ISSN 1330-3651 (Print), ISSN 1848-6339 (Online) https://doi.org/10.17559/TV-20240913001988
Original scientific paper

Prediction of Cities' Digital International Trade Competitiveness based on Neural Network

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Abstract: This paper adopts K-means neural network to analyze and study the direction, path and scope of influence of digitalization on the international competitiveness of 298 cities. The study shows that the degree of digitalization is positively correlated with the city's trade competitiveness. The breadth of digital development as a mediating variable will inhibit the promotion of digitized degree for the city's trade competitiveness. When the degree of financial development and the productive efficiency of the product are added as regulated variable, the inhibitory effect of the breadth of digital development on promoting competitiveness for digitized degree can be partially offset; and the digitized degree itself will weaken its positive promotion effect with the city's international trade competitiveness if it is overdeveloped. The study theoretically adopts K-means neural network to predict the impact mechanism of the digital economy on the city's international trade, and in practical application, it helps the city to formulate the future development planning direction and focus.

Keywords: city's trade competitiveness; digital depth; digital international trade; K-means neural network

1 INTRODUCTION

According to the Worldwide Digital Transformation Spending Guide published by the International Data Corporation (IDC), the global digital transformation investment scale has exceeded $1,5 trillion by 2022, and countries and industries are accelerating their digital transformation to find a breakthrough in international trade. Therefore, it is crucial to study the influence degree and influence mode of digitized degree on international trade competitiveness. The application of the digital economy provides new trade opportunities for countries with relatively backward economies to participate in digital services [1]. The application of economic digitization is more effective in middle-income countries and has a long-term impact in low-income countries [2]. The application of the digital economy works through the establishment of digital platform ecosystems, based on the application and development of digital infrastructure, which in turn generates the phenomenon of platformisation [3]. In terms of foreign trade, the digital economy has a positive impact on foreign trade exports [4]. It not only significantly promotes the growth of product exports in terms of price margin and extensive margin [5], but also leads to a significant improvement in the export product quality [6] and the manufacturing export competitiveness [7]. In terms of industrial structure, digitalization enables cities to increase the intensity of manufacturing trade and enhance the impact of trade between emerging economies [8], as well as to achieve urban sustainable development by strengthening green technology innovation and human capital [9]. At the same time, in China, the application of digital economy technology has problems such as uneven district development. Among them, the influence degree of the application of digital economy on the economy gradually decreases from the western region to the central and eastern regions [10].

Before deep learning technology to predict urban competitiveness, the data must be pre-processed. This includes steps such as data denoising, feature engineering, and data normalization. The ability of neural network models to handle high-dimensional and unstructured data makes them excellent at these tasks. The changes brought about by the digitized process challenge existing trade rules and the need for new trade rules [11]. At a time when the world is promoting the high-quality development of the digital economy and the in-depth application of digital industrial clusters, if the government pursues digital protectionism measures such as government restrictions on Internet access and data flow [12] and creates digital trade barriers, they will have the same effect as commodity barriers and will weaken the international trade competitiveness of the region [13]. In this paper, the regression analysis of multidimensional sample data sets is combined with the method proposed in literature [14]. Firstly, the data set samples are abstracted and clustered using the K-means algorithm to obtain the data feature set. In the data set, the clustering center is selected and iteratively divided, and then the weight coefficient of hidden layer in the neural network model is calculated according to the partition result. According to the trained classifier, the clustering result of the corresponding partition is output through the sample data, so as to obtain the sample feature points after the partition. For digital protectionism, countries are vigorously accelerating their own digital applications and strengthening their own digital trade legislation [15]. At the same time, they formally recognize the neutrality of digital technology as a regulatory principle in the World Trade Organization (WTO), and make appropriate self-definition restrictions when necessary. Under the premise of global good development to protect the digital economy, it also drives industrial communication among countries [16]. Among them, the input of both digital infrastructure and digital media can significantly promote the international competitiveness of the manufacturing industry [17]. It can be seen that the above research studies how the digital economy affects the city's international trade competitiveness from different perspectives and all dimensions, but fails to analyze the direction and degree of its impact on the city's trade competitiveness from the perspective of the digital economy itself.

Scholars have conducted extensive and profound research on the interaction between the digital economy and trade from different perspectives, and the research results have laid an important foundation for exploring the digital economy, trade development, and trade competitiveness. However, the current exploration and research on how the digital economy interacts with new technology, finance and production to enhance the city's international trade competitiveness and other perspectives mainly focus on the impact of the digital economy as a whole on trade competitiveness, and in particular lack influence difference of the digital economy in horizontal and vertical aspects on trade competitiveness. In this paper, the dimensionality of multidimensional data is reduced to two-dimensional data by K-means method and its clustering hyperparameters are obtained, so as to build an iterative feature learning model of neural network. To a certain extent, this paper smooths the influence of a few outliers in multidimensional data samples on the accuracy of the overall model, and improves the accuracy of the urban competitiveness prediction model in order to improve the classification results of large data sets. To a certain extent, this paper smooths the influence of special regions in urban agglomeration data samples on the prediction accuracy of the overall competitiveness, and improves the accuracy of the global regression analysis model in order to improve the classification results of large data sets. Finance, production and emerging technology can jointly affect the city's international trade competitiveness; it focuses on analyzing the impact of the application of the digital economy on the international competitiveness of the city itself at the urban areas level.

2 K-MEANS NEURAL NETWORK PREDICTION

At present, common regression algorithms reduce the empirical errors generated in the iterative process through data preprocessing processes such as feature selection and dimensionality reduction [18]. However, this process reduces the effective feature information content inside the data and affects the performance of subsequent combined models. In this paper, the algorithm first establishes the initial model of the multi-layer neural network according to the training samples, then uses K-means method to manage the input layer of the neural network, calculates the dimensionality attribute value of the data of multiple input layers to adjust the weight parameters, and makes the output layer obtain the best response value after iteratively weighted in the hidden layer [19]. Then, the maximum information dimension in the same kind of samples is calculated with the sample clustering feature points corresponding to the best response values, and the prediction model containing data feature information is constructed in the output layer neurons. Finally, in the output layer of the combined model, the data test results after sample set traversal are adjusted, the test set is compared and the accuracy is verified.

