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An Analysis of How Digital Technology Impacts Trade Costs—Based on the Empirical Data of RCEP Member Countries

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ABSTRACT

This paper explores how digital technology reduces trade costs using bilateral trade data from RCEP member countries and a panel fixed effects model. The findings show that digital technology significantly lowers trade costs, a conclusion that holds even after accounting for lag effects and various robustness checks. The impact of digital technology on trade costs follows an inverted U-shape: the effect is most significant in the current period, especially with a one-period lag, and diminishes over time. Larger economies and higher export levels strengthen this negative impact due to their reliance on exports and continuous improvements in domestic digital technology. The study recommends investing in digital infrastructure, formulating reasonable internet access policies, supporting digital skills development, and enhancing digital connectivity to bridge the digital divide, thereby promoting trade facilitation and efficiency.

KEYWORDS

Digital Technology; Trade Costs; RCEP; Panel Fixed Effects Model

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1. Introduction

Trade costs include various factors such as tariffs, transportation costs, time costs in logistics links, and information exchange costs. The application of digital technology may have a positive impact on these costs, such as reducing payment and customs declaration costs for cross-border transactions through online payment and electronic customs systems; but at the same time, the promotion of digital technology may also bring new costs, such as investment in information security and data privacy protection. The rapid development and popularization of digital technology is profoundly changing the global trade pattern. From e-commerce platforms to supply chain digitalization, digital technology plays an increasingly important role in trade activities. However, the application of digital technology is not only to improve efficiency and reduce costs, it may also have a complex impact on trade costs. RCEP is one of the largest free trade areas in the world, covering 15 countries in East Asia and Oceania, including a series of countries with huge economies, such as China, Japan, and South Korea. The trade activities between these countries have a huge impact on the global trade pattern. Through research based on the empirical data of RCEP member countries, we can fully reflect the actual impact of digital technology on trade costs and provide strong support for the formulation of more precise policies and strategies. At the same time, the economic differences and different degrees of digital technology application among RCEP member countries also provide rich samples and comparison objects for research, which is helpful for in-depth analysis of the impact mechanism and path of digital technology on trade costs. Therefore, the study of the impact of digital technology on trade costs based on the empirical data of RCEP member countries is both theoretically important and practically instructive. This not only helps to deeply understand the new characteristics and trends of trade development in the digital age, but also provides new ideas and methods for promoting regional trade cooperation and optimizing global trade rules.

2. Literature Review

2.1. Digital Technology and Trade Costs

In recent years, the impact of digital technology on trade costs has emerged as a crucial research area. Studies have demonstrated that these technologies enhance efficiency, reduce trade barriers, and ultimately lower trade costs (Ahmedov, 2020; Kersan-Skabic,2021; Azmeh et al., 2020). The global economy is undergoing a transformation where production, exchange, and consumption are increasingly digitized. The internet and cross-border data flows have become critical pathways for trade, facilitating online product transactions and integrating digital connectivity features that influence trade costs (Liu et al., 2024). Digital trade agreements enhance flows between nations, especially under specific rules (Suh and Roh, 2023). Major innovations typically focus on reducing transaction costs. One prominent characteristic of emerging digital technologies is their capacity to enable direct connections between supply and demand, bypassing traditional intermediaries such as firms, financial institutions, and regulatory bodies (Agmon, 2021). On the other hand, globalization reduces barriers to technology transfer and contributes to enhancing innovation and productivity (Abeliansky and Hilbert, 2017; Chiappini and Gaglio, 2024). The mutually reinforcing relationship between globalization and the adoption of digital technologies leads policymakers and practitioners to recognize globalization as a driver of competition and a determinant of productivity. By directly impacting technology adoption, globalization fosters innovation, enhances productivity, and consequently boosts competitiveness in the global market (Lund and Tyson, 2018; Skare and Soriano, 2021). Digitalization within firms enhances their likelihood of engaging in both exporting and importing activities. This influence is exerted directly and through increased productivity. Moreover, technological innovation plays a crucial role in reducing trade costs, thereby facilitating international trade (Añón Higón and Bonvin, 2024). Digital trade facilitates the diffusion of innovation and technology, thereby lowering production costs and enhancing competitiveness. This cycle of innovation and cost reduction is supported by Bloom et al. (2014), who demonstrate that digital technologies enhance productivity and reduce marginal production costs. However, the impact of digital technologies on trade costs varies between manufacturing and services (Mayer, 2021). Big data analysis of customer preferences in manufacturing is crucial, highlighting the significance of data governance and innovation policies in enhancing industrialization strategies in the digital era. Additionally, some research indicates that increasing government restrictions on global data flows and mandates for data localization erode the economic advantages of digital trade, significantly impacting trade costs (Meltzer, 2019).

