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Innovation Capabilities and Digitally Deliverable Service Exports in China and India: An ARDL-ECM Analysis, 2000-2024

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Abstract

This study examines how innovation capabilities shape Information and Communication Technology (ICT) service exports in China and India from 2000 to 2024. Amid the rapid expansion of digital trade, identifying the distinct growth trajectories of these two emerging economies is critical for policy insights. Using an Autoregressive Distributed Lag Error Correction Model (ARDL-ECM), we estimate long-run cointegration and short-run effects by modelling ICT export volume against resident patent applications while controlling for the real exchange rate, digital infrastructure, and human capital. Bounds testing confirms cointegration in both economies ($F = 33.622$ for China; $F = 17.536$ for India), with error correction terms of -0.839 and -0.366 (both $p < 0.01$), indicating rapid adjustment toward long-run equilibrium in China and a more gradual correction in India. Findings show that while China's export growth is mainly supported by long-run accumulation of digital infrastructure (0.859, $p < 0.01$) and human capital (0.867, $p < 0.01$) (with a minor direct impact of patent-based innovation), India's performance is dependent on innovation capability (0.488, $p < 0.05$) and exchange rate competitiveness (1.628, $p < 0.01$). Therefore, innovation and trade competitiveness are not synchronised across nations, and digital trade policy needs to be tailored to developmental levels.

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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. Recent statistics indicate that global digitally deliverable service exports reached USD 4.25 trillion in 2024, accounting for more than half of total global service exports (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 and represents a growing share of global service trade. At the same time, the ICT services as a percentage of service exports indicator clearly reveals cross-country differences and trends in digital trade volume (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. In contrast, India's innovation capability and exchange-rate competitiveness exert positive long-run effects on its ICT service exports in the long term, and the digital infrastructure has a short-term structural mediation effect. Overall, this study finds that innovation capability has varying effects across developmental stages and institutional contexts in shaping digital trade in deliverable services, providing evidence for balancing innovation policy with 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 examines how innovation capability shapes digitally deliverable service trade.

Literature Review

Existing literature identifies three drivers of digitally deliverable service trade, i.e., digital technology, innovation capability, and macroeconomic conditions. Their effects vary across countries and over time. Early empirical studies indicate that widespread internet adoption reduces cross-border trade costs and information asymmetries, thereby promoting 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). Digitally deliverable services are the

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fastest-growing component of global service trade and depend critically on digital infrastructure, policy, and the broader technology environment (Di et al., 2022; Herman & Oliver, 2023). For developing countries, they offer a pathway beyond traditional manufacturing constraints and into the global economic system, enabling access to new markets, fostering innovation, and creating job opportunities in the digital economy (Eichengreen & Gupta, 2013; Goswami et al., 2012). Innovation capability is widely considered an essential driving factor in the field of export upgrades and long-term growth potential. This effect is especially significant in 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, comparative research indicates that the positive effect of innovation capability on exports is not automatic. Institutional and structural factors constrain it, as the internationalisation pathways of Chinese and Indian firms make it clear (Aaronson & Leblond, 2018; Fortanier & Tulder, 2009). The institutional environment governing cross-border data flows further shapes the digital divide between rule-makers and rule-takers in the digital trade order (Aaronson & Leblond, 2018).

Apart from innovation capability, digital infrastructure and human capital are also considered the core fundamental factors for the progress of the digital service trade. Wide internet diffusion lowers trade costs and accelerates the spread of innovation (C. Freund & Weinhold, 2002; Goldfarb & Tucker, 2019). High-quality labour, in turn, underpins the effective absorption and utilisation of new technology (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 increasingly affects the service sector, potentially generating labour-market heterogeneity. 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). The digital industries of China and India are expanding rapidly, reflecting the ambition of emerging economies 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

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a better institutional environment. India and China represent key global markets, each possessing a large pool of IT engineers who deliver ICT outsourcing services and generate significant short-term returns. China's development is more reliant on digital infrastructure, whereas India's is more driven by innovation capability, leading to divergent development 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. ICT services are knowledge and technology intensive, and their competitive advantage depends not only on cost but also on sustained innovation in technology, products, and service delivery models. 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.

Although both economies are emerging giants, there are significant differences in their innovation systems, technology diffusion pathways, and mechanisms for transmitting innovation to exports. 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. Accordingly, by examining the innovation capabilities underlying ICT service exports in China and India, this study aims to clarify how competitiveness in digital services trade is formed and to provide empirical evidence for policies related to the digital economy and innovation.

