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Quantitative Measurement of Differential Efficiency of Digital Transformation on International Trade of Developing Countries Based on DEA Modeling

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ABSTRACT

This paper measures the international trade efficiency of developing countries based on the data envelopment analysis (DEA) model, and explores the impact of digital transformation on trade efficiency differentiation using regression analysis. Relevant data of 19 developing countries, including China, are selected, and the trade efficiency at each stage is calculated separately using the three-stage DEA model in this paper. The regression model is constructed to quantitatively analyze the impact of digital transformation in the differentiation of trade efficiency of developing countries. From 2011 to 2020, the trade efficiency of each developing country shows a wave-like upward trend, and the average value of the comprehensive average efficiency in the third stage is 0.728, but only China, Peru and Colombia have a higher than average level of trade efficiency, which intuitively demonstrates the trade efficiency differentiation of developing countries. Differentiation. The overall regression results show that the elasticity coefficient of digital transformation on the international trade efficiency gap is -0.274, indicating that digital transformation has a greater effect on narrowing the trade efficiency gap than widening it. And in the subregional regression, the elasticity coefficient of digital transformation in Asia is 1.398, and the elasticity coefficients in Africa and Latin America regions are -0.953 and -0.603 respectively, and the digital transformation has significantly different impacts on trade efficiency differentiation in different regions.

Keywords: DEA model, regression model, elasticity coefficient, digital transformation, international trade efficiency

1. Introduction

In today's era of globalization, international trade, as an important engine of economic growth, is undergoing profound changes. Among them, digital transformation is undoubtedly one of the most influential driving forces. Digital transformation, with its powerful innovation ability and efficient resource integration, is reshaping the pattern and operation mode of international trade [1-4].

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First, digital transformation has greatly improved the efficiency of international trade. In the past, information exchange and document processing in international trade often rely on paper documents and cumbersome manual processes, which is not only time-consuming and laborious, but also prone to errors and delays. Nowadays, through the digital information platform and electronic data exchange system, both sides of the trade can share information in real time, and quickly deal with orders, invoices, transport documents and other types of documents [5-8]. Secondly, digital transformation has expanded the market space of international trade. The Internet and digital technology to break the geographical and time constraints, so that enterprises can more easily access to global customers and markets. With the help of social media, online marketing and other means, small and medium-sized enterprises also have the opportunity to display their products and services in the international market, and compete with large enterprises [9-12]. Furthermore, digital transformation has promoted the innovation and upgrading of international trade services. The development of financial technology for international trade provides more convenient and diversified payment and financing solutions [13-15]. However, while digital transformation brings opportunities to international trade, it also brings challenges in terms of data security and privacy protection, exacerbation of international trade imbalance and international trade regulation [16-17].

This paper adopts a three-stage data envelopment analysis (DEA) model to quantitatively measure the national trade efficiency of developing countries. Each developing country is regarded as a decision-making unit (DMU) in the DEA model, and the evaluation index system of digital transformation and trade efficiency is constructed, and the indicators related to digital transformation are taken as the input variables of the DEA model, and the indicators related to trade efficiency are taken as the output variables of the model, and the three-stage DEA model is completed by combining the external environment variables, such as the total level of the economy. Taking the 2011-2020 data of 19 developing countries covering Asia, Africa and Latin America, such as China, India and Brazil, as the data source of this paper, the international trade efficiency of each developing country in the first, second and third phases is measured according to the constructed model, and the development trend of trade efficiency in the three phases and the differentiation among different countries are studied. The measured difference in trade efficiency is used as the dependent variable, and digital transformation and related control variables are used as independent variables to construct a regression model, and the regression analysis explores the role of digital transformation in widening or narrowing the gap of trade efficiency among developing countries.

2. Quantitative trade efficiency measurement model

In order to derive more accurate international trade efficiency values, this paper applies a three-stage data envelopment analysis (DEA) model. This model combines a nonparametric DEA model and a parametric SFA model, which divides the efficiency measure into three stages, with the first and third stages using a data envelopment analysis based on variable returns to scale, i.e., the BCC model. The second stage uses the stochastic frontier analysis model, i.e., the SFA model. Generally speaking, the slack variables of inputs or outputs are not only affected by managerial inefficiency, but also by the external environment and random errors, so it is inappropriate to attribute all the efficiency impacts to managerial inefficiency without removing these two parts, so it is necessary to remove these two parts through the second stage in order to obtain a more accurate efficiency value. For the trade measurement in this study, each developing country is regarded as a decision-making unit (DMU), and the trade efficiency value of each country is calculated through a three-stage DEA model using digital transformation-related indicators as input variables, trade efficiency-related indicators as output variables, and the total level of the economy, total fiscal expenditures and total employment as external environment variables. The three-stage DEA model is introduced next.

