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Digital Bridges or Digital Divides? The Impact of Innovation Capabilities on Digitally Deliverable Service Export

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Abstract

This study investigates the differentiated impact of innovation capabilities on Information and Communication Technology (ICT) service exports through a comparative macroeconomic analysis of China and India from 2000 to 2024. As digital services increasingly drive global trade, understanding the distinct growth pathways of emerging giants is essential for targeted policy formulation. Utilising an Autoregressive Distributed Lag Error Correction Model (ARDL-ECM), this research examines long-term cointegration relationships and short-term dynamic adjustments. We model ICT export volume against resident patent applications, controlling for real exchange rates, digital infrastructure, and human capital. Findings reveal country-specific trajectories: China's expansion relies heavily on long-term accumulation of digital infrastructure and human capital, with technical innovation showing limited direct impact. On the other hand, long-term innovation capability and exchange rate competitiveness significantly drive India's export performance. Ultimately, the translation of innovation into trade competitiveness is non-uniform, requiring policymakers to tailor strategies to specific developmental stages.

Keywords: Digital deliverable service, ICT service export, innovation capability, trade competitiveness

Introduction

With the rapid development of digital technology and the internet, digital delivery services have become the essential driving force behind the surge in global service trade. From the statistical report, the global digital deliverable service export volume reached 4.25 trillion dollars while continuing to increase rapidly and occupies over half of the global service export trade volume (World Trade Organization, 2024a). The digital deliverable service export volume is on a positive trend in 2024, and its overall increase is more than that of traditional commodity trade. The data indicates that in the global trade volume, the service trade grew by 27.2% compared to the previous year, the digitally deliverable service export volume accounts for an expanding proportion of global service trade. At the same time, the data provides the index of ICT service exports percentage of service exports, which shows each country's digital service trade volume difference and trend obviously (World Bank, 2024). While China and India are both emerging digital giants, their paths to dominance appear fundamentally different. Understanding these specific drivers is crucial for policy formulation. China's ICT service export depends on the long-term development of digital infrastructure and human capital, with innovation capability having a limited positive impact. On the contrary, India's innovation capability and real exchange rate competitiveness have a positive effect on the ICT service export in the long term, and the digital infrastructure has a short-term structural mediation effect. In conclusion, this study reveals that at different stages and within various institutional environments, innovation capability has a differentiated impact on the process of building digital deliverable trade, contributing evidence to support a balance between innovation policy and digital trade in emerging economies (World Trade Organization, 2024b). Policymakers should focus on their country's unique growth patterns, which are shaped by various economic factors. Against this background, this study focuses on how the innovation capability influences the digital deliverable service export trade.

Literature Review

Existing literature indicates that digital technology, innovation capability, and macroeconomic background contribute to the expansion of digital deliverable service trade. Its effects exhibit heterogeneity that varies by country and over time. The early-stage empirical analysis shows that widespread use of the internet can effectively reduce the cross-border trade cost and information asymmetry and trigger the progress of service trade. The subsequent study further indicates that digital technology can improve productivity rates and indirectly enhance factor allocation, thereby boosting trade expansion (C. L. Freund & Weinhold, 2004; C. Freund & Weinhold, 2002; Meijers, 2014). As the fastest-growing part of global service trade, the digital deliverable service relies on the digital infrastructure, policy, and technology environment, and it provides a new pathway for developing countries to overcome the traditional manufacturing constraints and merge into the global economic system (Di et al., 2022; Herman & Oliver, 2023; Goswami et al., 2012). Innovation capability is widely considered an essential driving factor in the field of export upgrades and long-term growth potential. Its effect is more obvious, especially in the field of knowledge-intensive and digital service sectors (Hausmann et al., 2007; Rodrik, 2018). Related empirical analysis also points out that strong innovation capability can contribute to promoting the service export volume, enhancing international competitiveness, and promoting inclusive growth (Nordås & Kim, 2013; Yeerken & Feng, 2024). However, some comparative research points out that the positive effect of innovation capability on the export is not automatically achieved but constrained by the institutional environment and structural factors. This phenomenon is obviously in the international pathway of Chinese and Indian corporations (Fortanier & Tulder, 2009).

Apart from innovation capability, digital infrastructure and human capital are also considered the core fundamental factors for the progress of the digital service trade. To illustrate that, the wide diffusion of the internet can reduce the trade cost and contribute to the spread of innovation, and high-quality labour is the security of effectively absorbing and utilising new technology (Nie, 2023; C. Freund & Weinhold, 2002; Meijers, 2014). In the aspect of macroeconomics, the exchange rate and trade openness also exert a mediating effect on the performance of exports (Dollar & Kraay, 2004; Thangavelu & Rajaguru, 2004). At the same time, digitalisation also triggers new problems of industrial structure and employment with the enhancement of service tradability. Global market competition is increasingly impacting on the service sector, potentially causing heterogeneity in the labour market. This phenomenon further highlights the importance of the division of short-term impact and long-term structural adjustment (Autor et al., 2014; Baldwin & Forslid, 2023; Furceri et al., 2022; Wihardja et al., 2024). China and India’s digital industries are developing at a rapid speed, which shows the ambition of new emerging countries to conquer a greater share of the tertiary industry in the global market. The ICT service export volume plays a core role in the global market, and it reflects the country’s soft power. The government accelerates the progress of the ICT sector and makes it contribute to the promotion of labour productivity. The transition in industrial structure empowers the country, while the diffusion of internet technology and human capital in developing countries is facilitated by a better institutional environment. India and China are the essential markets in the world; they have the numerous internet engineers to do the ICT outsourcing and attain considerable profit in the short run. China relies more on the digital infrastructure, and India relies on the innovation capability; these differences make the two countries follow totally different pathways.