2.2. Role of Digital Platforms in Reducing Trade Costs

Digital technologies, particularly the internet, play a crucial role in constructing digital trade platforms by reducing information asymmetries and lowering transaction costs, thereby enhancing market accessibility. Lendle et al. (2012) demonstrate that digital platforms enable SMEs to enter international markets with minimal initial investment, bypassing traditional intermediaries. Goldfarb and Tucker (2019) further support this view, noting that e-commerce platforms drastically lower the fixed costs associated with international trade. Cybersecurity also plays a crucial role in digital trade. Anderson and Moore (2022) emphasize that robust cybersecurity measures are essential for protecting digital trade infrastructures from cyber threats, ensuring smooth and secure operations. In mobile payments, the role of digital financial services in reducing trade costs is underscored by Suri and Jack (2016), who find that mobile money and digital payment systems facilitate faster and cheaper cross-border transactions, reducing reliance on traditional banking systems. Gomber et al. (2017) also confirm this, noting that fintech innovations reduce the cost and complexity of international transactions.

2.3. Far-reaching Impact of Digital Technologies in Logistics on Trade Costs

Digital technologies profoundly impact trade costs in logistics. Firstly, the digitalization of customs and border management has become crucial in reducing trade costs. Moïsé and Sorescu (2021) analyze the impact of digital customs procedures and find that they significantly reduce clearance times and associated costs. Secondly, blockchain technology and Artificial Intelligence (AI) are transforming trade logistics and reducing costs. The World Trade Organization reports that blockchain enhances supply chain transparency and reduces fraud, while AI optimizes logistics and inventory management, leading to cost savings. Similarly, Cong and He (2019) find that blockchain applications in trade finance reduce processing times and lower the risk of fraud, thereby reducing overall trade costs. Thirdly, several studies emphasize the integration of digital technologies in logistics and supply chain management.

In conclusion, recent research consistently underscores the transformative impact of digital technology on reducing trade costs. From improving market accessibility and efficiency to enhancing customs procedures, logistics, and financial transactions, digital technology plays a pivotal role in shaping the future of global trade. As digital adoption continues to grow, its role in lowering trade costs and fostering economic growth is likely to become even more pronounced.

3. Analysis of the mechanism of digital technology on trade costs

The impact of digital technology on trade costs is a broad and complex topic, including many factors such as lower communication costs, lower transportation and logistics costs, improved supply chain management, and simplified cross-border transactions.

Digital technology reduces communication costs. With the development of digital technology, from traditional voice communication to current multimedia communication, digitalization has changed many aspects of the communication industry: digital technology has made communication more diverse and convenient, including not only traditional voice communication but also video calls, real-time messaging, social media and other forms, meeting people's different communication needs; digital technology has greatly increased the speed of information transmission, from traditional telephones and emails to current emails and instant messaging tools, information can be transmitted in seconds or even milliseconds, greatly improving the efficiency of communication. A large number of buyers and sellers can more easily find each other and get in touch with them, which is very beneficial to the development of cross-border e-commerce, and also provides a good opportunity for small and medium-sized enterprises to open up new markets. Digital communication technology eliminates geographical restrictions, and people can communicate remotely through the Internet anytime and anywhere, making cross-border business cooperation, telemedicine, distance education, and remote work more convenient.