2.1. Phase 1: Data Envelopment Analysis Modeling

Data Envelopment Analysis models, referred to as DEA models [18], include two types, the CCR model, which is based on the assumption of constant returns to scale, and the BCC model, which is based on the assumption of variable returns to scale. In this paper, we choose the latter and construct the BCC model under input orientation as follows:

$$\theta^* = \min[\theta - \varepsilon(e^t s^- + e^t s^+)] \tag{1}$$

$$s.t.\begin{cases} \sum_{k=1}^{n} \lambda_k y_k - s^+ = y_0 \\ \sum_{k=1}^{n} \lambda_k x_k + s^- = \theta \\ \sum_{k=1}^{n} \lambda_k = 1 \\ \lambda_k \geq 0, s^+ \geq 0, s^- \geq 0 \end{cases} \tag{2}$$

In the formula, θ is the effective value of the decision unit, θ^* represents the combined efficiency of each decision unit, which is the product of pure technical efficiency and scale efficiency, x, y represents the n input vector and output vector, respectively, $\lambda_\kappa (k = 1, 2, \cdots, n)$ represents the weight vector of inputs and outputs for the digital transformation of each developing country, s^+ and s^- represent the relaxation variables of the input and output terms, respectively, and ε is an Archimedean infinitesimal quantity. With the BCC model, the three efficiency values for each decision unit can be derived, in addition to the input slacks for each input indicator, providing the data needed for the second-stage SFA regression.

2.2. Phase 2: Stochastic Frontier Analysis Modeling

The analysis in the first stage yielded the slack value of the input variables, i.e., the difference between the original value of the inputs and the target value, which is affected by three components, namely, environmental factors, stochastic perturbations and managerial inefficiency, and cannot be attributed entirely to managerial inefficiency. In this stage by constructing the SFA model [19], the slack value calculated in the first stage is decomposed into a function containing three independent variables, namely environmental factors, random disturbances and management inefficiency, from which the effects of environmental factors and random disturbances are eliminated, and the constructed SFA regression equation is expressed as follows:

$$S_{ik} = f_i(z_k; \beta_i) + v_{ik} + \mu_{ik} \tag{3}$$

In Eq. (3), S_{ik} denotes the slack variable of the i rd input of the k nd decision cell $(i = 1, 2, \cdots, m; k = 1, 2, \cdots, n); z_k = (z_{1k}, z_{2k}, \cdots, z_{pk})$ denotes the p observable environmental variable, and β_i denotes the parameter to be estimated for the selected environmental variable. $f_i(z_k; \beta_i)$ denotes the effect of the environmental variable on the slack variable S_{ik}, v_{ik} denotes the random disturbance term, and $v_i \kappa \sim N(0, \sigma_{vi}^2)$. μ_{ik} denotes the managerial inefficiency term, which is assumed to follow a truncated normal distribution, i.e., $\mu_{ik} \sim N^+(\mu_i, \sigma_{ii}^2)$. such that the closer the value of $\gamma = \sigma_{ii}^2 \div (\sigma_{ii}^2 + \sigma_{vi}^2)$, γ is to 1, the larger $\sigma_{\mu i}^2$ it is, indicating that the managerial factor dominates the error part of the model, and the closer the value of γ is to 0 indicates that the random error dominates the error part of the model.

With parameters such as β_i, σ^2 and γ calculated using maximum likelihood estimation, in order to make efficient adjustments to input slack, estimates of the random disturbance term v_{tk} and the management inefficiency term μ_k need to be calculated based on the above parameters. In this paper, the method shown in equation (4) is used to decompose the mixed error term $(\gamma_{ik} + \mu_{ik})$:

$$E[v_{ik} \mid v_{ik} + \mu_{ik}] = S_{ik} - f_i(z_k;\beta_i) - E[\mu_{ik} \mid v_{ik} + \mu_{ik}] \tag{4}$$

The management inefficiency term is estimated as shown below:

$$E\left[\mu_{ik} \mid v_{ik} + \mu_{ik}\right] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\varphi\left(\frac{\delta_k\lambda}{\sigma}\right)}{\phi\left(\frac{\delta_k\lambda}{\sigma}\right)} + \frac{\delta_k\lambda}{\sigma}\right] \tag{5}$$

The adjusted input values are then derived from equation (6) below:

$$x_{ik}^{*} = x_{ik} + \left[\max(z_k\ \beta_i) - z_k\ \beta_i\right] + \left[\max(v_{ik}) - v_{ik}\right] \tag{6}$$

In equation (6), x_{ik}^{*} is the value of the original input x_{ik} after adjustment. The second part represents placing all the decision-making units under the same environment and the same luck, i.e., eliminating the interference of the external environment, and the third part represents adjusting the random interference of all the decision-making units to the same situation, i.e., eliminating the influence of random errors, and the final x_{ik}^{*} is the value of the inputs after adjustment.

