industry is:

[1] This industry is called "Activities of households as employers; undifferentiated goods and services producing activities of households for own use", coded as "T97_T98" in ICIO.

$$digital\ input_{it} = \sum E_{dit} \quad (4)$$

since there are 4 digital industries in the input-output table of the 45 sectors, the digital input is the sum of the digital intermediate inputs of these 4 industries. d refers to 4 digital industries according to Table 1; E_{dit} refers to the intermediate input of digital industry d consumed per unit output of industry i in year t.

Finally, the level of industrial digitalization is measured as:

$$Dig_{it} = \frac{digital\ input_{it} \times TTL_{it}}{TML_{it}} \quad (5)$$

where Dig_{it} is the level of industrial digitalization of industry i in year t; digital $input_{it} \times TTL_{it}$ refers to the digital intermediate input of industry i in year t. TML_{it} refers to the intermediate input of industry i in year t.

4.2.2. Carbon dioxide emission intensity (CO2int)

Carbon dioxide emission intensity is the core dependent variable in this paper, defined as tonnes of CO2 per million of gross output. We use CO2 emission intensity rather than absolute emission values to exclude pollution effects resulting from production scale expansion. The data comes from the *CO2 emissions embodied in the international trade database (TeCO2)* in the STAN of OECD, matched with ICIO.

4.2.3. Other variables

To eliminate the influence of industry factors, we use industry scale, general government final consumption, compensation of employees, capital intensity and intermediate input rate as control variables. All data sourced from ICIO and *The Trade in Employment (TiM)* in the STAN database of OECD. Furthermore, to exclude the influence of macro factors at the national level, we use GDP, per capita GDP and government final consumption expenditure. According to the previous review, innovation activities and the misuse of energy affect pollution emissions (Ali, Bataka, Wonyra, Awade, & Braly, 2024; Shahbaz, Tiwari, & Nasir, 2013). Therefore, we also keep the national innovation which is based on the number of trademark applications and energy loss rate as control variables. Pollution will be transferred through trade, so the proportion of trade volume to GDP is in the regression. Those data are collected from the WDI database of the World Bank. Other variables used in the robustness test, endogenous test and mechanism analysis will be introduced in the corresponding chapters later. Table 2 presents the definitions and data sources of the variables used in this study.

The empirical analysis in this paper relies on data that covers 44 industries in South Africa from 2000 to 2018, Table 3 presents the descriptive statistics of all variables in this paper.

Table 2
Main variable definitions and data sources.

Variable	Definition	Data source
CO2int	Carbon dioxide emission intensity	OECD
Dig	The level of industrial digitalization	OECD
GFCF	Log of (industry gross fixed capital formation+1)	OECD
GGFC	Log of (industry final consumption expenditure of general government+1)	OECD
LABR	Log of (compensation of employees)	OECD
INTI	Industry ratio of intermediate input to output	OECD
CAPint	Industry ratio of gross fixed capital formation to employment	OECD
GDP	Log of (GDP + 1)	WDI
GDPPC	Log of (per capita GDP + 1)	WDI
GovExp	Ratio of government final consumption expenditure to GDP	WDI
Energy	Ratio of energy depletion to GNI	WDI
Innovation	Log of (trademark applications+1)	WDI
Trade	Log of (ratio of trade to GDP + 1)	WDI
ALT	Ratio of alternative and nuclear energy to total energy use	WDI
Elec	Ratio of electricity, gas, steam, and air conditioning supply to output	OECD
M&Q	Ratio of mining and quarrying of energy producing materials to output	OECD
TDig	Log of (digital input+1)	OECD
NoDig	Log of (intermediate input except for digital input+1)	OECD
DomDig	Ratio of domestic digital input to intermediate input	OECD
ForDig	Ratio of digital input from foreign country to intermediate input	OECD
RER	Weighted real exchange rate	WDI
AHS	AHS weighted average tariff rate of digital products	WITS
MFN	MFN weighted average tariff rate of digital products	WITS
TFP	Log of (total factor productivity+1)	OECD
Struct	Ratio of high-pollution factors input to intermediate input	OECD

Table 3
Descriptive statistics of the variables.

VarName	Obs	Mean	SD	Min	Max
CO2int	836	4.452	2.251	0.000	10.747
Dig	836	0.134	0.084	0.027	0.624
GFCF	836	4.688	2.243	0.000	10.164
GGFC	836	2.724	2.492	0.001	10.715
LABR	836	7.236	1.323	3.318	10.154
INTI	836	0.600	0.150	0.117	0.865
CAPint	836	0.449	0.853	0.000	6.068
GDP	836	26.324	0.156	26.035	26.510
GDPPC	836	8.581	0.084	8.413	8.658
GovExp	836	19.629	1.018	17.814	21.282
Energy	836	1.673	0.813	0.857	4.576
Innovation	836	10.319	0.199	9.922	10.555
Trade	836	4.089	0.088	3.953	4.302
ALT	836	2.554	0.263	2.222	3.182
Elec	836	0.014	0.021	0.000	0.136
M&Q	836	0.015	0.045	0.000	0.281
TDig	836	6.168	1.321	1.728	8.555
NoDig	836	8.811	1.209	4.553	11.035
DomDig	836	5.785	1.352	1.381	8.323
ForDig	836	4.950	1.265	0.965	7.993
RER	836	0.912	0.574	0.027	2.955
AHS	836	0.082	0.090	0.001	0.574
MFN	836	0.112	0.122	0.001	0.905
TFP	836	2.056	0.113	1.600	2.303
Struct	836	0.129	0.111	0.000	0.532

Table 4
Baseline regression results.