Digital technology reduces transportation and logistics costs. Cloud computing and big data analysis tools have automated business processes and greatly improved efficiency. For example, customs declarations and cargo transportation tracking can now be completed quickly and electronically, saving a lot of time and paperwork. By monitoring traffic conditions and road congestion in real-time, digital technology can help companies choose the best routes, and avoid congested areas and traffic accidents, thereby reducing transportation time and fuel consumption. In addition, digital technology can also reduce empty load rates and transportation mileage by optimizing freight modes, such as centralized transportation and multimodal transportation, thereby improving freight efficiency and further reducing transportation costs.

Digital technology improves supply chain management. Digital technology improves the transparency of supply chain management and also improves the efficiency of supply chain management. It can also help companies avoid over-purchasing and waste losses, reduce inventory costs, and improve customer satisfaction by predicting demand and optimizing inventory management. Through a digital logistics platform, different companies can share logistics information and resources, achieve optimal resource allocation, and reduce idleness and waste.

The use of digital payment platforms and blockchain technology has made cross-border transactions easier and safer, greatly reducing the cost of cross-border payments. This provides a more complete and efficient solution for the production and circulation, precision marketing, transaction fulfillment, and credit asset management of the entire trade ecosystem. Among them, modern cross-border payment technologies provide merchants with more flexible and efficient payment solutions, including real-time exchange rate conversion and multi-currency support. At the same time, these technologies can dynamically track the collection process, covering all aspects such as collection, collection, and refund, thereby improving the efficiency and transparency of capital flow management. By analyzing payment data through digital platforms, cross-border payment service companies can provide merchants with in-depth business insights, including business analysis, e-commerce platform trends, and consumer behavior analysis. This information helps merchants improve order conversion rates and better understand market dynamics.

Therefore, this paper’s initial assumption regarding the relationship between digital technology and trade costs is a negative effect, that is, digital technology can reduce trade costs to a certain extent.

4. Indicators selection and model construction

4.1. Indicator selection

4.1.1. Explained variable: bilateral trade costs

Using the indirect measurement method proposed by Novy (2012), we can calculate bilateral trade costs as follows:

$$cost_{ijt} = (\frac{x_{iit}x_{jjt}}{x_{ijt}x_{jit}})^{\frac{1}{2(\sigma-1)}} - 1 \tag{1}$$

In the equation (1), $cost_{ijt}$ represents the bilateral trade costs between country i and country j in year t, which is a relative conceptual value calculated based on the exports and GDP of both countries. x_{iit} and x_{jjt} respectively denote the domestic trade values of country i and country j in year t, while x_{ijt} represents the commodity trade value from country i to country j, and x_{jit} represents the commodity trade value from country j to country i. σ represents the elasticity of substitution of goods. Domestic trade values are calculated by subtracting total exports from the total income of a country for the year. The formula for the total income of a country is $Y_t = s \times GDP_t$, where s denotes the share of traded goods. Hence, the calculation formula for domestic trade values is: $X_{iit} = s \times GDP_{it} - E_{it}$, $X_{jjt} = s \times GDP_{jt} - E_{jt}$, where E represents the total exports of a country. Due to the potentially large data outcomes, which may lead to heteroscedasticity issues, this paper logarithmizes the bilateral trade costs before entering them into the econometric model. Total export data and bilateral trade data are sourced from the United Nations UNcomtrade database and the World Trade Organization database, while GDP data for each country are obtained from the World Bank database.

4.1.2. Core explanatory variables: digital technology

This study employs the methodology for assessing Internet development introduced by Nunn and Qian (2014) to develop a comprehensive index to measure digital technology level. We employ principal component analysis to calculate the level of digital technology development among 15 member countries from 2014 to 2021. The primary indicators include communication technology development, information technology development, and related service development. Secondary indicators comprise mobile network coverage, fixed telephone penetration rate, fixed broadband penetration rate, secure Internet servers (per million people), ICT service exports, publications on ICT-related topics, readiness for ICT frontier technologies, R&D expenditure as a percentage of GDP, telecommunications service revenue in US dollars, information and communication service exports, tertiary education enrollment rate, percentage of total education expenditure, government efficiency, and mobile cellular subscriptions (per 100 people), totaling 14 indicators. The comprehensive index of digital technology is calculated using the entropy method. To address heteroscedasticity issues, logarithms of digital technology variables are similarly included in the econometric model. Data on digital technology at the RCEP country level in this study are sourced entirely from the World Bank database.