2.3. Phase 3: Modified data envelopment analysis model

Using the adjusted input value x^{*}_{ik} obtained in the second stage to replace the original input value x_{ik} in the first stage, the adjusted input value and the original output value again using the BCC model for efficiency measurement, the resulting efficiency value is more real and accurate, only to exclude the environmental factors and the random interference of the management efficiency, better reflect the degree of inefficiency in management, representing the real efficiency level of the decision-making unit.

3. Digital transformation and trade efficiency indicator system construction

3.1. Digital transformation evaluation index system

In this paper, the indicator system for evaluating the level of digital transformation in developing countries will be constructed on the basis of three major principles: comprehensiveness and representativeness, hierarchy and systematicity, feasibility and data availability. The specific indicators set are as follows:

1) Digital transformation strategy. Digital strategy refers to the level of developing countries' awareness and understanding of digital transformation and potential opportunities and challenges. It involves the cognition, mindset and awakening of consciousness of managers in developing countries about digital technology and digital change. This paper argues that digital strategy includes three secondary indicators: digital strategy continuity, digital strategy breadth and digital strategy intensity. When exploring the sustainability and breadth of digital strategy, this study adopts a quantitative assessment method. First, continuity is measured based on the sum of the frequency of occurrence of digital keywords mentioned in the Management Discussion and Analysis (MD&A) section of the annual reports of digitized enterprises in developing countries in different years. This approach can reveal the extent to which developing countries are focusing on digital strategy over time. Second, for digital strategy breadth, the types of digital keywords mentioned in the MD&A section of the annual report are collected and categorized for each year. Finally, digital intensity refers to the degree of attention and emphasis that developing countries place on digital transformation in their strategic decision-making and resource investment, and is therefore quantified as the ratio of digital keywords to the total number of words in the section for each year.

2) Digital Transformation Inputs. First, digital transformation requires talents with appropriate skills and knowledge to drive and implement it. These talents usually possess expertise and skills in digital

technology, data analytics, artificial intelligence, etc., understand and apply advanced digital tools and technologies, drive digital innovation, and have a deep understanding of digital strategy. Therefore, when selecting the secondary indicators for this dimension, this paper integrates R&D personnel and personnel with digital backgrounds, and selects 2 indicators, the percentage of R&D personnel and the percentage of executives with digital backgrounds. At the same time, digital transformation requires the investment of appropriate capital, including technical equipment, software systems, data collection and analysis tools. These digital capitals can support developing countries to implement digital strategies and improve productivity, innovation and national competitiveness. Therefore, this paper selects digital software and digital hardware inputs as secondary indicators. Digital software input adopts the investment amount of software or information system in intangible assets, and digital hardware input adopts the investment amount of electronic equipment and computer category in fixed assets.

3) Digital transformation output. The output of digital transformation can contain three secondary indicators as innovation ability, growth ability and management ability. First, innovation capacity is portrayed by the number of invention patents granted. Through digital transformation, developing countries can apply new technologies and methods to realize innovation in products, services or processes, while invention patent is the exclusive right to protect new inventions or technological innovations, which is an important proof of developing countries' innovation achievements in the field of technology. Secondly, trade revenue can visualize the growth capacity of developing countries, which is measured by trade revenue. Digital transformation can bring economic benefits to developing countries through the application of digital technology, which can automate production processes, increase efficiency and reduce costs. Digital transformation can also provide better data analysis and decision support, enabling developing countries to more accurately grasp market demand, optimize resource allocation and reduce risks. Finally, the total asset turnover ratio, which can visualize the management capacity of developing countries, is used to characterize management capacity.

In summary, the indicator system for the level of digital transformation in developing countries includes 3 first-level indicators and 10 second-level indicators, as shown in table 1.

Table 1. The evaluation indicator system of digital transformation

Target layer	Primary indicator	Secondary indicator
The digital transformation level of developing countries	Digital transformation strategy	Strategic sustainability
		Strategic span
		Strategic strength
	Digital transformation investment	R&D personnel investment
		Digital executive investment
		Digital software investment
		Digital hardware investment
	Digital transition output	Innovative ability
		Growth ability
		Managerial ability

3.2. Trade Efficiency Evaluation Indicator System

3.2.1. Output indicators. The output indicators in the trade efficiency evaluation index system selected in this paper mainly include the degree of trade openness and trade competitive advantage [20].

1) Degree of trade openness. This indicator is a commonly used indicator to measure the degree of openness of each place, and this paper uses the degree of external dependence to evaluate the degree of trade openness.

2) Trade Competitive Advantage. This indicator is a commonly used indicator to measure the competitiveness of international trade, which refers to the ratio between the difference between the import and export of trade in goods and the total amount of import and export.

3.2.2. Input indicators. The input indicators in the trade efficiency evaluation index system selected in this paper mainly include three aspects: the level of economic development, human capital and infrastructure.