The improved neural network algorithm in this paper will obtain the data point corresponding to the maximum response value in the training sample set as the representative sample feature point, and then construct the K-means prediction model in the output layer. In this paper, sequence features are extracted and then K-means clustering is performed to obtain the feature set of data samples. This process is the key step to distinguish the feature significance in the algorithm. The algorithm flow is shown as follows.

Step 1: Construct the input layer boundary of K-means clustering according to Eq. (5).

Step 2: Calculate the iteration mode of the data sample, adapt the weight value of each iteration, establish the feature point x_i of the cluster after the training iteration, determine its classification, and obtain the output result of the optimal clustering.

Step 3: On the basis of classification iteration, find out the data points, and then screen the data.

Step 4: Until the clustering interval of the same kind is found for the remaining data points, the clustering center of the final clustering result corresponds to the neuron weight result of the input layer in the classifier of the algorithm in this paper.

Step 5: Calculate the generalization error of the sample at the output layer and adjust the output of the regression analysis results. The algorithm flow chart is shown in Fig. 1.

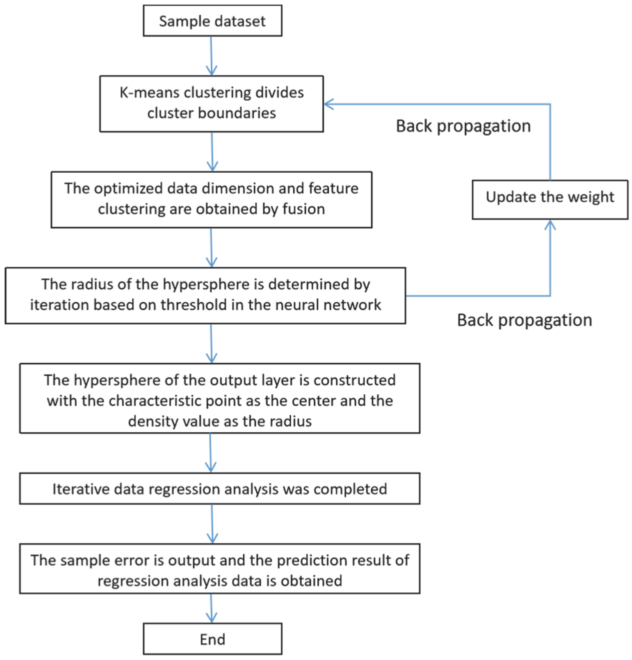

Figure 1 The workflow of K-means neural network

3 DESCRIPTIONS OF K-MEANS MODEL
3.1 Modeling

In order to verify the impact of digital economy on the city's international trade competitiveness, the basic model constructed in this paper is as follows:

Drawing on the research methodology of Yao Zhanqi and Xiong Qiyan [22] on the impact of digitization on the international competitiveness of regional economies, a benchmark regression equation is established based on the fact that the degree of digitization has an impact on the competitiveness of international trade to a certain extent:

$$\begin{aligned} &\ln Ctc_{it} = \\ &= \alpha_0 + \alpha_1 \cdot \ln Digy_{it} + \alpha \cdot \ln Control_{it} + \mu_{it} + \delta_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

$\ln Ctc_{it}$ is the international competitiveness of Chinese cities in region i in period t. $\ln Digy_{it}$ is the level of digital economy development in region i in period t, with $\ln Control_{it}$ they are the control variables. μ_{it}, and δ_{it} are city and time fixed effects, respectively, and ε_{it} is the randomized disturbance term

3.2 Description of Variables
3.2.1 Explained Variables

Competitiveness of cities in international trade (*Ctc*). The main methods for measuring international trade competitiveness are the comparative competitive advantage (RCA) and the trade competitiveness index (TC). Comparative Competitive Advantage (RCA) reflects the relative advantage of country i's exports of product *j* in comparison with the world average level of exports, and is suitable for calculating and comparing the competitiveness advantage of an industry in different countries. The trade competitiveness index (TC) indicates the proportion of a country's export-import trade balance to its total export-import trade, and is used to compare the international competitiveness of different regions, calculated as in Eq. (2).

$$Ctc_{it} = \frac{X_{it} - M_{it}}{X_{it} + M_{it}} \tag{2}$$

where Ctc_{it} denotes the city's international competitiveness of city *i* in year *t*, and X_{it} denotes the import value of city *i* in year *t*, and M_{it} denotes the export value of city *i* in year *t*.