Table 1. Digital technology classification indicators.

variable	First level indicator	Secondary indicators
Digital technology	Communication technology development	Mobile network coverage
		Fixed-line telephone penetration rate
		Fixed broadband penetration rate
		Secure Internet servers (per million people)
	Information Technology Development	ICT service exports
		Number of ICT-related papers published
		ICT cutting-edge technology readiness
	Related service development	R&D expenditure as a percentage of GDP
		Telecommunications service revenue USD
		Exports of information and communication services
		Higher education enrollment rate
		Education expenditure as a percentage of the total
		Government efficiency
		Mobile cellular subscriptions (per 100 people)

4.1.3. Other control variables

Other control variables mainly consist of some national-level characteristic variables. Among them, the variables lnDistance and Border reflect the geographical characteristics of the bilateral trading countries, with lnDistance representing the natural logarithm of the distance between the two countries, and Border indicating whether the countries share a border. Variables such as Comcol (whether they were former colonies of the same colonizer) and Comlang (whether they share a common language) reflect the shared linguistic and historical-cultural characteristics of the trading partners. Average tariff (lnTariff) reflects the control and application of tariff barriers in trading countries. Additional control variables reflecting economic scale have been added for stability testing and are also included in the table, including lnGDP (natural logarithm of GDP) and Openness (degree of openness). Detailed definitions of control variables are provided in Table 2.

Table 2. Variable Description and Data Source.

Variable Name	Variable definitions	Data Sources
Distance between two countries (*lnDistance*)	The logarithm of the spatial weighted distance between two countries	CEPII
Border	The dummy variable for whether the two countries share a border	CEPII
Comcol	Has it been jointly colonized by other countries since 1945?	CEPII
Common Language (*Comlang*)	Does more than 9% of the population speak the same language?	CEPII
Average tariff (*lnTariff*)	The logarithm of the average tariff rate applied to all products	World Bank
Economic size (*lnGDP*)	The logarithm of the GDP of each country	World Bank
Economic Openness (*Open*)	Total imports and exports divided by GDP	World Bank

4.2. Model Construction

This paper focuses on the panel data of historical bilateral trade among RCEP member countries as the research object. By employing econometric regression, it examines the impact of digital technology on trade costs, following the approach outlined by Ma Shuzhong et al. (2019). The model is set as follows:

$$lnTradecost_{ijt} = \beta_0 + \beta_1 ICT_{ijt} + \beta_2 controls_t + \lambda_\alpha + \mu_t + \varepsilon_{ijt} \tag{2}$$

In Equation 2, the dependent variable lnTradecostijt represents the average trade cost incurred when goods are exported from country i to country j in year t. ICT_{ijt} denotes the comprehensive level of digital technology development between country i and country j in year t. $controls_t$ represents the set of control variables related to bilateral trade costs in year t. λ_α and μ_t respectively represent country effects and time effects, while ε_{ijt} represents the random disturbance term.

4.3. Descriptive Statistics and Correlation Analysis

Before entering the econometric model, this paper applies Winsorization to the dependent and core explanatory variables at the 1st and 99th percentiles to address outliers in the data. Table 3 presents descriptive statistics for all variables entering the econometric model, including sample size, mean, median, standard deviation, minimum, and maximum values. Table 3 also includes a correlation analysis between the dependent variable and each explanatory variable. From the results of the correlation coefficient test, it can be preliminarily concluded that there is a statistically significant negative correlation between digital technology (lnICT) and trade costs (lnTradecost). To establish whether there is a logical causal relationship between them, multiple baseline regressions will be conducted next to observe whether the coefficients of the explanatory variables remain significantly negative. Additionally, the correlation coefficients between the dependent variable and other control variables are generally consistent with the expected direction.