	(1)	(2)	(3)	(4)
	CO2int	CO2int	CO2int	CO2int
Dig	−8.6931***	−5.3084**	−4.9832**	−4.7456**
	(0.8778)	(2.2150)	(2.2979)	(2.2601)
GFCF			0.0022	0.0012
			(0.0603)	(0.0587)
GGFC			0.1299	0.0993
			(0.0805)	(0.0753)
LABR			−0.7285***	−0.7356***
			(0.1912)	(0.1661)
INTI			−0.0153	−0.0477
			(0.6129)	(0.5908)
CAPint			−0.2965***	−0.2964***
			(0.0856)	(0.0896)
GDP				3.2795***
				(0.8451)
GDPPC				−3.7462**
				(1.5166)
GovExp				−0.1538***
				(0.0438)
Energy				−0.0151
				(0.0169)
Innovation				−0.3921
				(0.3338)
Trade				0.0641
				(0.3076)
_cons	5.6160***	5.1630***	10.1690***	−37.0564***
	(0.1387)	(0.2965)	(1.6268)	(11.0714)
IndustryFE	No	Yes	Yes	Yes
YearFE	No	Yes	Yes	No
N	836	836	836	836
r2_a	0.1041	0.9778	0.9804	0.9795

Note: Robust standard errors clustered at industry level are reported in parenthesis in column (2)–(4). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Empirical results

5.1. Baseline regression

Table 4 reports baseline results, column (1) regression only includes the core dependent and explanatory variable, controlling fixed effects and clustering robust standard error starting from column (2). In order to obtain more accurate results, industry control variables are added in column (3), and column (4) further adds national control variables. The results show that the coefficient of industrial digitalization (Dig) is significantly positive at the 1 % level in column (1) and 5 % in column (2) to column (4). The baseline results indicate that one unit increase in the proportion of digital intermediate input to total intermediate input leads to a reduction of 4.9832 t of CO2 per million of gross output in column (3) and 4.7456 t of CO2 per million of gross output in column (4). Similar to previous literature, industrial digitalization has a significant effect on reducing CO2 emissions, thus supporting Hypothesis 1.

From the perspective of control variables, compensation of employees (LABR) and capital intensity (CAPint) reduce industrial CO2 emissions. Higher compensation of employees indicates higher wages for employees and greater purchasing power, which indirectly reflects the prosperity of the industry. Similarly, higher capital intensity suggests that the industry possesses ample capital and is well-developed. Such industries often exhibit higher levels of technological sophistication and production efficiency, thereby providing favorable conditions for pollution control measures.

5.2. Endogeneity concerns

We study the effect of industrial digitalization on CO2 emissions, and there is a possibility of reverse causality. When there is a significant amount of CO2 emissions in the production process, industries tend to proactively adopt more advanced technologies or use cleaner materials due to government reward and punishment policies, social public opinion supervision, and their awareness of environmental protection. Therefore, the level of industrial digitalization will be increased to optimize the production links and reduce pollution emissions. To address endogeneity concerns and identify the causal effect of industrial digitalization on CO2 emissions reduction, we use instrumental variable estimation. It is found that imported digital products and services account for a large proportion of digital input, which is the main driving force for industrial digitalization. We follow Zhu and Tomasi (2020) and Zhang, Liu, & Wei (2023) by employing the tariff as instrumental variables for industrial digitalization.

The import tariff on digital products is an official policy formulated by the government and is not directly related to industrial digitalization. Thus, it meets the requirements for both the correlation and exogeneity of instrumental variables. Since tariffs are set at the national level, we calculated the proportion of digital products imported by each industry relative to the total digital imports of South Africa as weighting factors to construct the instrumental variable (IV). The tariff data is sourced from the World Integrated Trade Solution (WITS), and in this study, we use two types: Effectively Applied Tariffs (AHS) and Most-Favored Nation Tariffs (MFN). Effectively Applied Tariffs refer to the actual tariffs imposed by a country on imported goods which take into account various factors and reflect the real tariff burden. Most-Favored Nation Tariffs refer to the lowest tariff treatment agreed under the World Trade Organization members.

Table 5 indicates that the IVs we adopt for industrial digitalization are strongly relevant and reliable. The coefficient and significance of digitization become larger after adding instrumental variables. Specifically, the level of industrial digitalization increased by

Table 5
Endogeneity test.

	(1)	(2)	(3)	(4)
	Dig	CO2int	Dig	CO2int
Dig		−7.8273***		−7.6823***
		(1.8167)		(1.6872)
AHS	0.4143***			
	(0.1065)			
MFN			0.3202***	
			(0.0461)	
GFCF	0.0014	0.0121	0.0039	0.0115
	(0.0029)	(0.0615)	(0.0025)	(0.0613)
GGFC	−0.0032	0.1075	−0.0046	0.1087
	(0.0062)	(0.0772)	(0.0068)	(0.0779)
LABR	−0.0055	−0.6572**	−0.0159	−0.6609**
	(0.0243)	(0.2527)	(0.0225)	(0.2501)
INTI	−0.0399	0.1649	−0.0808	0.1557
	(0.0569)	(0.5916)	(0.0557)	(0.5896)
CAPint	−0.0042	−0.3258***	−0.0116	−0.3243***
	(0.0114)	(0.1150)	(0.0121)	(0.1149)
IndustryFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes
N	836	836	836	836
Cragg-Donald Wald F	647.134		805.361	

Note: Robust standard errors clustered at industry level are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

one unit, and CO2 decreased by 7.8273 and 7.6823 t per million of gross output, respectively, if effectively applied tariffs or most-favored nation tariffs used as IV. The estimation results of the regressions further confirm the causal correlations between industrial digitalization and the emissions of CO2.

5.3. Robustness test

5.3.1. Adjust the standard errors for clustering

Considering that there may still be some deviation in the baseline regression, this paper uses various methods to test the robustness and verify the emission reduction effect of industrial digitalization. Firstly, based on column (2) in Table 5, cluster robust standard errors at the industry-year level, as shown in Table 6 column (1). There is no change in the main coefficients of interest, supporting the baseline findings.

5.3.2. Substitute instrumental variable

The real exchange rate (RER) takes into account the changes in currencies and inflation of different countries, reflects the relative prices of goods and services and shows the real purchasing power of a currency. In the same way as import tariffs, we take the ratio of industry imports relative to the total national imports to serve as weighting factors to construct IV.

The results are shown in Table 6 column (2). Although the coefficient becomes smaller and is significant at the 5 % level, it can still be proven that digitalization reduces CO2 intensity.