3.2.2 Core Explanatory Variables

Degree of Digital Economy Development (*Dig*). The level of digitization can be assessed from two viewpoints: from the enterprise angle, digital industrialization and industrial digitization can establish the extent of digitization within the region, and from the governmental standpoint, digital governance can be utilized for evaluation. Among them, the evaluation of digital industrialization in the digital industry applies Hu Jabin et al.'s [20] methodology, which factors in the value-added of information transmission, software services and information technology services. Industry digitization is measured by Jiang Qiping, Liu Yuyang and Xu Binhong [21], using an industry-specific measuring method to determine the degree of digitization in the primary industry. This involves calculating the number of Taobao villages and the rural broadband penetration rate. Objective evaluations are excluded unless specifically noted as subjective. The text is clear, concise, and presented in simple sentences with a logical structure and causal connections. Technical abbreviations are explained when first used. Conventional academic sections are included, formatted consistently, and titles are factual and unambiguous. Language is clear, objective, and value-neutral, avoiding biased, emotional, figurative, or ornamental language. Passive tone is used, and first-person perspectives are avoided. High-level, standard language is employed consistently with technical terms. Sentences have a conventional structure and avoid unusual or ambiguous terminology. The style guide is adhered to with consistent citation, footnote, and formatting styles. Quotes are clearly marked, and filler words are avoided. The language is kept formal, avoiding contractions, colloquial words, informal expressions, and unnecessary jargon. Positions on subjects are made clear through hedging, avoiding biased phrases. Precise subject-specific vocabulary is used when conveying meaning more precisely than non-technical terms. The text is grammatically correct, free from spelling mistakes and punctuation errors. The degree of digital transformation of the secondary industry can be calculated using the total online retail sales of tangible goods and the R&D investment of large-scale industrial enterprises. Additionally, the degree of digital transformation can also be measured by considering the value added of telecommunication services and financial services. The value added of the telecommunication and financial sectors will be used to analyze the degree of digital transformation of the tertiary industry. The level of government digitization can be assessed by quantifying the number of pilot policies that have been implemented to measure the government's prioritization of digitization, evaluating the quantity of data and information technology infrastructures to gauge the level of governmental support for digitization, and by counting the number of government websites to determine the extent of digitization applied by the government. These factors can then be used to evaluate the government's level of digitization development.

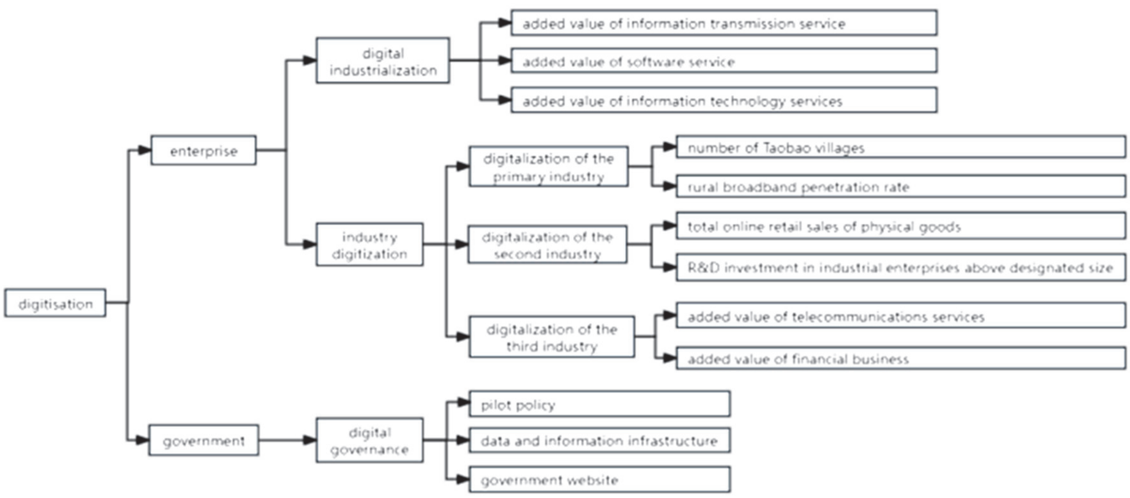

Figure 2 Calculation of the degree of development of the digital economy

3.2.3 Intermediate Variables

Breadth of digitization (*Bdig*). The scope of digitalization can be assessed by different methods, including quantifying the "quantity of financial institutions", "quantity of financial activity", and "number of financial sector employees" in the area. Another approach is to calculate the "quantity of financial institutions", "quantity of financial business", "number of financial workers", "number of mobile phones", "volume of telecommunication services", and "Internet usage" in the area to obtain a comprehensive measurement of the breadth of digital advancement. The second method of calculation is founded on the notion that third parties can perform online transactions related to insurance, finance, and payments by linking their bank cards, and employing third-party payment accounts connected to their bank cards to gauge the digitalization scope of a region in a specific year. This study employs the second approach, which utilizes the digital inclusion index calculation method offered and takes the digital breadth determined by the Digital Finance Research Centre at Peking University and the Ant Science and Technology Group Research Institute as the intermediate variable.

3.2.4 Moderating Variables

Degree of financial development (*Dfin*). The degree of financial development may be quantified as the ratio between the balance of loans from financial institutions and the value of regional production at year-end. Such ratio indicates the role of funds provided by financial institutions in the region as an economic lever.

Productivity (*Epro*). The ratio of large-scale industrial enterprises to their workforce reflects productivity, i.e. the average employee output in all city-based firms.

3.2.5 Control Variables

In this study, we use the number of invention patents examined and approved annually to represent the number of invention patents authorized (*Npa*), financial efficiency (*Efin*) as the balance of loans and deposits held by financial institutions at the year-end, the proportion of fiscal expenditure (*Pfis*) as annual local fiscal expenditure and annual regional gross domestic product, and the ratio of total annual imports and exports and annual regional gross domestic product to gauge the level of openness to international trade (*Dopen*). Technical abbreviations will be explained upon first use, and all language will adhere to academic standards of objectivity, clarity, and formality. The retail sales of consumer goods in urban areas, the current assets of all urban enterprises, and the output value of large-scale enterprises represent consumer consumption capacity (*Ccons*), firm vitality (*Venter*), and firm productivity (*Cpro*), respectively.