Overview of Innovation Capabilities on Digitally Deliverable Service Exports of China & India

Innovation Capabilities & ICT Service Export Performance in China & India

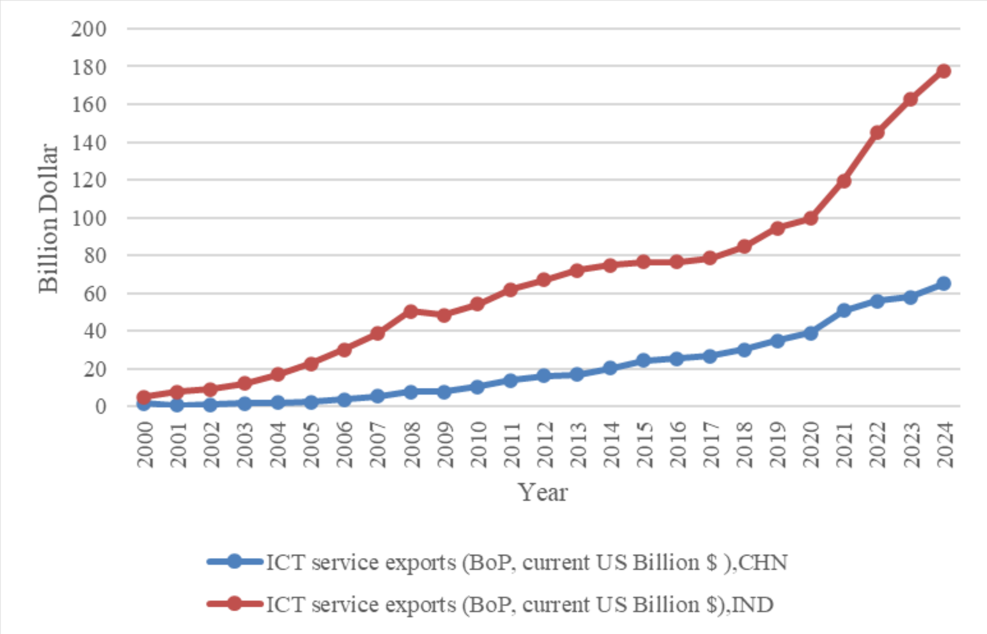
Against the background of accelerated development of the digital economy, innovation capability has already become the inner drive to promote the increase in digital deliverable service exports, and it has strategic significance for the new emerging economies like China and India. On the one hand, ICT service is characterised by being knowledge intensive and technology intensive, and its competitive advantages are not only dependent on the factor of cost but also rely on continuous technology innovation, product upgrades, and service mode innovation. The promotion of innovation capability facilitates the competitiveness of corporations in the global market and fosters the service export upgrade from low-value-added to high-value-added segments.

On the other hand, while both China and India are essential emerging economies, they have significantly different structures for their innovation systems, pathways for technology diffusion, and effects of transitioning innovation into outcomes. Comparing the relationship between innovation capability and ICT service export performance in China and India reveals how innovation drives digital service trade, considering their different development stages and institutional environments. Nevertheless, regarding the innovation capabilities of ICT service-exporting states in China and India, this study aims to deepen the analysis of how digital service trade competitiveness is formed and provide realistic evidence for formulating policies related to the digital economy and innovation.

As shown in Figure 1, the data reveals that China's and India's ICT service export volume is on an obviously upward trend during 2000-2024, and they have differences between growth pathways and stage characteristics. In 2000, India's ICT service export volume was higher than that of China, obviously, and it shows that India had international advantages in the field of software outsourcing and information services in the early stages. And after that, the volume of India's ICT service export is growing steadily and growing rapidly after 2005, and in the surge stage after 2020, the volume is 180 billion dollars in 2024, which shows that its service export mode is innovation-driven and global market-orientated.

In comparison, China's ICT service export volume is comparatively small at the early stage and is growing slowly. But after 2006, it goes into expansion mode; especially after 2010, its growth speed was boosted. With the progress of the digital economy and new-generation information technology, its speed is high and reaches its peak at 65 billion dollars in 2024.

Figure 1: ICT Service Exports, 2000-2024 (China and India)



Source: World Bank[1]

In summary, India's ICT service export has the advantage compared to China's, which shows a pronounced catch-up pattern. This phenomenon depicts the difference between the two countries in the field of the stage of development of ICT service export, foundational industry structure, and innovation drive system, and they give evidence of the aspect of innovation capability to analyse the digital service trade of the two countries.

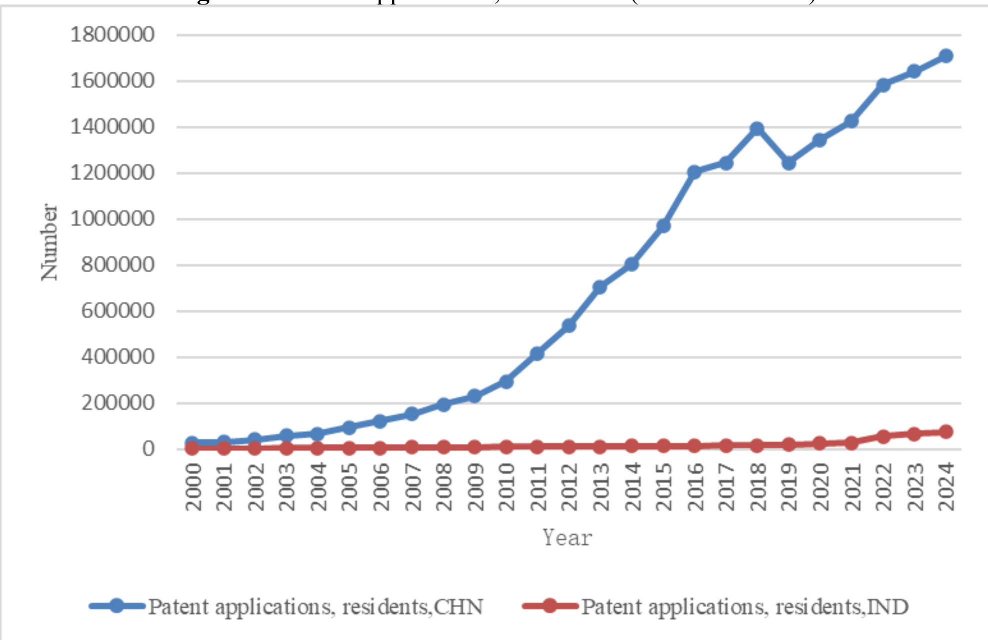
Innovation Capacity Measured by Patent Applications in China and India