1) Level of economic development. The level of economic development determines a country's international trade efficiency, which can promote the efficient allocation of social capital and the rational use of resources, so this paper selects the per capita GDP and tertiary industry added value accounted for the proportion of GDP to measure the level of economic development.

2) Human Capital. Human resource is the first resource. Human capital plays an important role in international trade. Therefore, this paper selects the percentage of population with specialized education and above to reflect the level of human capital.

3) Infrastructure level. Goods transportation capacity directly affects the development of foreign trade, considering the differences in the geographical environment of developing countries, this paper selects the goods turnover to measure the level of infrastructure.

The specific trade efficiency evaluation index system is shown in Table 2.

Table 2. Trade efficiency evaluation indicator system

Project	Primary indicator	Secondary indicator
Output	Trade openness	Dependence of foreign trade
	Trade competitive advantage	Trade competitive advantage
Investment	Economic development level	Per capita GDP
		Ratio of added value of third industry in GDP
	Human capital	Proportion of population wit vocational education or above
	Infrastructure level	Turnover of goods

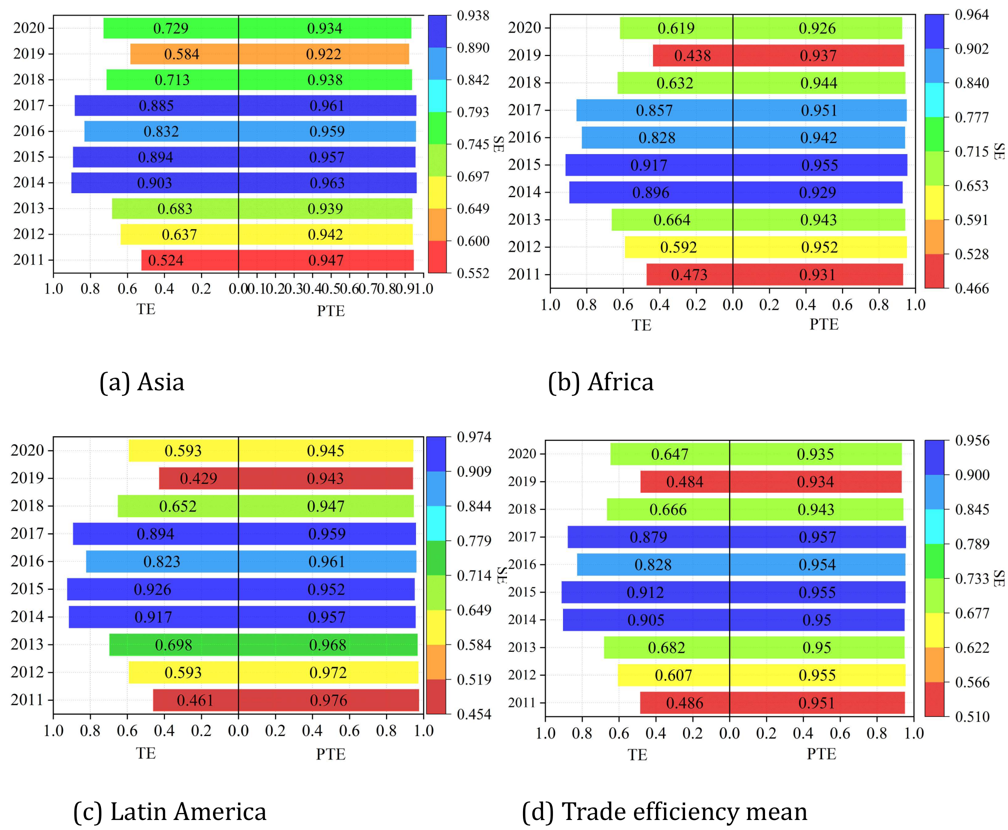
4. Empirical analysis

4.1. Data sources and sample selection

Nineteen developing countries, including China, India, Brazil, South Africa, Malaysia, the Philippines, Thailand, Indonesia, Bangladesh, Vietnam, Egypt, Nigeria, Kenya, Tanzania, Mexico, Argentina, Chile, Peru and Colombia, which geographically cover the three major regions of Asia, Africa and Latin America, were selected for this study. The data sources mainly include the World Bank database, the International Telecommunication Union database, and official statistics of each country. The data cover relevant digital transformation indicators and trade efficiency indicators from 2011 to 2020 to ensure that the results of the study are time-series and representative.