Table 1 Calculation methods and statistics for the main variable

Variant	Name		Calculation Method	Sample Size	Average Value	variance (statistics)
explanatory variable	Competitiveness of cities in international trade	*Ctc*	(Exports - Imports) / (Exports + Imports)	2,980	0,5709573	0,2813671
interpreted variable	Level of digital development	*Dig*	System of indicators for the development of the digital economy	2,949	209,6547	82,7344
intermediary variable	Breadth of digital development	*Bdig*	Breadth system of digital financial inclusion coverage	2,980	192,6181	65,8659
moderator variable	Level of financial development	*Dfin*	Balance of loans from financial institutions at the end of the year/regional production value	2,980	5,254915	5,427923
	Product productivity	*Epro*	Number of industrial enterprises above large scale/number of employees on board	2,980	46,76421	88,84897
control variable	Number of patents granted for inventions	*Npa*	Number of patents for inventions examined and approved per year	2,980	1860,347	3507,934
	Financial efficiency	*Efin*	Balance of loans from financial institutions at the end of the year / Balance of deposits from financial institutions at the end of the year	2,980	1,640372	0,629525
	Share of fiscal expenditure	*Pfis*	Expenditures from the general budget of local finances/Gross Regional Product	2,980	0,3612912	0,9165156
	degree of openness to the outside world	*Dopen*	Total exports and imports/gross regional product	2,980	0,0002725	0,0004721
	Consumer spending power	*Ccons*	Total retail sales of consumer goods in the region	2,980	1,05E + 07	1,44E + 07
	Corporate Vitality	*Venter*	Total current assets of all companies in the region	2,981	1,91E + 07	3,29E + 07
	Enterprise production capacity	*Cpro*	Gross industrial output value above scale	2,982	4,53E + 07	6,23E + 07

3.3 K-means Analysis Dataset

The experimental configuration set in this paper is Intel i7-6700 2.60GHz processor and 16GB memory. This paper adopts TensorFlow2.1 framework to implement. The import and export volumes for every city, scale of the industrial enterprises, number of workers employed, patent authorizations, financial institution loan and deposit balances, local treasury budgets, retail sales of consumer goods, liquid assets of regional firms, and total industrial production output values above a certain scale have been sourced from the EPSDATA database in Fig. 3.

Tab. 2 displays the descriptive statistics of each variable, indicating that the variance inflation factor (*VIF*) of each variable is less than 5. As a result, there are no significant issues of multicollinearity.

Table 2 Descriptive statistics of variables

	Ctc	*Dig*	*Npa*	*Efin*	*Pfis*	*Dopen*	*Ccons*	*Venter*	*Cpro*
Ctc	1								
Dig	−0,0045	1							
Npa	−0,1380	0,0164	1						
Efin	0,1078	−0,1178	−0,0168	1,0000					
Pfis	−0,0065	0,0124	−0,0935	-0,0999	1				
Dopen	−0,1656	−0,0600	0,3312	−0,0816	−0,1276	1			
Ccons	−0,0220	−0,1095	−0,0365	−0,0199	−0,0026	0,1068	1		
Venter	−0,0578	−0,0901	−0,0414	0,0161	0,0557	0,0553	0,8697	1	
Cpro	−0,0275	−0,0812	−0,0204	−0,0068	0,0042	0,1202	0,7370	0,8237	1
VIF		1,02	1,14	1,01	1,06	1,19	4,23	4,08	3,19

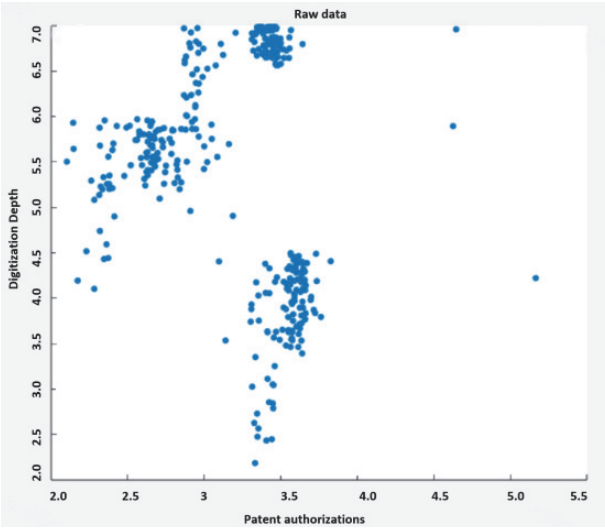

Figure 3 Raw data of K-means neural network

4 BASIC REGRESSION
4.1 Reference Regression

Tab. 3 presents the findings of the reference regression by adding solely the central explanatory variables in column (1), where the positive coefficient worth of 0,0952 for the degree of digital economic advancement is insignificant. This suggests that the digital economy may enhance the global competitiveness of the cities in China. Based on column (1), control variables are sequentially incorporated, and the outcomes are presented in columns (2) to (7) of Tab. 5. After including the control variables, the coefficients of the core variables increase gradually and all of them can achieve a significant level of 1%. This indicates that the level of digital economy development and control variables such as the number of authorized invention patents, financial ratio, the proportion of fiscal expenditures, city openness, consumer consumption capacity, enterprise vitality, enterprise production capacity, and total factor productivity can jointly influence the international trade competitiveness of cities, and the impact is relatively significant. Therefore, hypothesis 1 is supported. Hypothesis 1 is confirmed by significant results. Moreover, it suggests that urban digitization alone cannot positively affect urban trade competitiveness. Instead, it can only bolster urban international trade and foster urban economic growth through the combined efforts of production, consumption, economy, finance, and innovation.