Innovation capability is the essential inner drive for promoting the expansion of digital deliverable service exports. And the patent applications are considered as the common index to depict the innovation outcomes and technological activity, and it can reflect the change trend of innovation capability directly. The system comparison of the relationship of innovation capability and ICT service export performance between these two countries helps to reveal the inner mechanism of the drive of innovation on the digital

[1] World Bank. (2024). ICT service exports (% of service exports, BoP). World Bank Open Data. https://data.worldbank.org/indicator/BX.GSR.CCIS.ZS

service trade, against the background of various development stages and institutional environments. Nevertheless, from the aspect of the innovation capability of ICT service export states between China and India, this study can not only deepen the analysis logic of forming the digital service trade competitiveness but also provide the realistic evidence for formulating the targeted policy associated with the digital economy and innovation. This study can understand the differences in innovation system building, speed of innovation acceleration, and scale of innovation between China and India by comparing the long-term evolution of residents' patent applications in both countries.

Figure 2: Patent Applications, 2000-2024 (China and India)



Source: World Bank[2]

Figure 2 shows that the residential patent applications in China and India exhibit a clearly upward trend, with significant differences in both the magnitude of growth and the nature of evolutionary growth. Chinese patent applications have explosive growth and reach the peak of 1.7 million in 2024. In comparison, India's patent applications have a low start and grow steadily and show extremely advantageous advantages of the magnitude of innovation.

Overall, China has more advantages in innovation outcomes of expansion of magnitude, while India has the catch-up pattern. The

[2] World Bank, World Development Indicators (WDI): Patent applications (residents), China and India, 2000–2024. https://data.worldbank.org/indicator/IP.PAT.RESD?locations=CN-IN

differences between the two countries illustrate the background of ICT service exports in terms of their driving mechanisms and development modes.

Methodology

Variable Definition, Indicator Selection, and Data Description

Based on these transformed variables, time-series datasets for China and India covering the period from 2000 to 2024 are constructed for ARDL model estimation. Cointegration tests and error correction model analyses are then employed to systematically examine both the long-run effects of innovation capability and related control factors on digitally deliverable services exports, as well as the associated short-run dynamic adjustment processes.

The research selects the ICT service export volume as the dependent variable and chooses the patent applications as the independent variable. Then the paper chooses the real exchange rate, digital infrastructure, and human capital as the control variables with the support of the literature review. Using these variables, the study builds the ARDL-ECM model to analyse the long term and short-term effects of different factors on the digital delivery variables. The results of the analysis point out that the ICT export volume has a cointegration relationship associated with innovation capability and other macroeconomic factors in the long term.

Table 1: Variable Selection for the Determinants of Digitally Deliverable Service

Variable Type	Variable Name	Indicator	Symbol	Data Source
Dependent Variable	Digitally Deliverable Service Trade Scale	ICT service exports (BoP, current US$) (China, India)	$\ln \mathrm{ICT}_{i,t}$	World Bank
Independent Variable	Innovation Capability	Patent applications, residents (China, India)	$\ln \mathrm{PA}_{i,t}$	World Bank
Control Variables	Exchange Rate Competitiveness	Real effective exchange rate index (China, India)	$\ln \mathrm{REER}_{i,t}$	World Bank
	Digital Infrastructure Level	Individuals using the Internet (% of population) (China, India)	$\ln \mathrm{IUI}_{i,t}$	World Bank
	Human Capital Level	School enrolment, tertiary (% gross) (China, India)	$\ln \mathrm{SET}_{i,t}$	World Bank

Source: Author (s) interpretation

Model Specification

General Form of the ARDL Model: The autoregressive distributed lag (ARDL) model is a dynamic time-series framework that incorporates both lagged terms of the dependent variable and lagged terms of the explanatory variables. This model can capture dynamic interdependencies among economic variables and allows different explanatory variables to have distinct lag structures. The general form of the ARDL model can be expressed as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \sum_{m=0}^{q_j} \beta_{jm} X_{j,t-m} + \varepsilon_t \qquad (4-1)$$

where Y_t denotes the dependent variable, $X_{j,t}$ represents the j-th explanatory variable, p is the optimal lag order of the dependent variable, and q_j is the optimal lag length associated with the j-th explanatory variable. The term $\varepsilon_t$denotes a random disturbance term.

A key advantage of the ARDL approach is that it does not require all variables to be integrated of the same order. If the variables are integrated of order zero or one, that is, I (0) or I (1), they can be jointly included in the model. This feature makes the ARDL model particularly suitable and robust for time-series analysis under small-sample conditions. While the sample size (N=25) is limited by data availability, the ARDL bounds testing approach is specifically chosen for its robustness in small-sample studies compared to conventional cointegration techniques.