5.3.3. Lag explanatory variable

Generally, it may take a period for digitalization to play its role in production, and the pollution of the whole industry cannot be immediately changed. Therefore, we lag the industrial digitalization variable by one period and two periods to capture the possible lagged trend, as shown in column (3) and (4) of Table 6. This means that an increase of one unit in industrial digitalization not only reduces CO2 in the current year but also leads to a reduction of 7.1223 t of CO2 per million of gross output in the second year and 6.5039 t in the third year. The coefficients have decreased compared with the current period, indicating that the positive effect of digitalization on pollution is long lasting and weakens over time.

Table 6
Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Adjust cluster standard errors CO2int	Substitute IV CO2int	Lag 1 CO2int	Lag 2 CO2int	Substitute core explanatory variable CO2int	Change variables calculation method CO2int	Add control variables CO2int
Dig	−7.8273***	−6.2726**				−10.0727***	−7.0098***
	(0.6200)	(2.5285)				(3.0162)	(1.8666)
L.Dig			−7.1223***				
			(1.7602)				
L2.Dig				−6.5039***			
				(1.5099)			
TDig					−1.3127***		
					(0.2700)		
NoDig					0.9386***		
					(0.3409)		
Elec							9.5394**
							(3.8430)
M&Q							0.1031
							(1.8691)
ALT							−0.1934***
							(0.0705)
GFCF	0.0121	0.0067	0.0095	0.0113	−0.0128	0.0559	0.0021
	(0.0242)	(0.0616)	(0.0617)	(0.0603)	(0.0562)	(0.1067)	(0.0584)
GGFC	0.1075***	0.1197	0.1412*	0.1550*	0.1364	0.0116	0.0732
	(0.0367)	(0.0790)	(0.0795)	(0.0808)	(0.0961)	(0.0796)	(0.0630)
LABR	−0.6572***	−0.6962***	−0.7831***	−0.8007***	−0.3816	−0.5572	−0.8790***
	(0.0985)	(0.2220)	(0.2580)	(0.2427)	(0.3178)	(0.3653)	(0.0951)
INTI	0.1649	0.0664	0.0621	−0.0077	3.5312***	0.6190	−0.4210
	(0.2325)	(0.5880)	(0.6150)	(0.6203)	(1.1138)	(0.6435)	(0.6354)
CAPint	−0.3258***	−0.3098***	−0.4270**	−0.4079*	−0.2313***	−0.3708**	−0.3429***
	(0.0880)	(0.1011)	(0.1957)	(0.2301)	(0.0730)	(0.1642)	(0.1260)
IV	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	836	836	792	748	836	802	836

Note: Robust standard errors are clustered at industry-year level in column (1), and industry level in other columns. RER is used as IV in column (2), and MFN is used as IV in other columns. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3.4. Substitute core explanatory variable

We use digital intermediate input (TDig) as alternative indicator for industrial digitalization and add intermediate input except for digital input (NoDig) as the control variable into the model to control for potential bias. The results in column (5) of Table 6 show that one unit increase in digital intermediate input can significantly lead to 1.3127 t reduction in CO2 per million of gross output, while non-digital intermediate input increases by 0.9386 t CO2 per million of gross output. This can further prove the effect of digitalization in the process of industrial production.

5.3.5. Change variables calculation method

In this study, variables are measured by adding 1 and taking the logarithm. Nevertheless, studies have highlighted that log1plus regression lacks meaningful interpretation and suffers from inherent biases that tend to have the wrong sign in the expected value (Cohn, Liu, & Wardlaw, 2022). We estimate the regression without the addition of 1 to the logarithm in column (6) of Table 6, the results are similar to previous regression; despite adjusting indicators, industrial digitalization is still significantly and negatively linked to the emissions of CO2 from production.

5.3.6. Add control variables

Several studies have shown that energy consumption has been the main culprit for carbon emissions (Appiah, Li, & Korankye, 2021; Zakarya, Mostefa, et al., 2015). Alternative energy has become the heart of the newest wave of energy transformation due to its clean, low-carbon, and pollution-free characteristics (Lu, Liu, Mohsin, & Zhang, 2023; Yimen, Hamandjoda, & Meva' a, L., Ndzana, B., & Nganhou, J., 2018). We incorporate three ratios into the estimation to capture additional industrial factors affecting CO2 emissions: the ratio of alternative and nuclear energy to total energy use (ALT), the ratio of electricity, gas, steam, and air conditioning supply to output (Elec) and the ratio of mining and quarrying of energy producing materials to output (M&Q). The results in column (7) of Table 6 indicate that alternative and nuclear energy can reduce CO2. Electricity and gas supply are associated with increased CO2 intensity, while mining and quarrying have shown no significant impact.

5.4. Heterogeneity analysis

5.4.1. The heterogeneity in different industries

Due to the different production characteristics of industries, there may be differences in the effect of industrial digitalization on CO2 emissions. In this chapter, 44 industries are divided into primary industry, secondary industry, and tertiary industry according to the fourth edition of the *International Standard Industrial Classification of All Economic Activities (ISIC Rev4.0)*. Since there are too few samples in the primary industry, the results are not stable enough to make a judgment. Therefore, this paper focuses on the secondary and tertiary industries, results shown in Table 7.

The coefficient of industrial digitalization in the tertiary industry is statistically significant at 1 % level, which shows that one unit increase in industrial digitalization can effectively reduce 10.2490 t of CO2 emission per million output in the tertiary industry. Surprisingly, the coefficient on the secondary industry is statistically insignificant and has a smaller magnitude.