Table 3 Benchmark regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	reg1	reg2	reg3	reg4	reg5	reg6	reg7	reg8
ln*Dig*	−0,000842	0,0871	0,360***	0,366***	0,492***	0,507***	0,504***	0,507***
	(0,0551)	(0,0534)	(0,0957)	(0,0906)	(0,0861)	(0,0856)	(0,0861)	(0,0854)
ln*Npa*		−0,137***	−0,132***	−0,0524**	−0,00327	−0,0113	-0,0116	0,00211
		(0,0169)	(0,0168)	(0,0185)	(0,0182)	(0,0183)	(0,0183)	(0,0187)
ln*Dfin*			−0,182***	−0,199***	−0,251***	−0,275***	−0,274***	−0,268***
			(0,0531)	(0,0503)	(0,0476)	(0,0478)	(0,0480)	(0,0477)
ln*Pfis*				0,208***	0,142***	0,145***	0,146***	0,133***
				(0,0251)	(0,0246)	(0,0245)	(0,0246)	(0,0247)
ln*Dopen*					−0,171***	−0,156***	−0,156***	−0,155***
					(0,0190)	(0,0194)	(0,0194)	(0,0193)
ln*Ccons*						−0,0690**	−0,0577	−0,0487
						(0,0224)	(0,0407)	(0,0405)
ln*Venter*							−0,0118	−0,0203
							(0,0355)	(0,0353)
ln*Cpro*								0,0599**
								(0,0186)
_cons	−0,738**	−0,328	−1,520***	−1,640***	−4,214***	−3,001***	−2,974***	−3,266***
	(0,281)	(0,271)	(0,439)	(0,416)	(0,484)	(0,621)	(0,627)	(0,628)
N	590	590	590	590	590	590	590	590
R^2	0,000	0,102	0,119	0,212	0,308	0,319	0,319	0,331

The findings from the introduction of control variables indicate a significantly negative regression coefficient for the number of invention patents. This suggests that excessively high levels of innovation patents are not favorable for enhancing the international trade competitiveness of the city. It is possible that an increase in patented technology could create technical obstacles, impeding the flow of digital scientific and technological advancements. This impediment could result in a decrease in the city's export volume and ultimately reduce its international competitiveness. Additionally, the negative regression coefficient of the degree of openness suggests that higher degrees of openness could inhibit the enhancement of the city's competitiveness, passing the 1% significance test. Once the level of openness in the city reaches a high point, there will be a significant increase in import and export volume, leading to an impact on the domestic market. This will result in a period of rebalancing for the domestic market, during which production costs and the need for production enterprises to readapt will cause a loss of both capital and time. The city's competitiveness will be negatively affected as a result. Moreover, it is likely that financial expenditure, financial ratio, and production efficiency positively influence international competitiveness. This is because an increase in financial expenditure implies future development priorities for enterprises, while an increase in financial ratio can facilitate the practical implementation of digitalization. In addition, an improvement in production efficiency can aid the integration of digitalization with international trade, thereby enhancing the city's international trade competitiveness. The negative regression coefficients for consumption capacity and firm dynamism arise because high consumption capacity cities concentrate on internal circulation, reducing their motivation to seek external development. Conversely, industries located in regions lacking dynamism actively pursue new technologies to overcome production bottlenecks.

4.2 Robustness Check

To enhance the robustness of the empirical model and test results, this paper employs several measures to carry out robustness tests. Specifically, the first measure involves changing the time window. On September 4, 2016, Hangzhou hosted the G 20 summit where the G 20 formally adopted the "G 20 Initiative on Development and Cooperation in the Digital Economy". This marked the world's entry into the digital era and the flourishing of the digital economy. Meanwhile, the global trade volume decreased by 5,6% YoY in 2020, attributable to the cessation of global trade enforced by force majeure factors. Hence, the time stability test relies on the five-year data from 2016 - 2019 to evaluate the effect of time on the model's stability. Secondly, the research widens the geographical scope by analyzing data from 298 cities located in 31 provinces, making it extensive and inclusive. In the robustness test, every province chooses two cities that are not provincial capitals, and eliminates cities with high trade competitiveness and municipalities directly under the central government from the regression to verify the robustness of the model and to determine the stability and reliability of the model regression after excluding the impact of economic factors. Thirdly, the central variables are substituted, and the measure of digitization derived from the principal component analysis is converted into the digital progress index denoted by the digital inclusivity index for regression. This is done to ascertain the reliability and credibility of the model regression outcomes under the same index and varied calculation methods. After applying the above treatment, it is determined that the effects of digitization on international competitiveness remain consistent, implying the lasting stability and validity of the model.

Table 4 Robustness test results

	(9) Time span	(10) Area coverage	(11) Modification of variables
	reg9	reg10	reg11
ln*Dig*	0,252	0,0450	0,501***
	(0,601)	(0,0639)	(0,0852)
ln*Npa*	−0,00853	0,121***	0,000547
	(0,0308)	(0,0211)	(0,0187)
ln*Efin*	−0,190**	0,0432	−0,254***
	(0,0705)	(0,0440)	(0,0482)
ln*Pfis*	0,0509	0,0336	0,130***
	(0,0434)	(0,0281)	(0,0247)
ln*Dopen*	−0,139***	−0,206***	−0,155***
	(0,0332)	(0,0214)	(0,0193)
ln*Ccons*	0,0394	−0,0683	−0,00507
	(0,0772)	(0,0449)	(0,0466)
ln*Venter*	0,0776	0,0443	0,0271
	(0,0654)	(0,0446)	(0,0434)
ln*Cpro*	0,0271	0,0968***	0,0673***
	(0,0320)	(0,0192)	(0,0190)
ln*TC*	−0,164**	-0,0509	−0,0849
	(0,0619)	(0,0467)	(0,0451)
_*cons*	−2,361	−2,592***	−3,274***
	(3,517)	(0,583)	(0,627)
N	437	460	590
R^2	0,140	0,304	0,335

5 IMPACT MECHANISM TESTING

5.1 K-means Classification

The prediction findings of how digital breadth impacts the level of digitization that enhances the global trade competitiveness are exhibited in Tab. 8. Column (13) displays the correlation between the level of digitization and the mediating variable, while column (14) presents the city's trade competitiveness that integrate the breadth of digital financial coverage as a mediating variable, thereby reflecting its impact on the degree of digitization. The K-means classification reveals the presence of a mediating effect of digital breadth towards the degree of digitization and city trade competitiveness. Khan et al. [9] propose a classification algorithm based on data feature learning. By optimizing the feature learning process in the Convolutional Neural Network (CNN) model, the data features have higher discriminability for the classification of data sets. The mediating effect is −0,04623 (−0,402 × 0,115), and it represents a mediating effect ratio of −9,12%.