Core ADRL Model Specification: In line with the research objectives of this study, the scale of digitally deliverable service exports is taken as the dependent variable, and an autoregressive distributed lag (ARDL) model is constructed to examine the dynamic effects of innovation capability and related digital factors on digital service exports in China and India. The specific model is specified as follows:

$$\begin{aligned} \ln ICT_{i,t} = \alpha_0 &+ \sum_{k=1}^{p} \alpha_k \ln ICT_{i,t-k} + \sum_{m=0}^{q_1} \beta_{1m} \ln PA_{i,t-m} \\ &+ \sum_{m=0}^{q_2} \beta_{2m} \ln REER_{i,t-m} + \sum_{m=0}^{q_3} \beta_{3m} \ln IUI_{i,t-m} \\ &+ \sum_{m=0}^{q_4} \beta_{4m} \ln SET_{i,t-m} + \varepsilon_{i,t} \quad (4-2) \end{aligned}$$

where $\ln ICT_{i,t}$ denotes the scale of digitally deliverable service exports of country i (China or India) in year t, measured as the natural logarithm of ICT service exports (BoP, current US$). $\ln PA_{i,t}$ represents innovation capability, proxied by the natural logarithm of resident patent applications. $\ln REER_{i,t}$ is the real effective exchange rate index, capturing a country's price competitiveness in international markets. $\ln IUI_{i,t}$ denotes the level of digital infrastructure, measured by the natural logarithm of the share of individuals using the Internet. $\ln SET_{i,t}$ represents human capital, proxied by the natural logarithm of tertiary school enrollment. The term $\varepsilon_{i,t}$ is a random disturbance term. The parameters p, q_1, q_2, q_3, q_4 indicate the optimal lag orders for the corresponding variables.

ARDL-ECM Error Correction Model Specification: Once the existence of a long-run cointegration relationship among the variables has been established, the ARDL model can be reformulated as an error correction model (ECM), which integrates long-run equilibrium relationships with short-run dynamic adjustment processes. Consistent with the research framework on the relationship between innovation capability and digitally deliverable service exports, the general form of the ECM can be expressed as:

$$\Delta \ln ICT_{i,t} = \phi\left(\ln ICT_{i,t-1} - \theta_1 \ln PA_{i,t-1} - \theta_2 \ln REER_{i,t-1} - \theta_3 \ln IUI_{i,t-1} - \theta_4 \ln SET_{i,t-1}\right) + \sum_{j=1}^{s} \gamma_j \Delta Z_{i,t-j} + \varepsilon_{i,t} \quad (4-3)$$

where the term in parentheses represents the long-run equilibrium relationship between digitally deliverable service exports and innovation capability, along with the relevant control variables. The coefficient ϕ is the error correction term, which measures the speed at which the system adjusts back to its long-run equilibrium after a deviation. A negative and statistically significant value of ϕ indicates that deviations from the long-run equilibrium are corrected over time, and the larger the absolute value of phi, the faster the adjustment process.

The term $\Delta Z_{i,t-j}$ denotes the first differences of the dependent and explanatory variables, including $\Delta \ln ICT$, $\Delta \ln PA$, $\Delta \ln REER$, $\Delta \ln IUI$, and $\Delta \ln SET$. These variables capture the short-run effects of innovation capability, exchange rate competitiveness, digital infrastructure, and human capital on digitally deliverable service exports. The term $\varepsilon_{i,t}$ represents a random disturbance.

Descriptive Statistical Analysis: To depict the basic statistical characteristics of all variables' distribution before the empirical analysis, it is necessary to conduct descriptive statistics. Table 2 below describes the distribution of variables of ICT service export volume, innovation capability, real exchange rate, digital infrastructure, and human capital, and shows the mean, standard deviation, minimum, and maximum of these variables. The distribution of the variables demonstrates that the two countries' magnitude of digital service trade, innovation, and other factors vary.

Table 2: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
$\ln \text{ICT}_{1,t}$	23.1165	1.352	20.4113	24.8982
$\ln \text{ICT}_{2,t}$	24.5959	0.9699	22.3381	25.9036
$\ln \text{PA}_{1,t}$	12.7881	1.4124	10.1404	14.3508
$\ln \text{REER}_{1,t}$	4.6668	0.1429	4.4417	4.8679
$\ln \text{IUI}_{1,t}$	3.251	1.1532	0.5743	4.5218
$\ln \text{SET}_{1,t}$	3.4232	0.6745	2.0252	4.3422
$\ln \text{PA}_{2,t}$	9.2355	0.9693	7.6989	11.2182
$\ln \text{REER}_{2,t}$	4.3945	0.2318	4.0006	4.7056
$\ln \text{IUI}_{2,t}$	2.1536	1.4222	-0.6395	4.3202

Note: All variables are in natural logarithms; subscripts 1 and 2 denote China and India, respectively.
Source: Author (s) computations.

China

ARDL-ECM Estimation Results: By integrating long-run and short-run effects within a unified framework, the ARDL–ECM model provides a comprehensive perspective on how innovation capability, digital foundations, and macroeconomic factors shape China's ICT service export performance. Table 3 reports the estimation results for China.

Table 3: ARDL-ECM Estimation Results for the Determinants of China's ICT Service Exports

Variable	Long-run Coefficient (LR)	Short-run Coefficient (SR)
ECT(t−1)	−0.839* (0.079)	—
$\ln PA_t$	−0.031 (0.206)	—
$\ln REER_t$	−0.028 (0.465)	—
$\ln IUI_t$	0.859* (0.148)	0.291 (0.238)
$\ln SET_t$	0.867* (0.194)	—
Constant	—	14.915* (1.319)
N	24	—
R-squared	0.909	—

Note: Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Source: Author (s) computations.