Table 7
Heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
	the secondary industry CO2int	the tertiary industry CO2int	low-digital-skill industry CO2int	high-digital-skill industry CO2int	domestic and imported inputs CO2int
Dig	−6.0558	−10.2490***	−47.5881	−7.9508***	
	(5.2470)	(0.4678)	(27.2966)	(1.8333)	
DomDig					0.4205
					(0.3954)
ForDig					−0.9700***
					(0.3315)
GFCF	0.0318	−0.0143	−0.1114	0.0745	−0.0051
	(0.1368)	(0.0176)	(0.1387)	(0.0956)	(0.0649)
GGFC	0.0686	−0.0571	0.3592	0.0002	0.1521
	(0.1600)	(0.0837)	(0.2626)	(0.1032)	(0.1040)
LABR	−0.9613***	0.5573*	−0.0436	−0.6133*	−0.3225
	(0.3148)	(0.2855)	(0.6744)	(0.3143)	(0.2707)
INTI	−2.0155	1.6965***	1.7427	0.0941	2.0935*
	(1.2631)	(0.3364)	(2.0254)	(0.8034)	(1.1845)
CAPint	−0.2732**	−0.0703	0.1044	−0.3556**	−0.1627**
	(0.1041)	(0.1226)	(0.3033)	(0.1318)	(0.0761)
IV	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes
N	437	361	171	665	836
P-value	4.1932**		39.6372***		

Note: Robust standard errors clustered at industry level are reported in parenthesis. This table and all tables below use AHS as IV. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The coefficient difference test between groups is obtained by Fisher' s Permutation test (Bootstrap 1000 times).

A possible explanation is that the secondary industry mainly includes mining, manufacturing, construction, etc., which consume large amounts of energy and raw materials for production and produce industrial waste (Zhao, Min, Geng, et al., 2017). Heavy industry has a strong dependence on high-polluting energy and large-scale facilities. As a result, the attributes and structure of its input factors cannot be changed as much in the short term as the service industry. For example, the chemical industry cannot quickly transition from being an oil-dependent polluting sector to one that primarily utilizes solar energy. Moreover, the secondary industry faces high barriers to adopting and applying digital inputs, requiring a large amount of capital and supporting technology. Additionally, the use of digital inputs directly emits CO2 and this pollution may not be offset by productivity improvements (Afzal & Gow, 2016). These factors have led to the insignificant environmental optimization effect brought by the digitalization of the secondary industry.

The tertiary industry is mostly labor-intensive and technology-intensive and has a lower energy investment. Technological progress and labor efficiency brought by digitalization are likely to have significant impacts on these industries. Thus, industrial digitalization serves as a catalyst for the evolution of production methodologies within the tertiary industry. This transformative process leads to a noticeable reduction in emission intensity related to industrial pollution and waste (Jiang, Huang, & Yang, 2019).

In the primary industry, where agriculture, forestry, fishing, and animal husbandry dominate, the pollution resulting from the production process is considerably lower compared to other industrial sectors. This does not imply that digitalization has a negligible impact, modern agriculture has increasingly adopted digital technologies. Cramer and Chisoro-Dube (2021) find the fruit industry in South Africa has full access to technologies, including precision farming and post-harvest production technologies such as digital platforms and the Internet of Things. These technologies are transforming the structure of fruit production, enhancing productivity, and potentially affecting CO2 emissions.

5.4.2. The heterogeneity in different levels of industrial digital skill

Heterogeneity in the characteristics of technology will affect the process and impact of digitalization, such as the extent of complexity in ICT applications (Fareri, Apreda, Mulas, & Alonso, 2023). *Skills for Jobs* database of OECD provides an overview of the shortages and surpluses of skills across industries (See Table B). We use the "Digital Skills" index and take the average value to measure the level of digital skills of the industry. If the comparative need for digital skills of employees in an industry is greater than 0, it means that the industry has a high demand for digital skills and is classified as a high-digital-skill industry. Similarly, industries with a comparative need for digital skills less than 0 are identified as low-digital-skill industries. The regression results are shown in column (3) and (4) of Table 7. Our findings indicate that high-digital-skill industry provides robust infrastructure and talent pool, facilitating digital transformation and contributing to emission reductions. Conversely, industries with low digital skills face limitations due to inadequate digital foundations, and as a result, digitalization has no significant impact on CO2 emissions.

5.4.3. The heterogeneity in different sources of digital input

According to the input-output table, there are two sources of digital intermediate inputs: domestically produced digital intermediate products and services, and digital intermediate products and services imported from abroad. In column (5) of Table 7, we discuss the effects of domestic digital input (DomDig) and imported digital input (ForDig) on CO2 emissions, respectively. In comparison to domestic digital inputs, the coefficient for imported digital inputs is both larger and exhibits greater statistical significance. This suggests that in the process of industrial digital transformation, imported digital products and services play a more robust role in emissions reduction, while the emissions reduction effect of domestically sourced digital inputs is relatively weaker as shown by the

Table B
Low-digital-skill and high-digital-skill measured by Skill for Job database.

Nace	Description	Matched Industry in STAN	Digital Score
S	Other Service Activities	D94T96	−0.354
L	Real Estate Activities	D68	−0.225
A	Agriculture, Forestry and Fishing	D01T02, D03	−0.126
I	Accommodation and food service activities	D55T56	−0.119
B	Mining and Quarrying	D05T06, D07T08, D09	−0.094
F	Construction	D41T43	−0.07
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	D45T47	0.007
C	Manufacturing	D10T12, D13T15, D16, D17T18, D19, D20, D21, D22, D23, D24, D25, D26, D27, D28, D29, D30, D31T33	0.008
P	Education	D85	0.042
Q	Human Health and Social Work Activities	D86T88	0.092
D	Electricity, Gas, Steam and Air Conditioning Supply; Water Supply; Sewerage, Waste Management and Remediation Activities	D35, D36T39	0.123
R	Arts, Entertainment and Recreation	D90T93	0.144
H	Transportation and Storage	D49, D50, D51, D52, D53	0.147
K	Financial and Insurance Activities	D64T66	0.245
J	Information and Communication	D58T60, D61, D62T63	0.298
O	Public Administration and defence; Compulsory Social Security	D84	0.357
M-N	Professional, scientific and technical activities; administrative and support service activities	D69T75, D77T82	*

* Indicates missing data.

insignificant coefficient.

The reasons mainly include two aspects: First, the production of digital products relies on energy sources such as electricity and digital infrastructure, which are major contributors to carbon emissions. Consequently, as the input of domestic digital products increases, so does the consumption of production materials and digital infrastructure, leading to an increase in pollution emissions, thereby weakening or even offsetting the emissions reduction effect (Shehzad et al., 2020).