Table 3. Descriptive statistics.

Variable	N	Mean	p50	SD	Min	Max
lnTradecost	93	0.0590	-0.108	0.594	-1.011	1.409
lnICT	93	-0.0190	0.0170	0.486	-1.196	0.942
Border	93	0.140	0	0.349	0	1
Distance	93	3788	2887	2738	520.5	10241
Comlang	93	0.103	0	0.305	0	1
Comcol	93	0.0930	0	0.292	0	1
lnTariff	93	1.130	1.368	1.100	-2.120	2.451

Table 4. Correlation analysis.

Variable	*lnTradecost*	*lnICT*	*Border*	*Distan*	*Comlang*	*Comcol*	*lnTariff*
lnTradecost	1						
lnICT	-0.109**	1					
Border	-0.137	0.0370	1				
Distance	0.285**	-0.0510	-0.413***	1			
Comlang	-0.130	-0.0410	0.0700	0.0700	1		
Comcol	-0.0180	-0.0230	0.473***	-0.317***	0.127	1	
lnTariff	0.159	-0.158	0.140	-0.410***	-0.286***	0.197*	1

Note: The variable lnTradecost has a limited number of observations because in some countries (such as Singapore), international trade flows exceeded domestic trade in certain years (resulting in trade cost measurements less than 0, leading to no observable values after logarithm transformation). Additionally, lnTariff has missing data for certain countries in some years, which were filled using linear interpolation.

5. Empirical Analysis

5.1. Benchmark regression

The benchmark regression is conducted using the historical bilateral trade data of RCEP member countries from 2014 to 2021. Table 5 reports the benchmark regression results. Model (1) is a panel mixed regression model that only introduces the explained variables and explanatory variables without control variables, model (2) is a panel mixed regression model that introduces all variables, and model (3) is a panel regression model that adds fixed effects when all variables are introduced.

Based on the historical bilateral trade data of RCEP member countries from 2014 to 2021, baseline regressions were conducted. Table 5 reports the results of these baseline regressions. Model (1) represents a pooled OLS regression without control variables, including only the dependent variable and explanatory variables. Model (2) represents a pooled OLS regression including all variables. Model (3) represents a panel regression with fixed effects including all variables.

Table 5. Benchmark regression.

Variable	(1) No control variables	(2) No fixed effects	(3) Adding control variables and fixed effects
	lnTradecost	lnTradecost	lnTradecost
lnI	-0.011 **	-0.057***	-0.017***
	(0.004)	(0.017)	(0.006)
Border		-0.031***	-0.057***
		(0.015)	(0.017)

Distance		-0.008 (0.009)	-0.006* (0.003)
Comlang		0.003 (0.006)	0.018** (0.008)
Comcol		-0.003 (0.003)	-0.256*** (0.055)
lnTariff		-0.006 ** (0.003)	-0.011 ** (0.004)
country effect	no	no	yes
time effect	no	no	yes
Haussman test			35.23 [0.000]
N	93.000	93.000	93.000
r2	0.076	0.056	0.073

*Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; the numbers in parentheses represent t-values; the numbers in brackets represent the associated probability (p-value).*

According to the results of the baseline regressions, the coefficients of the explanatory variables in all three models are negative and highly significant, which is consistent with the conclusions of existing literature (Ahmedov, 2020; Kersan-Skabic, 2021). Therefore, digital technology (lnICT) indeed has a highly significant negative impact on trade costs (lnTradecost). From the results of the Hausman test, the p-value for Model (3) is 0.000, which is less than 1%, significantly rejecting the null hypothesis. Thus, the paper ultimately chooses the panel fixed effects model for econometric analysis. With the introduction of fixed effects, potential bias from omitted variables is eliminated. The coefficient of the core explanatory variable lnICT is adjusted from -0.057 to -0.017, and the t-statistic value is adjusted from 0.017 to 0.006. Although the negative coefficient decreases, it remains significant at the 1% level, indicating that the overall negative effect of digital technology on trade costs persists. Further econometric analysis is needed to test whether there is a logical causal relationship between the former and the latter and to ensure robustness.