Figure 1 shows that ICT service export volumes in both China and India trend upward over 2000-2024, but with markedly different growth pathways and stage characteristics. In 2000, India's ICT service exports already exceeded China's, reflecting India's early international advantage in software outsourcing and information services. Subsequently, India's ICT service exports exhibited steady growth, with a marked acceleration after 2005 and a rapid expansion phase after 2020. By 2024, exports reached approximately USD 180 billion, suggesting an innovation-driven and globally oriented service export model.

In comparison, China's ICT service exports were relatively small in the early period and grew slowly. After 2006, however, they entered an expansion phase, with growth accelerating particularly after 2010. With the

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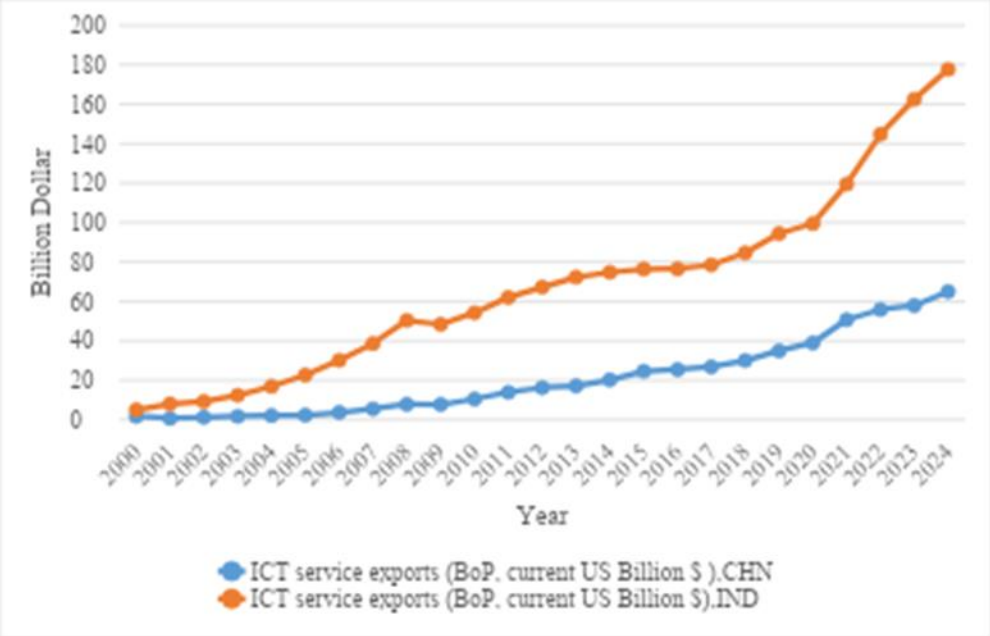
progress of the digital economy and new-generation information technology, its speed is high and reaches its peak at 65 billion dollars in 2024.

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



Source: World Bank[1]

In summary, India retains an absolute advantage in ICT service exports, while China displays a pronounced catch-up pattern. This contrast reflects differences between the two countries in their stage of ICT export development, underlying industry structure, and innovation systems, and motivates a closer examination of innovation capability as a driver of digital service trade.

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. Patent applications are widely used as a proxy for innovation outcomes and technological activity, and they can reflect the changing trend of innovation capability directly. A systematic comparison of innovation capability and ICT service export performance in these two countries reveals how innovation drives digital service trade across different developmental stages and institutional environments. By examining innovation capability in China's and India's ICT service exports, this study contributes in two ways. First, it deepens the analytical understanding of how