Second, digital products have high technical barriers. South Africa lacks the necessary R&D capital and talent to support the design and production of high-digital-technology products in the short term. As a result, there is a trend toward importing digital products that are more cutting-edge and environmentally friendly in terms of digital technology. In contrast, domestic digital products tend to have lower digital technology, resulting in a weaker effect on emissions reduction (Li, Zhang, & Li, 2023); another approach is to import intermediate products containing core digital technologies, process and transform them domestically, and incorporate them into production.

5.5. Mechanism analysis

According to our previous analysis, industrial digitalization contributes to the reduction of CO2 intensity. In this section, we employ a mediation model to further explore the mechanism of industrial digitalization on emission reduction from two aspects: increasing productivity and optimizing the factor input structure, and incorporate the instrumental variable of AHS in the model following Dippel, Ferrara, and Heblich (2020).

The model is as follows:

$$Mediator_{it} = \alpha_0 + \alpha_1 Dig_{it} + X_{it} + \delta_i + \delta_t + \varepsilon_{it} \tag{6}$$

$$\mathrm{CO2}\mathit{int}_{it} = \gamma_0 + \beta_2 \mathrm{Dig}_{it} + \alpha_2 \mathrm{Mediator}_{it} + \mathrm{X}_{it} + \delta_i + \delta_t + \varepsilon_{it} \tag{7}$$

where i is an industry, t is a year; $\mathrm{CO2}\mathit{int}_{it}$ is carbon dioxide emission intensity; Dig_{it} is the level of industrial digitalization; $\mathrm{Mediator}_{it}$ is mediator (productivity and factor input structure).

According to Baron and Kenny (1986) and Preacher and Hayes (2004), if β_1, α_1, α_2 are significant; the sign of β_2 remains unchanged, and the absolute value is less than β_1; $\alpha_1\alpha_2$ and β_1 has the same sign, then there has a mediating effect. Furthermore, if β_2 is not significant means a full mediating effect; if β_2 is significant and shares the same sign as β_1, this indicates a partial mediating effect.

5.5.1. Productivity mechanism

In order to explore the role of productivity in the relationship between industrial digitalization and CO2 emissions, we use the LP method to calculate the total factor productivity (TFP) of the industry and incorporate it into the regression as a mediator. Digital technology may convert repetitive work into machine work, thus allowing employees to focus more on high-value-added work, which improves employee productivity; it optimizes production links by managing equipment and resources, expedites the collection, analysis, and utilization of data, reducing losses caused by asymmetry information. Ultimately, this enhances total factor productivity, the results are presented in Table 8. The significant positive productivity coefficient in column (1) indicates that one percentage point increase in industrial digitalization corresponds to 0.1920 percentage points higher in productivity. The industrial digitalization

Table 8
Mechanism analysis.

	(1)	(2)	(3)	(4)
	TFP	CO2int	Struct	CO2int
Dig	0.1920*	−7.5357***	−0.9541***	−5.0742**
	(0.0996)	(2.0222)	(0.2245)	(2.1980)
TFP		−3.0758*		
		(1.5523)		
Struct				2.8855***
				(0.8964)
GFCF	−0.0119***	−0.0386	0.0066	−0.0069
	(0.0042)	(0.0616)	(0.0042)	(0.0568)
GGFC	0.0062	0.1163	−0.0038	0.1185*
	(0.0094)	(0.0783)	(0.0125)	(0.0620)
LABR	−0.3711***	−0.4097	−0.0073	−0.6361***
	(0.1120)	(0.2931)	(0.0266)	(0.1981)
INTI	−0.0748	0.6829	−0.0343	0.2638
	(0.0581)	(0.7146)	(0.0662)	(0.5114)
CAPint	−0.0109**	−0.2852***	−0.0148	−0.2830***
	(0.0053)	(0.1047)	(0.0117)	(0.0823)
IV	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes
N	836	836	836	836

Note: Robust standard errors clustered at industry level are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

coefficient in column (2) is 7.5357, which is significantly reduced compared to 7.8273 in Table 8. Therefore, hypothesis H2 can be verified, industrial digitalization enhances industry productivity, thereby reducing CO_2 emissions. These findings align with the theoretical analysis mentioned above.

5.5.2. Factor input structure mechanism

We divide the industries whose carbon dioxide emission intensity is in the top 10 % as high-pollution industries. The input structure (Struct) is measured by the proportion of input from high-pollution factors to intermediate input and used as the mediator. The results are shown in columns (3) and (4) of Table 8. Obviously, the more products and services inputs from high-pollution industries are used, the higher CO_2 emission intensity in the production. Industrial digitalization can reduce the ratio of high-pollution input to intermediate input by technology spillover effect and input substitution. Firstly, as production materials, digital inputs directly replace those traditional high-pollution production materials, decreasing the share of high-pollution inputs; secondly, digitalization brings advanced technologies, which are often used to transform traditional raw materials from high-pollution into low-pollution; Thirdly, as digital inputs increase, the industry tends to aggressively seek other high-tech materials to match those digital inputs, thereby maximizing the utilization of production factors. These high-tech materials often possess cleaner attributes, so digitalization can reduce the proportion of input from high-pollution factors to intermediate input, and optimize the factor input structure to reduce CO_2 in production, which verifies hypothesis H3.

5.6. Further analysis

As mentioned above, industrial digitalization in South Africa significantly reduces the intensity of CO_2 emissions in production. In this section, we compare South Africa with the other four BRICS countries in Table 9.

The results show that industrial digitalization in Brazil, South Africa, and China has emission reduction effects. The coefficients for South Africa and Brazil are significant at the 1 % level, with Brazil's coefficient being the highest in absolute terms (11.2287), followed by South Africa (7.8273). It can be seen that the digitalization of industries in Brazil is developing rapidly and has the most significant positive effect on the environment, related to that the Brazilian federal government has attached great importance to and made strategic actions for digital transformation in recent years (Bower, 2023; de Lima & da Silva, 2023). The industrial digitalization coefficient in China is significant at the 10 % level, weaker than the other 2 countries. However, industrial digitalization in India and Russia has not found any obvious effect.