Table 3 presents the results of the ARDL-ECM regression model: the ICT service export volume of China not only has a steady relationship with the explanatory variables but also has a different effect in the long term and short term. From the ECT variable, the ECT(t−1)'s coefficient is -0.839 (P<0.01), which portrays that while ICT service export volume is away from the long-term balance states, it has the proportion of 83.9% to be modified, and it shows the adjustment speed and long-term balance capability. In the long-term effect, the digital infrastructure and human capital both have a significant positive effect on the ICT service export with the coefficients of 0.859 ($P<0.1$) and 0.867 ($P<0.1$), respectively, which illustrates that the improvement of internet usage and acceleration of human capital are the essential factors to boost ICT service export in China.

On the contrary, the innovation capability and real exchange rate's long-term coefficients are −0.031 ($p = 0.883$) and −0.028 ($p = 0.953$), respectively, which do not pass the significance test, and the result shows that after controlling for the digital infrastructure and human capital, the factors of patent applications and exchange rate have a limited effect in the long term. This insignificant impact of patent applications on China's ICT exports suggests that China's digital trade expansion may be driven more by business model innovation and platform infrastructure (e.g., Alibaba, Tencent ecosystems) rather than technical patenting, or that there is a lag between patent filing and export commercialisation. As for the short term, the coefficient of the first differenced term of the digital infrastructure term is 0.291, but it does not reach the significance level. The result shows that the short-term fluctuation of the usage rate of the internet doesn't have a significant effect on the ICT service export. And the ICT service export relies on the long-term acceleration.

Cointegration test: Before estimating the ARDL-ECM model, it is necessary to examine whether a stable long-run cointegration relationship exists between China's ICT service export scale and innovation capability, together with the relevant control variables. To this end, this study adopts the Bounds Testing approach proposed by Pesaran, Shin, and Smith (2001) to test for a long-run equilibrium relationship among ICT service exports, innovation capability, exchange rate competitiveness, digital infrastructure, and human capital. This method does not require all variables to be integrated of the same order and allows a mixture of I (0) and I (1) variables, making it particularly suitable for macroeconomic time-series analysis with relatively small samples. The cointegration test results provide an essential econometric basis for the specification of the ARD-ECM model and the interpretation of long-run coefficients.

Table 4: Cointegration Test Results

Statistic	Value	10% Critical Value I (0)/I (1)	5% Critical Value I (0)/I (1)	p-value (I (0)/I (1))	Conclusion
F-statistic	33.622	2.896 / 4.226	3.615 / 5.176	0.000 / 0.000	Cointegration
t-statistic	-10.587	-2.567 / -3.677	-2.963 / -4.156	0.000 / 0.000	Cointegration

Source: Author (s) computations.

The results reported in Table 4 indicate the presence of a strong and stable long run cointegration relationship between China's ICT service exports and the explanatory variables. Specifically, the F-statistic equals 33.622, which is far above the upper bound critical value of 7.614 at the 1% significance level. Moreover, the corresponding p-values under both the I (0) and I (1) assumptions are 0.000, allowing the null hypothesis of "no cointegration" to be decisively rejected.

Model Diagnostics and Robustness Checks: To ensure the reliability and stability of the ARDL-ECM model's results, before the illustration of the regression coefficient, it is necessary to conduct a systematic test for the basic hypothesis. The model diagnostics and robustness checks are mainly testing whether the model has the problem of autocorrelation, heteroskedasticity, and normality. After testing the reasonableness of the model and whether the result is interrupted by the exogenous shocks. As a direct diagnostic method, the standardised residual time series can reflect the stability of the model's fit over the sample period and reveal potential structural changes.

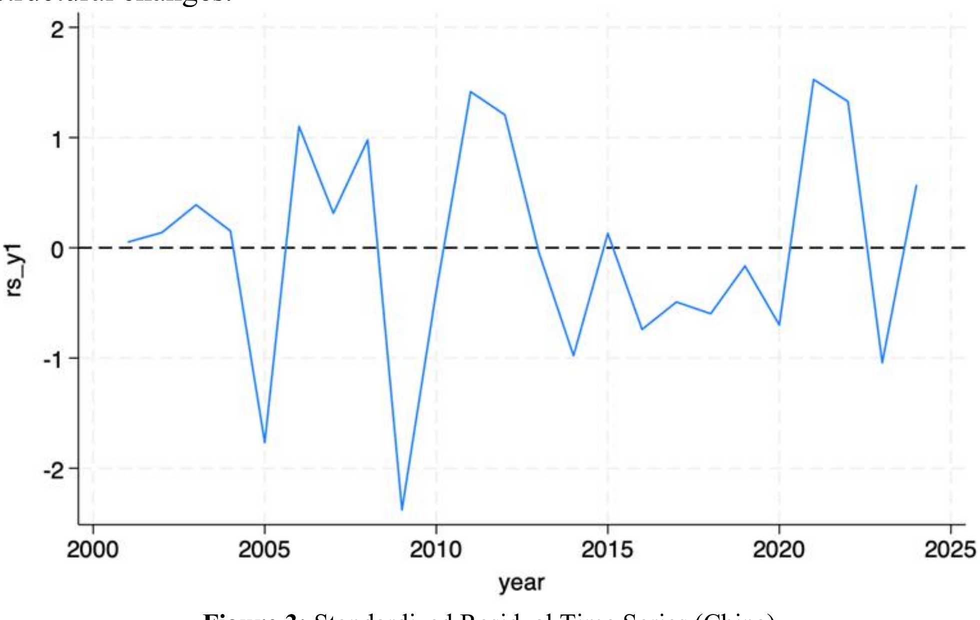


Figure 3: Standardized Residual Time Series (China)

From Figure 3, we can tell that the residual fluctuates around zero, and most of the time, the value is in the range of ±2, which is reasonable and does not show a systematic and continuous deviation trend. The figure depicts that the model is in steady mode. Although in some specific years, there are big moves existing, but they are not continuous and do not have a structural breakpoint. Therefore, the results indicate that the observed fluctuations are due to short-term shocks rather than errors in the model setup. Combined with the test result, the study can draw the conclusion that the ARDL-ECM model is stable, and its parameter estimation is not affected by the violation of classical assumptions.