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

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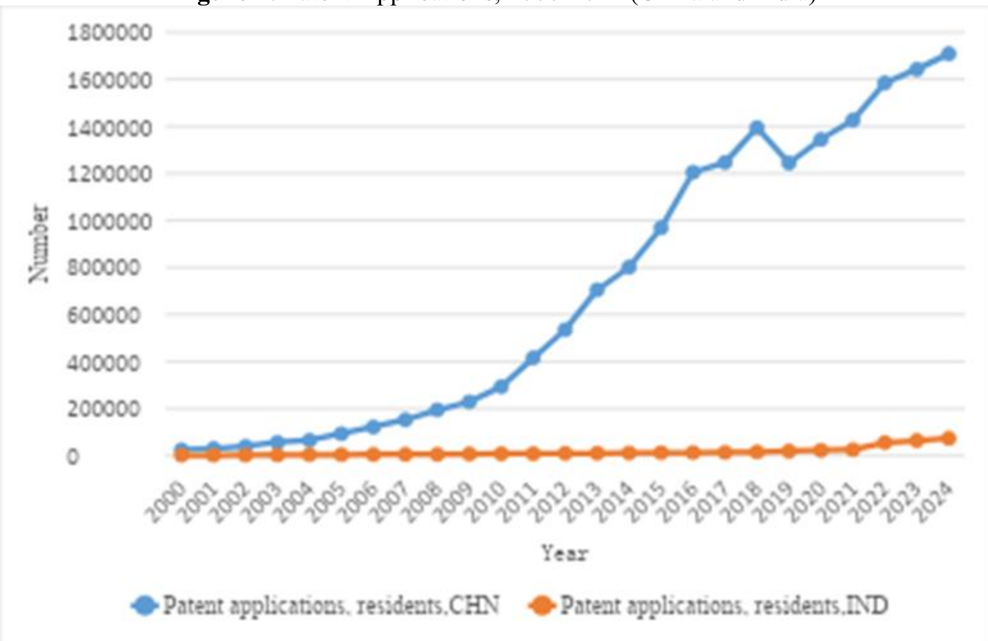
digital trade competitiveness is formed. Second, it provides empirical evidence to inform targeted policy on the digital economy and innovation. By comparing the long-term evolution of resident patent applications in both countries, this study identifies differences in innovation-system development, the pace of innovation, and the scale of innovation activity between China and India.

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 grew explosively, peaking at 1.7 million in 2024. By comparison, India started from a low base and grew steadily, with China holding a clear quantitative advantage in innovation output.

Overall, China has more advantages in innovation outcomes of expansion of magnitude, while India has the catch-up pattern. The differences between the two countries illustrate the background of ICT service exports in terms of their driving mechanisms and development modes.

[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

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Methodology

This section sets out the empirical strategy used to estimate the long-run and short-run effects of innovation capability and related macroeconomic factors on digitally deliverable service exports in China and India. The procedure follows a sequential flow: variable definition and data description; unit root testing to confirm the order of integration; lag length selection; ARDL model estimation; bounds testing for cointegration; reformulation as an error correction model; diagnostic verification; and descriptive analysis of the transformed series. Each stage is described below in sufficient detail to ensure replicability.

Variable Definition, Indicator Selection, and Data Description

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 and short-term effects of different factors on the digital delivery variables.

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)	$ln\, ln\, ICT_{i,t}$	World Bank
Independent Variable	Innovation Capability	Patent applications, residents (China, India)	$ln\, ln\, PA_{i,t}$	World Bank
Control Variables	Exchange Rate Competitiveness	Real effective exchange rate index (China, India)	$ln\, ln\, REER_{i,t}$	World Bank
	Digital Infrastructure Level	Individuals using the Internet (% of population) (China, India)	$ln\, ln\, IUI_{i,t}$	World Bank
	Human Capital Level	School enrolment, tertiary (% gross) (China, India)	$ln\, ln\, SET_{i,t}$	World Bank

Source: Author (s) interpretation

All variables are transformed into natural logarithms prior to estimation, for three reasons. First, the transformation stabilises the variances of variables that span several orders of magnitude, most notably ICT service exports and resident patent applications, both of which grow substantially over the sample period. Second, the coefficients are readily interpreted as long-run elasticities, as is common in the international trade and growth literature.

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Third, this process helps counter the effect of different scales in China and India and makes the country-specific time series more comparable. Time-series data for China and India are then constructed on the basis of these variables for ARDL modelling and cointegration tests, and error correction model analyses are applied to investigate the long-run impacts of innovation capability and control variables on digital deliverable service exports and the short-run dynamic adjustments of services exports.

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.

Unit Root Testing

Although the ARDL bounds testing procedure (Pesaran et al., 2001) accommodates a mixture of I(0) and I(1) variables, the presence of any I(2) series would invalidate the asymptotic critical values and yield spurious inference. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are therefore applied to each variable in both log levels and first differences to verify the order of integration. Level tests include a constant and a linear trend, reflecting the trending behaviour of the macroeconomic series, while first-difference tests include a constant only. ADF lag lengths are selected by the Akaike Information Criterion, and the Phillips-Perron tests employ the Newey-West automatic bandwidth selector. The full results are reported in Table 2.