The possible reason is that while industrial digitalization improves productivity and output, it may overlook the cleaner transformation of technologies and processes. Industries still use traditional raw materials and production methods with high energy consumption and high pollution. Fang, Jiang, Hussain, Zhang, and Huo (2022) proposed that Russia's abundant mineral and energy resources will lead to the migration of polluting manufacturing industries, so pollution will not decrease in the short term despite an increase in digital inputs from abroad. Therefore, industrial digitalization in Russia and India cannot fully realize its emission-reduction effect.

6. Conclusions and policy implications

The green attribute of industrial digitalization is in line with the pursuit of high-quality economic development in Africa, conforming to the global sustainable development trend. In the critical period of economic transformation and upgrading, how to fully exploit the emission reduction effect of industrial digitalization should be a matter of public concern in the world with strong practical significance.

We use the OECD input-output table to explore the impact of the industrial digitalization of 44 industries in South Africa on the carbon dioxide emission intensity in production from 2000 to 2018. The findings reveal that industrial digitalization significantly reduces the CO_2 emission intensity in production through increasing productivity and optimizing factor input structure mechanisms. The effect of industrial digitalization on CO_2 emission is more prominent for the tertiary industry and those industries with high digital skills. The imported digital input from abroad has a greater impact on CO_2 emissions than domestic digital input. Among the BRICS countries, industrial digitalization in Brazil has the leading position in reducing emissions, followed by South Africa and China, while the industrial digitalization of India and Russia does not affect pollution. Based on the above conclusions, we aim to provide evidence to support Africa's industrial transformation and green economy, as well as provide guidance to developing countries worldwide. This study proposes the following countermeasures and suggestions:

Digitalization, with its unique attributes, can simultaneously address both production and environmental conservation concerns, providing South Africa with new opportunities to develop a more environmentally-sound future. Therefore, in the process of industrial digital transformation, it is important to consider cleaner technology innovations alongside productivity improvements, so as to create environment-friendly industries and achieve sustainable development.

According to our study, imported digital inputs play a great role in technology spillovers. It is imperative for the South African government to give support on the importation of digital technologies and products, reducing digital trade barriers would be an effective approach. Additionally, heterogeneity analysis indicates that talent is a prerequisite for digital technology applications. Industries should increase incentives for digital skills in respect of on-the-job training to fully utilize digital inputs and integrate advanced technologies into local production processes, thereby achieving a balance of improving productivity and reducing pollution. For developing countries, digital transformation presents an important opportunity to improve the position of the global value chain and contribute to pollution treatment. Governments should develop a comprehensive digitalization strategy that defines digitalization

Table 9
Further analysis.

	(1)	(2)	(3)	(4)	(5)
	South Africa	China	Russian	India	Brazil
	CO2int	CO2int	CO2int	CO2int	CO2int
Dig	−7.8273***	−1.2085*	−1.6758	−17.7527	−11.2287***
	(1.8167)	(0.6511)	(1.3256)	(20.7731)	(3.8503)
GFCF	0.0121	0.0005	−0.0482	−0.0098	−0.1450
	(0.0615)	(0.0303)	(0.0627)	(0.0706)	(0.0997)
GGFC	0.1075	0.0353	0.0863**	0.0453	−0.0041
	(0.0772)	(0.0424)	(0.0376)	(0.0729)	(0.0718)
LABR	−0.6572**	−0.0817	−0.0927	−0.2435	−0.0289
	(0.2527)	(0.0988)	(0.0982)	(0.2407)	(0.1858)
INTI	0.1649	0.8085**	0.5451	1.0450	0.6455
	(0.5916)	(0.3691)	(0.7258)	(0.8420)	(0.9710)
CAPint	−0.3258***	−0.0043*	0.0099***	−0.0217***	−0.0066
	(0.1150)	(0.0022)	(0.0017)	(0.0078)	(0.0075)
IV	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes
N	836	836	836	836	836

Note: Robust standard errors clustered at industry level are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

goals, policy frameworks, and visions to coordinate and guide digital development.

There may be some limitations in this study. We have not conducted a cost-benefit analysis due to data limitations. Although there has been substantial evidence for various benefits of industrial digitalization, not all countries and industries are equally equipped and suited to undertake this transformation. More attention should be paid to the costs of digitization. Firstly, digital patents and equipment often require a significant amount of funding, especially in countries with weak R&D capabilities that rely on importing digital products; secondly, digitalization is supported by skilled professionals and digital infrastructure, such as base stations and industrial internet platforms, which need investment from government or enterprises. Finally, even though this paper shows that digitalization has the benefit of reducing CO2 emissions, its effects vary depending on the circumstances. Pollution is a complex consequence of forces connected with various interrelating factors, countries and industries should consider whether to use digitalization or other more suitable ways for pollution control according to their current status and characteristics.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Appendix

Table A
Industry Description.

Industry Code in STAN	ISIC 4 Corresponding Division	Description
D01T02	01, 02	Agriculture, hunting, forestry
D03	3	Fishing and aquaculture
D05T06	05, 06	Mining and quarrying, energy producing products
D07T08	07, 08	Mining and quarrying, non-energy producing products
D09	9	Mining support service activities
D10T12	10, 11, 12	Food products, beverages and tobacco
D13T15	13, 14, 15	Textiles, textile products, leather and footwear

(*continued on next page*)

Table A (*continued*)

Industry Code in STAN	ISIC 4 Corresponding Division	Description
D16	16	Wood and products of wood and cork
D17T18	17, 18	Paper products and printing
D19	19	Coke and refined petroleum products
D20	20	Chemical and chemical products
D21	21	Pharmaceuticals, medicinal chemical and botanical products
D22	22	Rubber and plastics products
D23	23	Other non-metallic mineral products
D24	24	Basic metals
D25	25	Fabricated metal products
D26	26	Computer, electronic and optical equipment
D27	27	Electrical equipment
D28	28	Machinery and equipment, nec
D29	29	Motor vehicles, trailers and semi-trailers
D30	30	Other transport equipment
D31T33	31, 32, 33	Manufacturing nec; repair and installation of machinery and equipment
D35	35	Electricity, gas, steam and air conditioning supply
D36T39	36, 37, 38, 39	Water supply; sewerage, waste management and remediation activities
D41T43	41, 42, 43	Construction
D45T47	45, 46, 47	Wholesale and retail trade; repair of motor vehicles
D49	49	Land transport and transport via pipelines
D50	50	Water transport
D51	51	Air transport
D52	52	Warehousing and support activities for transportation
D53	53	Postal and courier activities
D55T56	55, 56	Accommodation and food service activities
D58T60	58, 59, 60	Publishing, audiovisual and broadcasting activities
D61	61	Telecommunications
D62T63	62, 63	IT and other information services
D64T66	64, 65, 66	Financial and insurance activities
D68	68	Real estate activities
D69T75	69 to 75	Professional, scientific and technical activities
D77T82	77 to 82	Administrative and support services
D84	84	Public administration and defence; compulsory social security
D85	85	Education
D86T88	86, 87, 88	Human health and social work activities
D90T93	90, 91, 92, 93	Arts, entertainment and recreation
D94T96	94,95, 96	Other service activities