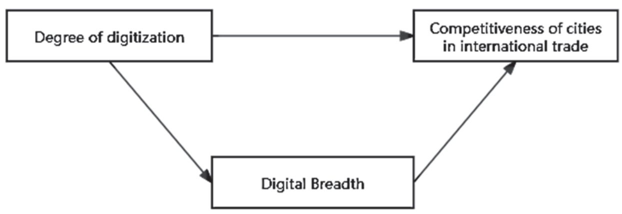

Figure 4 Mediating effects of digitization and cities' international trade competitiveness

Column 13 of Tab. 5 displays a regression coefficient of −0,402 between the digital economy and the breadth of digital financial coverage, which is statistically significant at the 1% level. This indicates that digital development has a negative correlation with digital breadth, meaning that as digitization progresses, the corresponding breadth of digitization decreases. Column 14 illustrates that once digital breadth is added, the depth of digitization for urban competitiveness decreases. The coefficient decreases from

0,507 to 0,152. While the depth of digitization deepens, the pursuit of digitization breadth carries on expanding, which unavoidably affects the digitalization degree of the economy towards boosting international trade competitiveness. This indicates that the depth and breadth of digitization cannot coexist.

By further advancing digitization, the city has enhanced its technological capabilities and widened its utilization of enterprise digitalization to increase the worth of its products. This has resulted in a competitive edge in local trade, as well as an elevation of the city's international trading competitiveness.

Table 5 Classification results by K-mean

		(12)	(13)	(14)
		Ctc	*Bdig*	*Ctc*
variant	ln*Dig*	0,507***	−0,402***	0,152**
		−0,0854	(0,0180)	(0,0575)
	ln*Npa*	0,00211	−0,00483	−0,0175
		−0,0187	(0,00835)	(0,0191)
	ln*Efin*	−0,268***	0,0437	0,0734
		−0,0477	(0,0402)	(0,0943)
	ln*Pfis*	0,133***	−0,00561	0,143***
		−0,0247	(0,0109)	(0,0253)
	ln*Dopen*	−0,155***	−0,0105	−0,138***
		−0,0193	(0,00846)	(0,0199)
	ln*Ccons*	−0,0487	0,0906***	0,00249
		−0,0405	(0,0201)	(0,0475)
	ln*Venter*	−0,0203	0,121***	0,0135
		−0,0353	(0,0191)	(0,0464)
	ln*Cpro*	0,0599**	−0,0877***	−0,0750
		−0,0186	(0,0195)	(0,0457)
	ln*Bdig*			0,115
				(0,0975)
Bootstrap Inspection	95% confidence interval			[0,0003225; 0,0010636]
	value of intermediary effect			0,00018665
_cons		−3,266***	5,350***	−2,058**
		−0,628	(0,241)	(0,761)
N		590	590	590
R^2		0,331	0,600	0,289
time control		yes	yes	yes
city control		yes	yes	yes

The use of digital technology can enhance the international trade competitiveness of a city. This, in turn, can foster the development of upstream and downstream enterprises due to the presence of external economy. As a result, the overall quality of the industry can be improved. From a vertical standpoint, an enterprise within the industry chain assumes the role of the first adopter of cutting-edge technology. Upon clearing the technological hurdle, it can significantly enhance production efficiency, product quality and cost-effectiveness, improve revenue, and maximize profits. Simultaneously, the industry can opt to utilize the product to gain a larger market share by reducing its price, which allows downstream enterprises to procure high-quality, cost-effective products. This will inevitably boost upstream product demand, leading to the entire industry chain's development and an expansion of the digital economy's scope of application. When digital technology is maturely applied to an industry, it can lead to technological outreach. This causes the digital economy to be applied to the industry as a whole, resulting in overall industry development and increased coverage of digital applications, thereby expanding digital breadth. However, the simultaneous development of digital depth and breadth will inevitably lead to competition for resources, hindering the effective allocation of these resources and ultimately resulting in wastage. Therefore, the degree of digitalization's digital breadth plays a crucial role in inhibiting the process of urban international trade competition.

5.2 Classification Test of Urban Competitiveness

Tab. 6, paragraphs (16) to (18) indicate that through the use of digital breadth as an intermediate variable, the degree of financial development and product production efficiency have a modulating effect on the degree of digitization in the digital international trade process. The moderating effect of digital breadth as an intermediate variable is also observed. Technical abbreviations are clarified upon first usage. The language remained neutral, objective and formal. The appropriate grammar, spelling and structure were maintained. When solely considering the degree of financial development in the digital depth and breadth as a moderator, the regression coefficient for digital depth is significantly positive. This shows that the degree of financial development can enhance the level of digitalization, thereby impacting the city's trade competitiveness and expediting the progress of international trade in the locality. If we solely consider the moderating influence of product production efficiency, it assumes a moderating function in the course of mediating factors and final trade competitiveness. As indicated in column (17) of Tab. 10, in comparison to the regression coefficient of 0,152 found when using only digitalization breadth as the mediating factor, its coefficient improved marginally, and its significance has met the 5% level, rendering it even more significant. When examining the effect of the level of digitalization, this suggests that the rise in product efficiency counteracts the decrease in the city's global commerce competitiveness resulting from the extent of digitalization. By examining the joint effect of financial development and product production efficiency, with both variables acting as moderating factors, and their impact on the relationship between explanatory and mediating variables, it is evident that the competitiveness of the city in international trade is significantly enhanced. By examining the joint effect of financial development and product production efficiency, with both variables acting as moderating factors, and their impact on the relationship between explanatory and mediating variables, it is evident that the competitiveness of the city in international trade is significantly enhanced. The regression coefficient is 0,31; indicating statistical significance at the 1% level.