Table 5: Summary of Model Diagnostics and Robustness Tests (China)

Test Type	Method	Statistics / Lags	p-value	Conclusion
Autocorrelation	Portmanteau (Q)	lags (1)	0.6396	Passed
Autocorrelation	Portmanteau (Q)	lags (2)	0.2788	Passed
Autocorrelation	Cumby–Huizinga	1–12	Mostly > 0.10	Largely Passed
Normality	Skewness–Kurtosis	Joint	0.5839	Passed
Heteroskedasticity	White test (imtest, white)	—	0.2687	Passed
Heteroskedasticity (Supplementary)	Breusch–Pagan	—	0.0205	Potential Presence Indicated
Stability	Standardized Residual Plot	rs_y1	—	No Obvious Structural Break

From Table 5, the data reveals that the ADRL-ECM model is aligned with the classic economic assumptions, and the result is highly reliable. From the autocorrelation test, the Portmanteau (Q) test has the value of 0.6396 and 0.2788 at the stage of lags (1) and lags (1), respectively, which does not reject the null hypothesis. The Cumby-Huizinga test's P value is larger than 0.1 at the 1-12 stage. This shows that the residuals of the model don't have a significant autocorrelation problem. In the characteristics of normality, the Skewness-Kurtosis test's p-value is 0.5839 and obeys the normal distribution. The Heteroskedasticity White test's result shows that the P value is 0.2687 and that there is no significant heteroskedasticity problem. And the Breusch-Pagan test does not show a significant heteroskedasticity problem. In the step-forward aspect, the standardised residual plot does not show a structural break. This shows that the model has good dynamic stability.

In short, the diagnostic supports that the ADRL-ECM model of China's set is reasonable and gives a steady foundation for the empirical results.

India

ARDL-ECM Estimation Results: This study builds an ARDL–ECM model based on the previously defined framework and variable selection. The model empirically analyses both the long-run equilibrium relationship and the short-run dynamic adjustment process between India's ICT service export scale and innovation capability, exchange rate competitiveness, digital infrastructure, and human capital.

Table 6: ARDL–ECM Estimation Results for the Determinants of ICT Service Exports in India

Variable	Long-run Coefficient (LR)	Short-run Coefficient (SR)
ECT(t−1)	−0.366* (0.078)	—
$\ln PA_t$	0.488 (0.200)	—
$\ln REER_t$	1.628* (0.345)	—
$\ln IUI_t$	0.377 (0.212)	−0.226 (0.088)
$\ln SET_t$	0.169 (0.446)	—
Constant	—	4.407* (1.417)
N	24	—
R-squared	0.839	

Note: Standard errors are reported in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: Author (s) computations.

Table 6 details the results of the ARDL-ECM model of India reveals ICT service export volume in the long-term and short-term. From the ECT, we can see the coefficient of ECT(t-1) is −0.366 (P<0.01), which shows that while the ICT service export volume is away from the balance of the state, it has the proportion of 36.6% to correct in the first stage. It shows that the ICT service export volume of India has a long-run self-correcting ability but is also adjusted slowly. In the long run, the innovation capability's coefficient is 0.488 (P<0.05), which shows that the patent applications are positively associated with the ICT service export volume of India. The real exchange rate's long-run coefficient is 1.628 (P<0.001), which depicts that the exchange rate is significantly associated with the ICT service export volume of India.

On the contrary, the coefficient of digital infrastructure and human capital in the long run is 0.377 (P=0.093) and 0.169 (P=0.708). The former variable is on the 10% significant level, and the latter one does not pass the significance test. The results show that the diffusion of the internet and tertiary education has little impact on ICT service export. In the short-term effect, the digital infrastructure's first difference term's coefficient is -0.226 (P=0.02), which shows that the usage is associated with structural adjustment and cost growth in the short-term, and it will form the stage constraint to the ICT service export.

In summary, the ICT service export volume of India relies more on the innovation capability and exchange rate competitiveness in the long term, while the digital infrastructure plays the mechanism of adjustment in the short term.

Cointegration Test: This method allows the included variables to be integrated in order I (0) or I (1) and maintains relatively high testing power under limited sample sizes, making it well-suited to the time-series framework employed in this study.

Table 7: Bounds Test Results for Cointegration

Statistic	Value	10% Critical Value I (0) / I (1)	5% Critical Value I (0) / I (1)	p-value (I (0) / I (1))	Conclusion
F-statistic	17.536	2.896 / 4.226	3.615 / 5.176	0.000 / 0.000	Cointegration
t-statistic	−4.702	−2.567 / −3.677	−2.963 / −4.156	0.002 / 0.021	Cointegration

Source: Author (s) computations.

As shown in Table 7, the results of the cointegration test provide strong evidence of a stable long-run relationship between India's ICT service exports and the explanatory variables. Specifically, the F-statistics is 17.536, which is well above the upper bound critical value at the 5% significance level (I (1) = 5.176). In addition, the associated p-values under both I (0) and I (1) assumptions are close to zero, allowing the null hypothesis of "no cointegration" to be rejected with a high degree of confidence. The t-statistic is −4.702, whose absolute value exceeds the I (1) upper bound critical value at the 5% level (−4.156) and is statistically significant, further supporting the existence of a long-run equilibrium relationship from an auxiliary testing perspective.