References

Abendin, S., & Duan, P. (2021). International trade and economic growth in Africa: The role of the digital economy. *Cogent Economics & Finance, 9*(1), 1911767.

Acemoglu, D., & Azar, P. D. (2020). Endogenous production networks. *Econometrica, 88*(1), 33–82.

Afzal, M. N. I., & Gow, J. (2016). Electricity consumption and information and communication technology (ict) in the n-11 emerging economies. *International Journal of Energy Economics and Policy, 6*(3), 381–388.

Agrawal, A., & Goldfarb, A. (2008). Restructuring research: Communication costs and the democratization of university innovation. *American Economic Review, 98*(4), 1578–1590.

Alcácer, J., Cantwell, J., & Piscitello, L. (2016). Internationalization in the information age: A new era for places, firms, and international business networks? *Journal of International Business Studies, 47*, 499–512.

Ali, E., Bataka, H., Wonyra, K. O., Awade, N. E., & Braly, N. N. (2024). Global value chains participation and environmental pollution in developing countries: Does digitalization matter? *Journal of International Development, 36*(1), 451–478.

Amjad, M. S., Rafique, M. Z., & Khan, M. A. (2021). Leveraging optimized and cleaner production through industry 4.0. *Sustainable Production and Consumption, 26*, 859–871.

Appiah, M., Li, F., & Korankye, B. (2021). Modeling the linkages among CO 2 emission, energy consumption, and industrialization in sub-Saharan African (SSA) countries. *Environmental Science and Pollution Research, 28*, 38506–38521.

Asongu, S. A. (2018). ICT, openness and CO 2 emissions in Africa. *Environmental Science and Pollution Research, 25*, 9351–9359.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173.

Basu, S., & Fernald, J. (2007). Information and communications technology as a general-purpose technology: Evidence from US industry data. *German Economic Review, 8*(2), 146–173.

Berkhout, F., & Hertin, J. (2004). De-materialising and re-materialising: Digital technologies and the environment. *Futures, 36*(8), 903–920.

Bogner, E., Voelklein, T., & Schroedel, O. (2016). Study based analysis on the current digitization degree in the manufacturing industry in Germany. *Procedia CIRP, 57*, 14–19.

Bower, L. (2023). Brazil as a leader in digital transformation. In *Proceedings of the 16th international conference on theory and practice of electronic governance* (pp. 80–85).

Brannlund, R., & Persson, L. (2012). To tax, or not to tax: Preferences for climate policy attributes. *Climate Policy, 12*(6), 704–721.

Cijan, A., Jenič, L., Lamovšek, A., & Stemberger, J. (2019). How digitalization changes the workplace. *Dynamic Relationships Management Journal, 8*(1), 3–12.

Cohn, J. B., Liu, Z., & Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics, 146*(2), 529–551.

Coreynen, W., Matthyssens, P., & Van Bockhaven, W. (2017). Boosting servitization through digitization: Pathways and dynamic resource configurations for manufacturers. *Industrial Marketing Management, 60*, 42–53.