Regarding the regression results of other control variables, they are generally consistent with theoretical expectations. The coefficient of Border is significantly negative, indicating that sharing a border is conducive to reducing trade costs, and border trade can indeed reduce transportation costs. The coefficient of the proxy variable lnDistance representing the geographical characteristics between bilateral trading countries is negative, indicating that greater distance between countries can also reduce trade costs. This may be due to country-specific heterogeneity; for example, countries like China, with initiatives like the Belt and Road, may have lower trade costs when trading with distant countries. The coefficient of the proxy variable Comcol representing historical colonial relationships is significantly negative, suggesting that countries that were once colonized by the same country have lower trade costs in their trade exchanges. This may be related to shared colonial language, cultural customs, and reduced unnecessary costs. For instance, Hong Kong, having experienced Western cultural influence, thrives in trade exchanges with many countries. The coefficient of the proxy variable Comlang representing shared language is positive, suggesting that a common language does not necessarily reduce trade costs. This may be due to the lagged nature of language; further endogeneity tests will be conducted to refine this. The coefficient of the proxy variable lnTariff representing tariff levels is significantly negative, indicating that reducing tariffs can reduce trade costs.

5.2. Endogeneity test

Due to the limitations of data availability and the potential for omitted variable bias as well as endogeneity arising from interrelated variables, there may be endogeneity issues in the relationship between digital technology and trade cost reduction. While this study employs a panel fixed effects model that controls for country and time effects to some extent to alleviate omitted variable bias-induced endogeneity problems, it may not eliminate endogeneity concerns. Digital technology can reduce trade costs, but the decrease in trade costs may also lead a country to accumulate more wealth over the long term, with some of that wealth potentially being used to further develop digital technology. This suggests a potential bidirectional causality between digital technology and trade costs. Details are provided in Table 6.

To address endogeneity as much as possible, this study adopts the commonly used lagged variable method. The explanatory variable (lnICT) is lagged by one period and two periods separately, and regression is conducted again. The results still show a significant negative impact of digital technology, with the effect being most pronounced when lagged by one period. The coefficient for the lagged one-period variable is -0.473, indicating a significant negative effect of digital technology on trade costs, with a certain lag effect, which is reasonable. On one hand, the advancement of digital technology is an ongoing process, and the digital achievements of a particular year cannot be immediately implemented and require continuous validation and improvement. On the other hand, the application of digital technology in areas such as communication technology, trade automation, and supply chain management also takes time to realize the overall reduction in trade costs.

Table 6. Endogeneity test.

Variable	(1) lag one period lnTradecost	(2) lag two periods lnTradecost
L.lnICT	-0.473 ***	
	(0.146)	
L2.lnICT		-0.354 **
		(0.191)
Border	-0.444 *	-0.403
	(0.224)	(0.249)
Distance	0.000	0.000
	(0.000)	(0.000)
Comlang	-0.413 *	-0.593 *
	(0.239)	(0.324)
Comcol	0.497 *	0.415
	(0.290)	(0.325)
lnTariff	-0.095	-0.050
	(0.075)	(0.085)
N	81.000	69.000
r2	0.244	0.174
r2_a	0.111	0.015

5.3. Robustness test

Since 2020, the outbreak of the COVID-19 pandemic resulted in a paralysis of the global trade system. Measures such as border closures, shutdowns, and city lockdowns led to a significant reduction in international trade activities. Many countries implemented export restrictions, leading to a sharp decline in exports, and the global supply chain was severely disrupted, with the flow of goods no longer smooth. Therefore, the data for the years 2020 and 2021 used in the above analysis are relatively abnormal compared to previous years. Hence, this study will conduct robustness tests from two perspectives, as detailed in Table 7.