Model Diagnostics and Robustness Tests: To ensure the reliability and stability of the ARDL-ECM model's results, before the illustration of the regression coefficient, it is necessary to conduct a systematic test for the basic hypothesis. The model diagnostics and robustness checks are mainly testing whether the model has the problem of autocorrelation, heteroskedasticity, and normality. After testing the reasonableness of the model and whether the result is interrupted by the exogenous shocks. As a direct diagnostic method, the standardised residual time series can reflect the stability of the model's fit over the sample period and reveal potential structural changes.

From Figure 4, we can tell that the residual fluctuates around zero, and most of the time, the value is in the range of ±2, which is reasonable and does not show a systematic and continuous deviation trend. The figure depicts that the model is in steady mode. Although in some specific years, there are big moves existing, but they are not continuous and do not have a structural breakpoint. Therefore, the results indicate that the observed fluctuations are due to short-term shocks rather than errors in the model setup. Combined with the test result, the study can draw the conclusion that the ARDL-ECM model is stable, and its parameter estimation is not affected by the violation of classical assumptions.

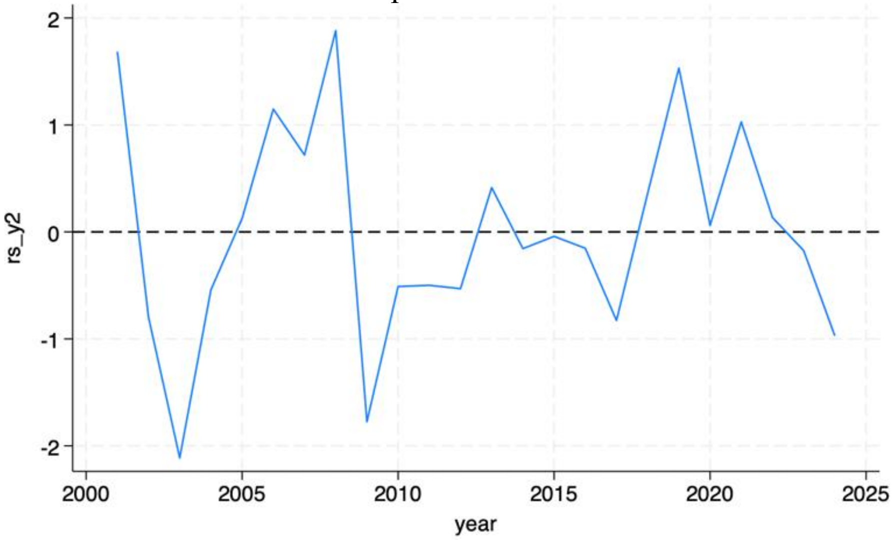


Figure 4: Standardized Residual Time Series (India)

The data from Table 8 reveals that the ADRL-ECM model is aligned with the classic economic assumptions, and the result is highly reliable. From the autocorrelation test, the Portmanteau (Q) test has the value of 0.591 and 0.685 at the stage of lags (1) and lags (1), respectively, which does not reject the null hypothesis. The Cumby–Huizinga test's P value is larger than 0.1 at the 1-12 stage. This shows that the residuals of the model don't have a significant autocorrelation problem. In the characteristics of normality, the Skewness-Kurtosis test's p-value is 0.694 and obeys the normal distribution. The Heteroskedasticity White test's result shows that the P value is 0.753 and that there is no significant heteroskedasticity problem. And the Breusch-Pagan test does not show a significant heteroskedasticity problem. In the step-forward aspect, the standardised residual plot does not show the structural break. This shows that the model has good dynamic stability.

In conclusion, the diagnostic supports that the ADRL-ECM model of India's set is reasonable and provides a robust foundation for the empirical results.

Table 8: Diagnostic and Robustness Test Results (India)

Test Type	Method	p-value	Conclusion
Autocorrelation	Ljung–Box Q (1) / Q (2)	0.591 / 0.685	Passed
Autocorrelation	Cumby–Huizinga (1–12)	Mostly > 0.10	Passed
Heteroskedasticity	Breusch–Pagan	0.694	Passed
Heteroskedasticity	White test	0.753	Passed
Normality	Skewness–Kurtosis	0.967	Passed
Stability	Standardized Residual Plot (rs_y2)	—	Stable

Discussion and Summary of Empirical Results

At the foundational empirical analysis of the influence factors on ICT service export volume of China and India, it is necessary to summarise the results systematically of the two countries and to reveal the long-term relationship of balance. Short-term adjustment, dynamic adjustment characteristics, and effect mechanism differences.

Consequently, the empirical results confirm that ICT service exports have a long-term cointegration relationship with innovation capability, digital infrastructure, human capital, and real exchange rate. China has the characteristics of steady and rapid adjustment speed in the long term, while India does have the same relationship, but its adjustment speed is relatively slow, and the export expansion is more focused on the innovation capability and exchange rate competitiveness. The table below shows the details of the comparison of the two countries.