Technologies like digitization, employed in the amplification of digitised industries, are more likely to be economically profitable, owing to basic scientific research. However, implementation of the technology as well as its depth necessitates financial support. Therefore, augmenting financial development and liquidity decreases the adverse impact of digitalization expansion on the city's international trade competitiveness. The expansion of digital breadth may reduce resources available for digital deepening, but to some extent, it enhances the technology sector's overall level. Furthermore, it increases product production efficiency and compensates for the loss of resources resulting from digital deepening, leading to a decrease in product output. The improvement in product efficiency cancels out some of the impact on urban international trade caused by the simultaneous rise of digital breadth.

Table 6 Moderating effect test results

		(15)	(16)	(17)	(18)
		Ctc	*Ctc*	*Ctc*	*Ctc*
variant	*Dig*	0,152**	0,300***	0,169**	0,310***
		(0,0575)	(0,0651)	(0,0570)	(0,0645)
	Bdig	0,115	−0,166	0,117	−0,153
		(0,0975)	(0,114)	(0,0964)	(0,113)
	Dfin		−0,254***		−0,244***
			(0,0556)		(0,0551)
	Epro			0,0742***	0,0699***
				(0,0194)	(0,0191)
	control variable	containment	Containment	containment	containment
Bootstrap Inspection	95% confidence interval	[0,0003225; 0,0010636]	[−0,1290062; −0,0013787]	[−0,0069862; −0,0000675]	[−0,3791078; −0,0159726]
	value of intermediary effect	0,00018665	0,03364719	0,00147956	0,09363459
_cons		−2,058**	−1,177	−2,461**	−1,592*
		(0,761)	(0,773)	(0,760)	(0,773)
N		590	590	590	590
R_2		0,289	0,314	0,307	0,330
time control		yes	yes	yes	yes
city control		yes	yes	yes	yes

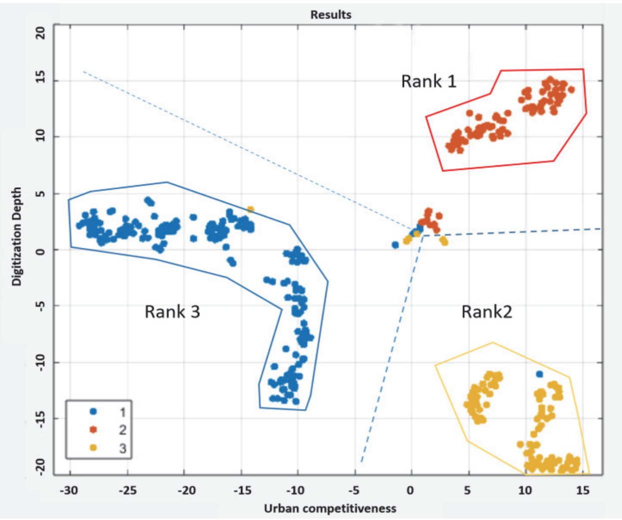

Figure 5 Classification test of digitization and cities' international trade competition

From the perspective of hierarchy, it still presents a "Rank 1, Rank 2, Rank 3" state in Fig. 5. First-tier cities Beijing, Shanghai, Guangzhou, Shenzhen, Hong Kong and Taipei have the smallest urban competitiveness gap, which is in 'Rank 1' level. The difference between second-tier cities is second. The comprehensive economic competitiveness within the first and second tier cities is relatively close and the competition is fierce. Third-tier cities are relatively less digital and less competitive internationally, which are in 'Rank 3' level.

5.3 Threshold Effect Test

After examining digitalization breadth as an intermediary variable and the degree of financial development and product productivity as moderators for moderation, it is essential to explore the digital economy by taking into account the non-linear advantages it provides for enhancing the trade competitiveness of cities. To enhance the credibility of the experiment and its results, we simultaneously conducted a threshold effect regression analysis for both models that narrowed the time horizon and regulated the city horizon, based on the original regression. Tab. 11 displays results from the threshold test, with the degree of digital economy serving as the threshold variable and city trade competitiveness as the explanatory variable under the K-means neural network with varying conditions. It is evident that the initial regression fulfilled the double-threshold K-means neural network, and the novel time and region regressions satisfied the three-threshold examination. An analysis of the *P*-value reveals that only the double-threshold test generated a more significant impact in the original K-means neural network, thereby choosing the double-threshold effect directly. In the recent time K-means neural network, the single-threshold, double-threshold and triple-threshold are all statistically significant. However, only the triple-threshold model is able to pass the 1% test. Therefore, it would be more appropriate to select the triple-threshold test. Both the double-threshold and triple-threshold passed the 5% significance in the new regional regression test. However, the *P*-value of the double-threshold test is lower, and the 95% confidence interval of the triple-threshold K-means neural network is essentially overlapped with that of the two-threshold model. Consequently, the two-threshold K-means neural network is chosen.

In the initial regression analysis, if the digitization measurement is below the 4,2841 threshold value, it increases at the 4,2841 threshold value and further increases beyond the 5,4552 threshold. In the three-stage model, the regression coefficients have a positive value and pass the 1% significance test, although their effect of facilitating has decreased.

During the years 2016 - 2019, which saw a concentration in the digital economy, three thresholds, namely 5,596; 5,623 and 5,644, were observed. This led to the segmentation of the regression into four stages, in which the first and third segments of digitalization development exerted a significant negative impact on the competitiveness of the city and the impact intensified. The fourth stage also showed an inhibitory effect, but it was less significant.