Table 2: Results of Augmented Dickey–Fuller and Phillips–Perron Unit Root Tests

Variable	ADF (Level)	PP (Level)	ADF (1st Diff)	PP (1st Diff)	Order of Integration
ln*ICT* (China)	−1.803 (0.703)	−2.514 (0.321)	−3.647*** (0.005)	−7.097*** (0.000)	I(1)
ln*PA* (China)	1.123 (1.000)	1.095 (1.000)	0.466 (0.984)	−2.887** (0.047)	I(1)
ln*REER* (China)	−3.694** (0.023)	−1.395 (0.862)	−2.959** (0.039)	−3.123** (0.025)	I(1)
ln*IUI* (China)	−4.944*** (0.000)	−3.862** (0.014)	−1.593 (0.487)	−1.802 (0.379)	I(0)
ln*SET* (China)	−2.892 (0.165)	−3.163* (0.092)	−2.640* (0.085)	−2.342 (0.159)	I(1)[a]
ln*ICT* (India)	−3.268* (0.072)	−3.368* (0.056)	−3.454*** (0.009)	−3.454*** (0.009)	I(1)
lnPA (India)	−1.184 (0.914)	−0.859 (0.960)	−4.431*** (0.000)	−4.439*** (0.000)	I(1)

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ln*REER* (India)	−2.000 (0.601)	−1.557 (0.809)	−2.120 (0.237)	−4.309*** (0.000)	I(1)
ln*IUI* (India)	−3.938** (0.011)	−3.929** (0.011)	−3.660*** (0.005)	−4.531*** (0.000)	I(0)
ln*SET* (India)	−1.882 (0.664)	−0.982 (0.946)	−1.452 (0.557)	−3.072** (0.029)	I(1)

Notes: Reported values are test statistics with p-values in parentheses. Level tests include a constant and linear trend; first-difference tests include a constant only. ADF lag length is selected by the Akaike Information Criterion. Phillips–Perron tests use the Newey–West automatic bandwidth selector. *, **, and *** denote rejection of the unit root null at the 10%, 5%, and 1% levels, respectively. The order of integration is determined by the preponderance of evidence across the two tests in levels and first differences.

[a] For lnSET (China), the first-difference results are borderline; supplementary tests on the second difference decisively reject the unit root null (PP: $t = -7.53$, $p < 0.001$), confirming that the series is at most I(1) and is not I(2).

Source: Author(s) computations

The tests indicate that two variables-ln*IUI* for China and ln*IUI* for India-are stationary in their levels and therefore I(0), reflecting the fact that internet diffusion has approached saturation over the sample period and exhibits trend-stationary dynamics. The remaining eight series are integrated of order one, consistent with their underlying growth trajectories. For one borderline case (ln*SET*, China), where the first-difference evidence is mixed, supplementary tests on the second difference decisively reject the unit root null, confirming that the series is at most I(1). Crucially, none of the ten series is integrated of order two, satisfying the precondition for the validity of the bounds testing approach. The combination of I(0) and I(1) regressors makes the ARDL framework uniquely appropriate for this study, as conventional cointegration techniques such as the Johansen procedure would require all variables to share the same order of integration.

Lag Length Selection

The order of the lag (p for the dependent variable and q_1, q_2, q_3, q_4 for the explanatory variables) is chosen using the Akaike Information Criterion (AIC). Due to the small sample (N = 25), the maximum lag length is limited to two periods. This restriction preserves degrees of freedom while still capturing meaningful short-run dynamics. AIC is preferred to the Schwarz Bayesian Criterion in this context because it retains more dynamic information in finite samples, which is desirable for modelling the adjustment processes that are central to this study. The lag combinations chosen by AIC for China and India are provided in Tables 4 and 7, respectively.

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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:

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

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.

This feature, combined with its robustness in finite samples (Narayan, 2005), makes the ARDL model particularly suitable for the present study, in which data availability constrains the sample to N = 25. In comparison with conventional cointegration techniques such as the Johansen procedure, the ARDL bounds testing approach delivers more reliable inference under such small-sample conditions (Narayan, 2005; Pesaran et al., 2001).

Core ARDL Model Specification: In line with the research objectives, the scale of digitally deliverable service exports is the dependent variable, and the country-specific ARDL specification used to examine the dynamic effects of innovation capability and related digital factors is given by:

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

where $ln\, ln\, ICT_{i,t}$ 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$). $ln\, ln\, P\, A_{i,t}$ represents innovation capability, proxied by the natural logarithm of resident patent applications. $ln\, ln\, REER_{i,t}$ is the real effective exchange rate index, capturing a country's price competitiveness in international markets. $ln\, ln\, IUI_{i,t}$ denotes the level of digital infrastructure, measured by the natural logarithm of the share of individuals using the Internet. $ln\, ln\, SET_{i,t}$ represents human capital, proxied

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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.