Model (1) adds control variables: lnGDP and Openness. Model (2) excludes exceptional years: 2020-2021. In Model (1), a panel fixed effects model is employed with front and rear 1% trimming of the dependent variable (lnTradecost) and the core explanatory variable (lnICT) after adding two control variables. The regression results show that the coefficient of the explanatory variable (lnICT) is adjusted to -0.256, and it remains significant at the 1% level, indicating that adjusting the number of control variables does not change the negative impact of digital technology on trade costs. In Model (2), the regression is conducted using the same method after excluding the two years affected by the pandemic. It is found that the coefficient of the explanatory variable (lnICT) is adjusted to -0.018, and it remains significant at the 5% level, indicating that excluding the exceptional years does not change the negative impact of digital technology on trade costs.

In summary, although there are differences in the regression coefficients of lnICT, its negative effect remains unchanged, and the significance level is still very high. This indicates that the basic conclusion of this study regarding the negative impact of digital technology on trade costs is reliable.

Table 7. Robustness check.

Variable	(1) Add control variables lnTradecost	(2) Eliminate abnormal years lnTradecost
lnICT	-0.256 ***	-0.018 **
	(0.055)	(0.008)
Border	-0.251	0.000
	(0.222)	(0.235)
Distance	0.000	0.000 ***
	(0.000)	(0.000)
Comlang	-0.446	-0.200
	(0.273)	(0.249)
Comcol	0.316	0.212
	(0.305)	(0.292)
lnTariff	-0.038	0.177 *
	(0.084)	(0.096)
lnGDP	0.059	
	(0.036)	
Open	0.029	
	(0.165)	
Country Effect	yes	yes
Time Effect	yes	yes
N	93.000	71.000
r2	0.132	0.198

6. Conclusions and Implications

Through an empirical analysis of bilateral trade data from RCEP member countries, this study found that digital technology significantly reduces trade costs. Specifically, the results indicate that the impact of digital technology follows an inverted U-shaped relationship: in the short term, the effect of digital technology on reducing trade costs is most pronounced, but this impact gradually diminishes over time. Additionally, countries with larger economies and higher export levels exhibit a stronger negative effect of digital technology on trade costs, suggesting that these countries are more effectively leveraging digital technology to optimize their trade activities. This finding echoes the research of Suh and Roh (2023), which indicates that larger economies have an advantage in digital trade as they are better able to leverage digital technology to optimize supply chains and reduce transaction costs. This result underscores the importance of economic scale in the application of digital technology, suggesting that policymakers should consider the economic characteristics of a country when promoting the adoption of digital technology.

RCEP is a large-scale free trade agreement covering various areas such as goods trade, services trade, cross-border investment, and more. The following concise recommendations are made for digital trade: Firstly, increase investment in digital infrastructure and establish rational internet access policies. Despite the expansion of data-intensive services, the development of digital connectivity technology and information infrastructure has lagged, limiting digital trade growth. Support through funding and policy reforms is needed to enhance and broaden digital infrastructure. Secondly, enhance digital skills training for individuals and businesses. The proliferation of the internet and big data does not automatically ensure active digital trade participation. It is crucial to integrate digital skills training into education systems, helping workers adapt to technological changes and improve their digital competencies, thereby reducing training time costs and unemployment risks. Thirdly, strengthen digital connectivity to bridge the digital divide. Collective efforts and funding should be directed towards the construction of large-scale communication facilities, improving the stability and inclusiveness of digital trade. Economies should cooperate to advance both physical and digital infrastructure, optimize foreign investment policies, and enhance policies related to trade-related services.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Author contributions

Conceptualization, Juan Meng, Hao Lu, and Shengxiang Shen; investigation, Juan Meng, and Hao Lu; resources, Juan Meng; writing—original draft preparation, Hao Lu, and Juan Meng; writing—review and editing, Juan Meng; project administration, Juan Meng and Shengxiang Shen; funding acquisition, Juan Meng and Shengxiang Shen. All authors have read and agreed to the published version of the manuscript.

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