Table 7 Threshold effect test results and confidence intervals

Mould	Test Methods	Sum of Squares of the Residuals	Mean Square Error	*F*-value	*P*-value	95% Confidence Interval
regression (chemistry)	Single-threshold test	61,647	0,1063	5,856	0,107	[3,650; 5,690]
	Double-threshold Test	61,1462	0,1054	7,433*	0,057	[3,650; 5,690]
	Triple-threshold Test	60,9006	0,105	4,697	0,127	[3,976; 5,690]
New Time Returns	Single-threshold test	51,1594	0,1437	8,349**	0,040	[5,459; 5,747]
	Double-threshold Test	49,6484	0,1395	6,761**	0,043	[5,443; 5,747]
	Triple-threshold Test	48,222	0,1355	12,257***	0,000	[5,569; 5,646]
Return of new regions	Single-threshold test	40,9604	0,091	4,827	0,153	[3,599; 5,727]
	Double-threshold Test	40,6275	0,0903	3,965*	0,087	[3,599; 5,726]
	Triple-threshold Test	39,9487	0,0888	4,353*	0,095	[3,599; 5,727]

A dual-stage analysis, excluding regions with higher economic development, reveals a reduction in the regression coefficient as compared to the initial analysis, while statistical significance remains the same. The regression coefficient experiences a gradual decline in three scenarios: values below 5,537, ranging from 5,593 to 5,537, and exceeding 5,644. Thus, under conditions of excessive digitization, the digital economy's impact on urban trade competitiveness decreases.

Table 8 Estimated results of threshold effects under different conditions

		Regression (chemistry)		New Time Returns		Return of new regions	
		Ratio	*T*-test value	ratio	*T*-test value	ratio	*T*-test value
Threshold variables	*Dig* < 4,2841	0,3441246***	4,09				
	4,2841 < *Dig* < 5,4552	0,3010302***	4,54				
	5,4552 < *Dig*	0,2672807***	4,16				
	Dig < 5,596			−0,0639941***	−3,6		
	5,596 < *Dig* < 5,623			0,0387283**	2,46		
	5,623 < *Dig* < 5,644			−0,0751782***	−3,46		
	5,644 < *Dig*			−0,0138781	−0,67		
	Dig < 5,537					0,2534121***	2,89
	5,537 < *Dig* < 5,593					0,2105092***	3,03
	5,593 < *Dig*					0,1781033***	2,64
_*cons*		−2,027213	−1,34	2,420888	0,25	−2,28514	−1,36
control variable		yes		yes		yes	
Year fixed effects		yes		yes		yes	
sample size		460		360		460	
R^2		0,2927		0,1299		0,2927	

5.3 Urban Competitiveness Prediction

In this paper, through the improved neural network model output of K-means method, more reasonable prediction results are obtained after the sample classification is trained and merged by clustering features, which avoids data overfitting and improves the accuracy of urban competitiveness prediction. The sparse sample data points in multidimensional data will affect the prediction performance of the whole model, resulting in poor prediction results of other algorithms.

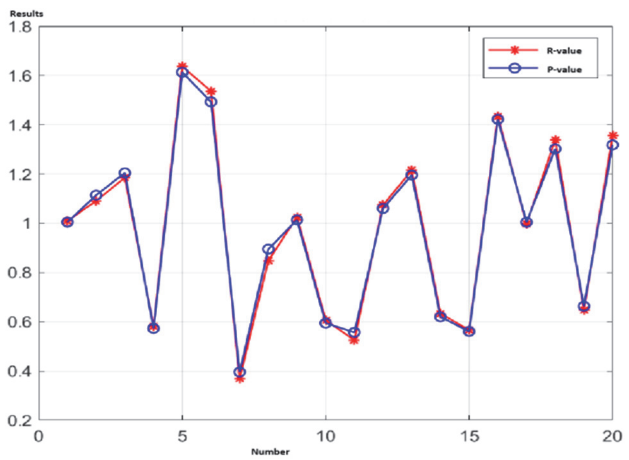

Figure 5 Prediction results of digitization and cities' international trade competition

In this paper, cluster intervals in similar samples are calculated according to the characteristic points of the sample dimension, and a reasonable neural network prediction model is constructed according to the training of each cluster interval. From the sample data sets of different regions, it can be concluded that the improved algorithm in this paper has the same good data analysis effect in different data sets.

6 CONCLUSIONS

This study examines the impact of digitalization on the global competitiveness of cities using year-end statistical yearbooks from Chinese cities (2011 - 2020), import and export data from China Customs, and information from the Digital Finance Research Center at Peking University and Ant Technology Group Research Institute.

The study employs base regression, mediation regression, and threshold effect analysis to investigate the impact's direction, method, and magnitude. It concludes that increased digitalization depth can enhance urban areas' international competitiveness. Digitalization breadth can mediate the global competitiveness of cities, but the depth and breadth of digitization do not jointly enhance trade competitiveness as effectively as direct development. In other words, the breadth of digitalization development as a mediator variable curbs the promotion of digitalization degree on trade competitiveness. When seeking to boost the city's competitiveness in trade, strengthening financial development and enhancing product efficiency are key. This, in turn, deepens digitization and expands the scope of digitization, improving the city's international competitiveness while reducing the inhibiting effect on the breadth of digitization as an intermediate factor. Digital development has the potential to bolster a city's international trade competitiveness, yet a threshold effect exists. Once this threshold is exceeded, the degree to which digital development promotes a city's trade competitiveness diminishes gradually.

When traditional K-means neural networks perform regression analysis on non-single dimensional data sets, a small number of singular samples have a high impact cost, resulting in a low accuracy of regression analysis prediction. Therefore, this paper proposes a method based on the K-means prediction algorithm of the K-means neural network data set, that is, the input layer of the neural network is optimized through the K-means algorithm structure, and the optimal response in similar samples is calculated according to the characteristic points of the city sample corresponding to the model, and the clustering boundary containing the data characteristic information is constructed to improve the prediction reliability of the city competitiveness. Finally, the results of comparison and verification show that the performance of the proposed algorithm is better than the common K-means prediction algorithm in the data set, and it has certain practical significance and practicability. The preceding results have considerable practical value for using digital economy in international trade of urban areas, to achieve high-quality economic growth through city-wide marketing initiatives.

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