4.2. Measuring the efficiency of developing countries' international trade

4.2.1. Stage 1 DEA Efficiency Measurement. The first stage of traditional DEA efficiency evaluation measured the comprehensive technical efficiency (TE), pure technical efficiency (PTE), scale efficiency (SE) and input factor slack variables of 19 DMUs (cities) in developing countries from 2011 to 2020 year by year based on input-oriented DEA-BBC model by applying DEAP2.1 software, in which SE=TE/PTE, and then separately calculate the average efficiency value of 19 developing countries, and calculate the overall efficiency mean value of Asia, Africa and Latin America respectively, and finally the overall trade efficiency mean value of developing countries, and carry out descriptive statistics on the above efficiency values, and the results are shown in Fig. 1, in which (a)-(d) denote the average values of the Asian countries, the African countries, the Latin American countries and the trade efficiency mean values, respectively. As can be seen from the figure, according to the geographical location of developing countries, developing countries in Asia have the highest level of combined technical efficiency, followed by Latin American countries, and African countries are at the bottom. In terms of time series, the integrated technical efficiency (TE) and pure technical efficiency (PTE) of digital transformation show a wave-like upward evolutionary trend in developing countries in Asia, Africa and Latin America, and this change trend is basically consistent with the development path of developing countries. In terms of the average value of international trade efficiency in developing countries, the overall level of pure technical efficiency (PTE) is higher than that of integrated technical efficiency (TE), and it is overall at a higher level, close to the efficiency frontier.



(a) Asia (b) Africa

(c) Latin America (d) Trade efficiency mean

Fig. 1. The first phase calculates results

The study further selects the specific efficiency values of developing countries in the four periods of 2013, 2015, 2017 and 2019 for in-depth analysis, and the results are shown in Tables 3 to 6, where C1-C19 indicate the 19 developing countries selected in this paper, respectively, and IRS denotes increasing returns to scale, DRS denotes decreasing returns to scale, and "-" indicates constant returns to scale, the same below. From the table, it can be seen that the average value of comprehensive technical efficiency of each developing country is stable between 0.618 and 0.718 in these four years, the average value of pure technical efficiency is stable between 0.826 and 0.918, and the average value of returns to scale is stable between 0.710 and 0.818. Horizontally, China's international trade efficiency has been maintained at 1, and two developing countries, Egypt and Kenya, have a combined technical efficiency of 1 in 2019.Vertically, the gap in the combined technical efficiency difference among developing countries was small in 2013, and the digital transformation and development was relatively balanced among countries, but after two transitions in 2015 and 2017, the countries in 2019 The gap in the value of comprehensive technical efficiency between them has been widening, indicating that the efficiency of international trade between countries has differed significantly in recent years.

Table 3. The first phase of international trade efficiency(2013)

	Country	PTE	SE	TE	Scale compensation
2013	C1	1.000	1.000	1.000	-
	C2	0.988	0.644	0.636	DRS
	C3	0.878	0.827	0.726	DRS
	C4	0.604	1.000	0.604	-
	C5	0.968	0.901	0.872	DRS
	C6	0.699	0.554	0.387	IRS
	C7	0.629	0.585	0.368	IRS
	C8	0.952	0.913	0.869	IRS
	C9	0.686	0.573	0.393	IRS
	C10	0.958	1.000	0.958	-
	C11	0.881	0.535	0.471	IRS
	C12	0.923	0.563	0.52	IRS
	C13	0.962	0.966	0.929	IRS
	C14	0.987	0.919	0.907	IRS
	C15	0.959	0.756	0.725	IRS
	C16	0.914	0.705	0.644	IRS
	C17	0.957	0.864	0.827	IRS
	C18	0.831	0.849	0.706	IRS
	C19	0.633	0.902	0.571	DRS
Mean		0.864	0.769	0.690	

Table 4. The first phase of international trade efficiency(2015)

	Country	PTE	SE	TE	Scale compensation
2015	C1	1.000	1.000	1.000	-
	C2	0.928	0.550	0.510	DRS
	C3	0.507	0.881	0.447	DRS
	C4	0.584	0.486	0.284	IRS
	C5	0.957	0.903	0.864	DRS
	C6	0.492	1.000	0.492	-
	C7	0.611	0.390	0.238	IRS
	C8	0.945	0.954	0.902	IRS
	C9	0.709	0.458	0.325	IRS
	C10	0.866	1.000	0.866	-
	C11	0.906	0.404	0.366	IRS
	C12	0.961	0.571	0.549	IRS
	C13	0.948	0.924	0.876	IRS
	C14	0.946	0.829	0.784	IRS
	C15	0.893	1.000	0.893	-
	C16	0.988	0.542	0.535	DRS
	C17	0.960	0.843	0.809	DRS
	C18	0.896	0.602	0.539	IRS
	C19	0.638	0.740	0.472	IRS
Mean		0.826	0.710	0.618	

Table 5. The first phase of international trade efficiency(2017)