Table 9: A Comparative Summary of ARDL–ECM Empirical Results on the Determinants of ICT Services Exports in China and India (2000–2024)

Comparison Dimension	China	India	Comparison Dimension
Dependent Variable	ICT Services Exports	ICT Services Exports	Dependent Variable
Existence of Long-run Cointegration (Bounds Test)	Yes: F = 33.622, t = −10.587, p-value (I (0)/I (1)) = 0.000 / 0.000 (Cointegration)	Yes: F = 17.536, t = −4.702, p-value (I (0)/I (1)) = 0.000 / 0.000; 0.002 / 0.021 (Cointegration)	Existence of Long-run Cointegration (Bounds Test)
Error Correction Term ECT(t−1)	−0.839* (0.079), p = 0.000 (Significant)	−0.366* (0.078), p = 0.000 (Significant)	Error Correction Term ECT(t−1)
Speed of Long-run Adjustment	Faster: approx. 83.9% per period	Slower: approx. 36.6% per period	Speed of Long-run Adjustment
Innovation Capacity (lnPA), Long-run Effect	−0.031 (0.206), p = 0.883 (Not significant)	0.488** (0.200), p = 0.026 (Significantly positive)	Innovation Capacity (lnPA), Long-run Effect
Exchange Rate Competitiveness (lnREER), Long-run Effect	−0.028 (0.465), p = 0.953 (Not significant)	1.628*** (0.345), p = 0.000 (Significantly positive)	Exchange Rate Competitiveness (lnREER), Long-run Effect
Digital Infrastructure (lnIUI), Long-run Effect	0.859*** (0.148), p = 0.000 (Significantly positive)	0.377* (0.212), p = 0.093 (Weakly significant positive)	Digital Infrastructure (lnIUI), Long-run Effect
Digital Infrastructure (ΔlnIUI), Short-run Effect	0.291 (0.238), p = 0.239 (Not significant)	−0.226** (0.088), p = 0.020 (Significantly negative)	Digital Infrastructure (ΔlnIUI), Short-run Effect
Human Capital (lnSET), Long-run Effect	0.867*** (0.194), p = 0.000 (Significantly positive)	0.169 (0.446), p = 0.708 (Not significant)	Human Capital (lnSET), Long-run Effect
Goodness of Fit (R-squared)	0.909	0.839	Goodness of Fit (R-squared)
Residual	Q (1) p = 0.6396; Q (2) p	Q (1) p = 0.5905; Q (2)	Residual

Autocorrelation (Portmanteau / Ljung–Box)	= 0.2788 (Passed)	p = 0.6846 (Passed)	Autocorrelation (Portmanteau / Ljung–Box)
Residual Autocorrelation (Cumby–Huizinga)	Lags 1–12 mostly p > 0.10 (Largely passed)	Lags 1–12 mostly p > 0.10 (Passed)	Residual Autocorrelation (Cumby–Huizinga)
Normality (Skewness–Kurtosis)	p = 0.5839 (Passed)	p = 0.9665 (Passed)	Normality (Skewness–Kurtosis)
Heteroskedasticity (White Test)	p = 0.2687 (Passed)	p = 0.7525 (Passed)	Heteroskedasticity (White Test)
Heteroskedasticity (Supplementary Breusch–Pagan)	p = 0.0205 (Possible mild heteroskedasticity indicated)	p = 0.6944 (Passed)	Heteroskedasticity (Supplementary Breusch–Pagan)
Dynamic Stability (Standardized Residual Plot)	rs_y1: No obvious structural breaks	rs_y2: Overall stable	Dynamic Stability (Standardized Residual Plot)

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. “Long-run effects” refer to the long-run coefficients derived from the ARDL model, while “short-run effects” refer to the first-differenced terms in the error-correction model.
Source: Author (s) interpretation.

Based on the ARDL-ECM empirical results for ICT services exports in China and India, it can be observed that the development mechanisms of digital services trade in the two countries exhibit both commonalities and pronounced differences. With respect to shared features, the Bounds Test results for both countries provide strong evidence of stable long run cointegration relationships, and the error correction terms are significantly negative in each case. This indicates that, following short-term shocks, ICT services exports in both China and India can converge back to their long-run equilibrium paths through internal adjustment mechanisms.

China and India’s digital industries are developing at a rapid speed, which shows the ambition of new emerging countries to conquer a greater share of the tertiary industry in the global market. The ICT service export volume plays a core role in the global market, and it shows the soft power of the country. The government accelerates the progress of the ICT sector and makes it contribute to the promotion of labour productivity. The transition of industry structure empowers the country, and the diffusion of internet technology and human capital in the developing countries makes it true with a better institutional environment. India and China are the essential markets in the world; they have the numerous internet engineers to do the ICT outsourcing and generate substantial short-term economic returns. China relies more on the digital infrastructure, and India relies on the innovation capability; these differences make the two countries follow totally different pathways. This study shows that at different stages and in different settings, the ability to innovate affects how digital trade is developed, and it helps support the balance between innovation policies and digital trade in emerging economies.

Conclusion

As emerging economies strive to upgrade their positions in the global value chain, the digital economy presents a critical frontier. This study utilised ARDL-ECM modelling to comparatively analyse the determinants of ICT service exports in China and India from 2000 to 2024, focusing explicitly on innovation capabilities alongside macroeconomic constraints.

The empirical findings confirm that the mechanisms driving digital trade competitiveness are highly heterogeneous and stage dependent. Rather than a universal pathway, we observe distinct national paradigms. China's export expansion is predominantly anchored in the long-term accumulation of structural assets namely, digital infrastructure and human capital. In this context, the direct long-term impact of technical patenting is muted, suggesting an export model driven by scale and platform facilitation. In contrast, India's trajectory exemplifies an innovation-led model, where long-term export viability is deeply intertwined with direct innovation capability and sustained by favourable real exchange rate competitiveness.

These divergent pathways highlight that the successful translation of innovation into international trade performance is profoundly mediated by a country's foundational industry structure and institutional environment. For policymakers formulating digital trade strategies, the implications are clear: blindly adopting a generalised innovation model is insufficient. To build digital bridges rather than widening digital divides, emerging economies must tailor their policy interventions to their unique structural advantages, balancing infrastructure investments with targeted innovation incentives to secure a sustainable share of the global tertiary market.

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