Cramer, C., & Chisoro-Dube, S. (2021). The industrialization of freshness and structural transformation in south African fruit exports. In *Structural transformation in South Africa* (pp. 120–142). Oxford University Press.
Danish, K. N., Baloch, M. A., Saud, S., & Fatima, T. (2018). The effect of ICT on CO2 emissions in emerging economies: Does the level of income matters? *Environmental Science and Pollution Research, 25*, 22850–22860.
Dao, V., Langella, I., & Carbo, J. (2011). From green to sustainability: Information technology and an integrated sustainability framework. *The Journal of Strategic Information Systems, 20*(1), 63–79.
Dippel, C., Ferrara, A., & Heblich, S. (2020). Causal mediation analysis in instrumental-variables regressions. *The Stata Journal, 20*(3), 613–626.
Edquist, H., & Henrekson, M. (2017). Do R&D and ICT affect total factor productivity growth differently? *Telecommunications Policy, 41*(2), 106–119.
Fang, H., Jiang, C., Hussain, T., Zhang, X., & Huo, Q. (2022). Input digitization of the manufacturing industry and carbon emission intensity based on testing the world and developing countries. *International Journal of Environmental Research and Public Health, 19*(19), 12855.
Fareri, S., Apreda, R., Mulas, V., & Alonso, R. (2023). The worker profiler: Assessing the digital skill gaps for enhancing energy efficiency in manufacturing. *Technological Forecasting and Social Change, 196*, Article 122844.
Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner Production, 252*, Article 119869.
Gibbon, P., Bair, J., & Ponte, S. (2008). Governing global value chains: An introduction. *Economy and Society, 37*(3), 315–338.
Gobble, M. M. (2018). Digitalization, digitization, and innovation. *Research-Technology Management, 61*(4), 56–59.
Hao, X., Li, Y., Ren, S., Wu, H., & Hao, Y. (2023). The role of digitalization on green economic growth: Does industrial structure optimization and green innovation matter? *Journal of Environmental Management, 325*, Article 116504.
Higón, D. A., Gholami, R., & Shirazi, F. (2017). ICT and environmental sustainability: A global perspective. *Telematics and Informatics, 34*(4), 85–95.
Hirsch-Kreinsen, H. (2016). Digitization of industrial work: Development paths and prospects. *Journal for Labour Market Research, 49*(1), 1–14.
Jiang, T., Huang, S., & Yang, J. (2019). Structural carbon emissions from industry and energy systems in China: An input-output analysis. *Journal of Cleaner Production, 240*, Article 118116.
Khuntia, J., Saldanha, T. J. V., Mithas, S., et al. (2018). Information technology and sustainability: Evidence from an emerging economy. *Production and Operations Management, 27*(4), 756–773.
Lei, X., Shen, Z. Y., Štreimikienė, D., Baležentis, T., Wang, G., & Mu, Y. (2024). Digitalization and sustainable development: Evidence from OECD countries. *Applied Energy, 357*, Article 122480.
Leontief, W. (1970). Environmental repercussions and the economic structure: An input-output approach. *The Review of Economics and Statistics*, 262–271.
Li, H., Zhang, Y., & Li, Y. (2023). The impact of digital inputs on pollution reduction in Chinese manufacturing enterprises. *Journal of Cleaner Production, 428*, Article 139393.
Li, Y., Dai, J., & Cui, L. (2020). The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. *International Journal of Production Economics, 229*, Article 107777.
de Lima, D. B., & da Silva, A. P. B. (2023). A comparative documentary analysis of the Brazilian digital transformation strategies adopted in the enabling thematic axes of 2018 and 2022. In *International conference on WorldS4* (pp. 115–122).
Lipsey, R. G., Carlaw, K. I., & Bekar, C. T. (2005). *Economic transformations: General purpose technologies and long-term economic growth*. Oup Oxford.
Liu, Y., Yang, Y., Li, H., & Zhong, K. (2022). Digital economy development, industrial structure upgrading and green total factor productivity: Empirical evidence from China's cities. *International Journal of Environmental Research and Public Health, 19*(4), 2414.
Lu, L., Liu, Z., Mohsin, M., & Zhang, C. (2023). Renewable energy, industrial upgradation, and import-export quality: Green finance and CO2 emission reduction nexus. *Environmental Science and Pollution Research, 30*(5), 13327–13341.
Machado, C. G., Winroth, M., Carlsson, D., Almström, P., Centerholt, V., & Hallin, M. (2019). Industry 4.0 readiness in manufacturing companies: Challenges and enablers towards increased digitalization. *Procedia CIRP, 81*, 1113–1118.
Meng, F., & Zhao, Y. (2022). How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environmental Science and Pollution Research, 29*(52), 79497–79515.
Miller, R. E., & Blair, P. D. (2009). *Input-output analysis: Foundations and extensions*. Cambridge University Press.
Mondejar, M. E., Avtar, R., Diaz, H. L. B., et al. (2021). Digitalization to achieve sustainable development goals: Steps towards a smart green planet. *Science of the Total Environment, 794*, Article 148539.
Oberfield, E. (2018). A theory of input-output architecture. *Econometrica, 86*(2), 559–589.
de Oliveira Neto, G. C., Correia, J. M. F., Silva, P. C., de Oliveira Sanches, A. G., & Lucato, W. C. (2019). Cleaner production in the textile industry and its relationship to sustainable development goals. *Journal of Cleaner Production, 228*, 1514–1525.
Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research, 139*, 303–311.
Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers, 36*, 717–731.
Røpke, I., & Christensen, T. H. (2012). Energy impacts of ICT–insights from an everyday life perspective. *Telematics and Informatics, 29*(4), 348–361.
Salahuddin, M., & Alam, K. (2016). Information and communication technology, electricity consumption and economic growth in OECD countries: A panel data analysis. *International Journal of Electrical Power & Energy Systems, 76*, 185–193.
Shahbaz, M., Tiwari, A. K., & Nasir, M. (2013). The effects of financial development, economic growth, coal consumption and trade openness on CO2 emissions in South Africa. *Energy Policy, 61*, 1452–1459.
Shehzad, K., Xiaoxing, L., Sarfraz, M., & Zulfiqar, M. (2020). Signifying the imperative nexus between climate change and information and communication technology development: a case from Pakistan. *Environmental Science and Pollution Research, 27*, 30502–30517.
Simpson, D., & Tsukui, J. (1965). The fundamental structure of input-output tables, an international comparison. *The Review of Economics and Statistics*, 434–446.
Skender, F., & Ali, İ. (2019). A digitalization and industry 4.0. *International Scientific Journal Vision, 4*(2), 47–62.
Tranos, E., Kitsos, T., & Ortega-Argilés, R. (2021). Digital economy in the UK: Regional productivity effects of early adoption. *Regional Studies, 55*(12), 1924–1938.
Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144.
Yimen, N., Hamandjoda, O., & Meva' a, L., Ndzana, B., & Nganhou, J.. (2018). Analyzing of a photovoltaic/wind/biogas/pumped-hydro off-grid hybrid system for rural electrification in sub-Saharan Africa—Case study of Djoundé in northern Cameroon. *Energies, 11*(10), 2644.
Zakarya, G. Y., Mostefa, B. E., et al. (2015). Factors affecting CO2 emissions in the BRICS countries: a panel data analysis. *Procedia Economics and Finance, 26*, 114–125.
Zhang, H, Liu, Q., & Wei, Y. (2023). Digital product imports and export product quality: Firm-level evidence from China. *China Economic Review, 101981*.
Zhang, Q., Jiang, X., Tong, D., et al. (2017). Transboundary health impacts of transported global air pollution and international trade. *Nature, 543*(7647), 705–709.
Zhang, W., Zhang, T., Li, H., & Zhang, H. (2022). Dynamic spillover capacity of R&D and digital investments in China's manufacturing industry under long-term technological progress based on the industry chain perspective. *Technology in Society, 71*, Article 102129.
Zhao, R., Min, N., Geng, Y., et al. (2017). Allocation of carbon emissions among industries/sectors: An emissions intensity reduction constrained approach. *Journal of Cleaner Production, 142*, 3083–3094.
Zhong, R. Y., Xu, X., Klotz, E., et al. (2017). Intelligent manufacturing in the context of industry 4.0: a review. *Engineering, 3*(5), 616–630.
Zhu, M., & Tomasi, C. (2020). Firms' imports and quality upgrading: Evidence from Chinese firms. *The World Economy, 43*(5), 1371–1397.