	Country	PTE	SE	TE	Scale compensation
2017	C1	1.000	1.000	1.000	-
	C2	0.916	0.758	0.694	DRS
	C3	0.932	0.945	0.881	IRS
	C4	0.674	1.000	0.674	-
	C5	0.707	0.719	0.508	DRS
	C6	0.553	0.966	0.534	IRS
	C7	0.714	0.570	0.407	IRS
	C8	0.987	0.957	0.945	IRS
	C9	1.000	0.714	0.714	IRS
	C10	0.858	0.817	0.701	IRS
	C11	0.911	0.552	0.503	IRS
	C12	0.951	0.560	0.533	DRS
	C13	0.968	1.000	0.968	-
	C14	0.965	0.941	0.908	IRS
	C15	0.906	0.803	0.728	IRS
	C16	0.944	1.000	0.944	-
	C17	0.970	0.949	0.921	IRS
	C18	0.899	0.664	0.597	IRS
	C19	0.783	0.625	0.489	IRS
Mean		0.876	0.818	0.718	

Table 6. The first phase of international trade efficiency(2019)

	Country	PTE	SE	TE	Scale compensation
2019	C1	1.000	1.000	1.000	-
	C2	0.967	0.677	0.655	IRS
	C3	0.936	1.000	0.936	-
	C4	0.725	0.450	0.326	IRS
	C5	0.808	0.479	0.387	IRS
	C6	1.000	0.758	0.758	DRS
	C7	0.803	0.454	0.365	IRS
	C8	0.892	0.529	0.472	IRS
	C9	1.000	0.555	0.555	DRS
	C10	0.852	0.859	0.732	IRS
	C11	1.000	1.000	1.000	-
	C12	0.935	0.536	0.501	IRS
	C13	1.000	1.000	1.000	-
	C14	0.917	0.998	0.915	IRS
	C15	0.888	0.653	0.580	IRS
	C16	1.000	0.790	0.790	DRS
	C17	0.954	1.000	0.954	-
	C18	0.893	0.636	0.568	IRS
	C19	0.872	0.476	0.415	IRS
Mean		0.918	0.729	0.679	

4.2.2. Stage 2 DEA Efficiency Measurement. Since the DEA model in the first stage lacks the consideration of external environmental factors and random disturbance terms, it is difficult to measure the real level of indicators related to digital transformation in developing countries, so the influence of external environmental factors and random disturbance terms is further removed by the SFA model.

The digital transformation strategy, digital transformation inputs and digital transformation outputs obtained from the DEA model in the first stage are taken as the explanatory variables, and total fiscal expenditure, total economic level and total employment are taken as the revealing variables to analyze whether the external environmental variables have a significant effect on the input slack variables, and the test results are obtained by building the SFA regression model and applying the Frontier 4.1 software to make calculations As shown in Table 7, R1-R3 in the table denote digital transformation strategy input slack variables, digital transformation input slack variables, digital transformation output input slack variables, respectively, and ***, **, **, * denote the significant level of 1%, 5%, 10%, respectively, the same below. As can be seen from the table, the one-sided error likelihood ratio test for the three input slack variables measured by the first stage DEA passed the 1% significance test, rejecting the original hypothesis and indicating that the SFA regression model is reasonable. And the γ values of the input slack variables tend to be closer to 1. The empirical estimation results of σ^2 and γ also pass the 1% significance test, indicating that the management inefficiency in the mixed error term has a greater impact on the slack variables, while the impact of random errors is smaller. Except for the effect of the total economic level on the digital transformation input slack variable, the rest of them can pass the 10% significance test, which indicates that the total economic level does not have a significant effect on the digital transformation inputs, which is also in line with the reality that all developing countries are increasing the expenditure on digital transformation inputs. In addition, the effects of the three environmental variables on the input slack variables of digital transformation strategies reach the 1% significance level, indicating that the selected environmental variables have a relatively large impact on the input slack variables, in which the increase of the total level of the economy shows a positive correlation with the attraction of resources for foreign trade inputs in developing countries. Total fiscal expenditure and total employment have a significant bootstrapping effect on the flow of input resources for foreign trade in developing countries, which is due to the fact that an increase in total fiscal expenditure will effectively increase the financial and human investment in digital transformation. In order to eliminate the influence of external environmental variables and random error terms, it is necessary to measure the random variables through the SFA model and eliminate their influence on the efficiency value, so as to obtain the adjusted input value and then re-measure the efficiency of foreign trade.

Table 7. The SFA returns of second phase

Variable	R1	R2	R3
Constant	-2.58*** (0.047)	-3.462*** (0.371)	-2.987*** (0.504)
Total economic level	0.148*** (0.032)	-0.236 (0.352)	1.215* (0.542)
Total finance expenditure	-0.239*** (0.031)	-1.239*** (0.319)	1.019* (0.472)
Total employment	0.154*** (0.027)	2.894*** (0.297)	-0.583* (0.326)
σ^2	0.458*** (0.032)	32.718*** (1.984)	88.439*** (5.762)
γ	0.647*** (0.038)	0.284*** (0.036)	0.487*** (0.037)
Log-likehood-function	-1248.367	-6174.358	-6794.368
LR test of one-side error	663.498***	98.043***	399.752***

4.2.3. Stage 3 DEA Efficiency Measurement. By adjusting the input variables in 2011-2020, the input-oriented DEA-BBC model and DEAP2.1 software are used again to merge them with the original output variables to obtain the integrated technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) of the digital transformation word configuration excluding the external environment and random error factors, and the developing countries' The average value of the efficiency value as the efficiency value of each continent, to get the third stage 2011-2020 nineteen developing countries international trade comprehensive technical efficiency value, the results are shown in Figure 2. From the figure, it can be seen that the comprehensive technical efficiency value of international trade of developing countries in 2011-2020 in the third stage has a wave-like upward trend on the whole, in which the comprehensive technical efficiency value of China is always 1, which represents the highest level of international trade efficiency of developing countries. Overall, the average efficiency value of developing countries' international trade is 0.728, of which there are only 3 countries above the average efficiency level (China, Peru, Colombia), and the trade efficiency value of the remaining 16 countries is lower than the average efficiency level, indicating that the gap between the efficiency of developing countries' international trade is more disparate.

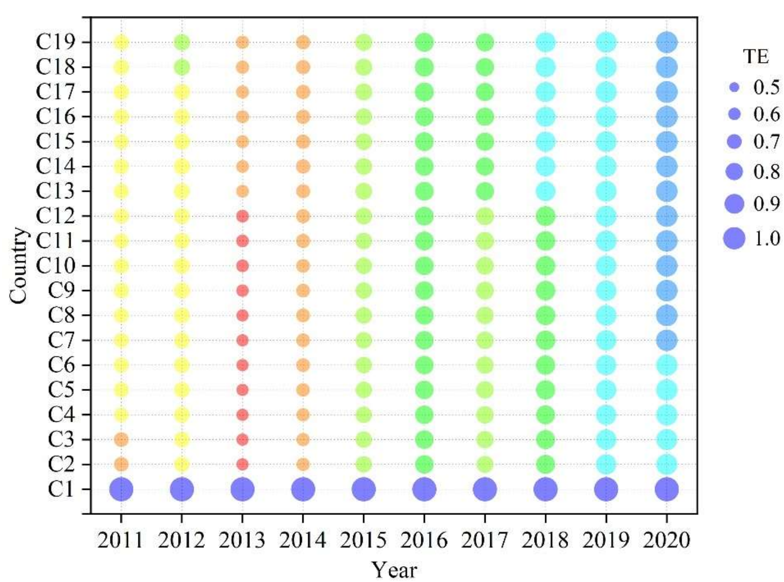


Fig. 2. International trade efficiency

4.3. Analysis of the impact of differentiation

4.3.1. Regression modeling. Multiple linear regression models are constructed to analyze the degree of influence of each factor on trade efficiency by taking the difference in trade efficiency as the dependent variable, and each indicator in the digital transformation index system and other control variables that may affect trade efficiency (R&D investment intensity, R&D personnel investment intensity, industrial development efficiency, degree of opening up to the outside world and so on) as the independent variables. The regression model constructed is as follows:

$$TE_{ij} = \beta_0 + \beta_1 DT_{ij} + \beta_2 K_{ij} + \beta_3 L_{ij} + \beta_4 PR_{ij} + \beta_5 Open_{ij} + \varepsilon_{ij} \tag{7}$$

Where TF is the international trade efficiency gap, DT is the level of digital transformation, K is the intensity of R&D investment, L is the intensity of R&D personnel investment, PR industrial development efficiency, $Open$ is the index of degree of openness to the outside world, i denotes individuals, j denotes time, $\beta_1, \beta_2, \cdots, \beta_5$ is the regression coefficient, and ε is the random error term.

4.3.2. Analysis of regression results:

1) Regression analysis of country data. The baseline regression is first conducted using ordinary least squares, and the Hausman test indicates that a fixed effects model should be used for estimation. Considering the potential endogeneity problem of the model, two-stage least squares is then used for estimation. In the selection of instrumental variables, firstly, the first-order lag terms of the respective variables are conservatively adopted as instrumental variables, based on which the cross-multiplication terms of the number of telephones per 100 people in each developing country in 2012 and the amount of Internet investment in each country in the previous year are adopted as the instrumental variables for the level of digital transformation, and the amount of Internet investment is expressed in terms of the investment in the whole society's fixed assets of the information transmission, computer services and software industry, and the instrumental variables are noted as IV_Phone, and then the TSLS estimation is performed separately. The results are shown in Table 8. As can be seen from the table, the elasticity coefficient of digital transformation on the efficiency gap of international trade is -0.274, and passes the statistical test at 1% significance level, while the estimation results using IV-TSLS have been consistent with the baseline regression results, indicating that the endogeneity of the model did not cause fatal impact on the estimation results, and the results have a good reliability. Taken together, the elasticity coefficient of digital transformation on the international trade efficiency gap of developing countries is negative, and the role of digital transformation in narrowing the trade efficiency gap is greater than that of widening it, which is generally conducive to narrowing the international trade efficiency gap and promoting efficiency convergence.

Table 8. Regression analysis results of national data

Variable	Reference regression	Endogenous analysis	
		First order hysteresis	IV_Phone
$Cons$	-0.086 (-0.513)	0.589 (0.764)	-0.023 (-0.104)
K	-0.107*** (-2.674)	0.132 (0.563)	-0.071** (-1.992)
L	0.004 (0.128)	-0.238 (-0.105)	-0.029 (-0.607)

DT	-0.274*** (-8.573)	-0.369*** (-3.258)	-0.219*** (-5.247)
PR	-0.039 (-1.293)	-0.041 (-0.472)	-0.047 (-1.632)
Open	-0.157*** (-2.758)	-0.368 (-1.337)	-0.136** (-2.408)
Hausman	11.384*	—	—
P	0.000	0.000	0.000
R^2	0.897	0.862	0.834

2) Sub-regional regression. On the basis of the regression of data in each country, and then regression analysis based on subregional data, Hausman test results show that the Asian region adopts the fixed effect model, and the African and Latin American regions adopt the random effect model, and the results are shown in Table 9. The elasticity coefficients of digital transformation in Asia, Africa and Latin America are 1.398, -0.953 and -0.603 respectively, and all of them pass the statistical test, so the digital transformation in the Asian region widens the trade efficiency gap of developing countries, while the digital transformation in Africa and Latin America narrows the trade efficiency gap between them and other developing countries. This is mainly because, in terms of infrastructure, economic development and other aspects of the Asian region has a greater advantage in comparison, the digital transformation makes the Asian region's leading edge has been continuously consolidated, the driving role of digital technology in trade efficiency has been continuously enhanced, thus widening the innovation gap. For Africa and Latin America, digital transformation has led to a better integration of digital technology and industrial development, and with the help of digital technology, we can better absorb the experience of advanced regions and industries; at the same time, digital transformation also plays an important role in external resource allocation, cost reduction and efficiency enhancement, etc., which can effectively improve the trade efficiency of Africa and Latin America and narrow the gap of international trade efficiency among developing countries.

Table 9. Regression analysis result of regional data

Variable	Asia	Africa	Latin America
Cons	3.676*** (2.457)	-2.709 (-1.438)	-0.042 (-0.075)
K	-0.438* (-1.847)	0.182 (0.393)	-0.017 (-0.093)
L	0.258 (1.109)	-0.479 (-0.873)	-0.011 (-0.087)
DT	1.398** (4.032)	-0.953** (-3.818)	-0.603*** (-4.682)
PR	-1.793*** (-3.713)	0.315 (0.781)	0.029 (0.196)
Open	0.254 (0.839)	0.327 (0.592)	-0.208 (-1.306)
Hausman	31.452***	—	—
P	0.000	0.000	0.000
R^2	0.873	0.504	0.398

5. Conclusion

This paper uses a three-stage DEA model to quantitatively measure the international trade efficiency of developing countries in the process of digital transformation, and constructs a regression model based on the quantitative results to analyze the impact of digital transformation in the trade efficiency gap between countries.

1) In the first stage of measurement, developing countries located in Asia have the highest level of integrated technical efficiency, followed by Latin American countries, and African countries have the lowest level of integrated technical efficiency. However, in terms of time, the comprehensive technical efficiency of each developing country shows a wave-like upward trend from 2011 to 2020. In the second stage, the SFA model removes the effects of the external environment and the random interference term, so that the efficiency measurement results in the third stage more clearly show the trend of wave-like increase in the efficiency value. Meanwhile, in the third stage of the measurement, China's comprehensive technical efficiency value in 2011-2020 is always 1. The average value of trade efficiency of developing countries is 0.728, but only three countries, China, Peru and Colombia, have trade efficiency exceeding this average value, and the trade efficiency of the remaining 16 countries is below the average standard. It shows that the international trade efficiency of developing countries is seriously differentiated.

2) The elasticity coefficient of digital transformation on trade efficiency gap is -0.274, which is significant at 1% level and passes the Hausman statistical test. It shows that the overall narrowing effect of digital transformation on the trade efficiency gap of developing countries is greater than the widening effect, and the trade efficiency gap between various developing countries can be effectively narrowed by realizing digital transformation. However, in the subregional regression, the elasticity coefficient of digital transformation in Asia is 1.398, and the elasticity coefficients in Africa and Latin America are -0.953 and -0.603, which suggests that the digital transformation in Asia will widen the trade efficiency gap among developing countries, while the digital transformation in Africa and Latin America will narrow the trade efficiency gap among developing countries. The main reason for this result is that Africa and Latin America borrow digital technology to better optimize the allocation of foreign trade resources, thus effectively improving the efficiency of international trade. Therefore, developing countries in Africa and Latin America need to vigorously accelerate the pace of digital transformation to minimize the international trade efficiency gap with Asian countries and countries

in other regions.

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