Bounds Testing for Cointegration: Following ARDL estimation, the existence of a long-run cointegration relationship is assessed using the bounds testing procedure (Pesaran et al., 2001). The null hypothesis of "no cointegration" is examined through an F-test on the joint significance of the lagged level terms in the conditional ARDL specification. The computed F-statistic is compared against two sets of asymptotic critical values: a lower bound under the assumption that all regressors are I(0), and an upper bound under the assumption that all are I(1). An F-statistic exceeding the upper bound rejects the null and confirms the presence of a long-run relationship; one falling below the lower bound supports non-cointegration; intermediate values are inconclusive. A complementary t-test on the lagged dependent variable provides auxiliary evidence on the speed of adjustment toward equilibrium. Country-specific bounds test results are reported in Tables 5 and 8.

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:

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

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 $\Delta \ln \ln ICT$, $\Delta \ln \ln PA$, $\Delta \ln \ln REER$, $\Delta \ln \ln IUI$, and $\Delta \ln \ln SET$. 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.

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Diagnostic and Stability Tests: The reliability of the estimated ARDL-ECM models is verified through a battery of standard residual diagnostics and stability checks. Residual autocorrelation is assessed using the Portmanteau (Ljung-Box) Q test and the Cumby-Huizinga test for higher-order serial correlation. Heteroskedasticity is examined via the White test, with the Breusch–Pagan test serving as a supplementary check. Normality of the residuals is verified using the joint Skewness-Kurtosis test. Dynamic stability is evaluated through visual inspection of standardised residual time-series plots to detect potential structural breaks. Country-specific diagnostic results are reported in Tables 6 and 9. Together, these diagnostics ensure that the ARDL-ECM specifications satisfy the classical regression assumptions and provide a reliable basis for interpreting the estimated long-run and short-run coefficients.

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 3 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 3: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
$ln\, ln\, ICT_{1,t}$	23.1165	1.352	20.4113	24.8982
$ln\, ln\, ICT_{2,t}$	24.5959	0.9699	22.3381	25.9036
$ln\, ln\, PA_{1,t}$	12.7881	1.4124	10.1404	14.3508
$ln\, ln\, REER_{1,t}$	4.6668	0.1429	4.4417	4.8679
$ln\, ln\, IUI_{1,t}$	3.251	1.1532	0.5743	4.5218
$ln\, ln\, SET_{1,t}$	3.4232	0.6745	2.0252	4.3422
$ln\, ln\, PA_{2,t}$	9.2355	0.9693	7.6989	11.2182
$ln\, ln\, REER_{2,t}$	4.3945	0.2318	4.0006	4.7056
$ln\, ln\, IUI_{2,t}$	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 4 reports the estimation results for China.

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Table 4: 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)	—
$ln\, ln\, PA_t$	−0.031 (0.206)	—
$ln\, ln\, REER_t$	−0.028 (0.465)	—
$ln\, ln\, IUI_t$	0.859*** (0.148)	0.291 (0.238)
$ln\, ln\, SET_t$	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 4 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) coefficient of -0.839 ($p < 0.01$) indicates that 83.9% of any short-run deviation from long-run equilibrium is corrected within one period, and it shows the adjustment speed and long-term balance capability. In the long-term effect, digital infrastructure and human capital both have a significant positive effect on ICT service exports, with coefficients of 0.859 ($p < 0.01$) and 0.867 ($p < 0.01$), respectively, indicating that the expansion of internet usage and the accumulation of human capital are essential factors driving ICT service exports in China.

By contrast, the long-run coefficients on innovation capability (-0.031, $p = 0.883$) and the real exchange rate (-0.028, $p = 0.953$) are not statistically significant, indicating that once digital infrastructure and human capital are accounted for, patent applications and exchange rate movements exert a limited long-run influence on China's ICT service exports. 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

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rate of the internet doesn't have a significant effect on the ICT service export. ICT service exports therefore depend on long-run accumulation rather than short-run fluctuations.

Cointegration test: Prior to interpreting the ARDL-ECM estimates, 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 (Pesaran et al., 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 ARDL-ECM model and the interpretation of long-run coefficients.

Table 5: 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 5 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 5% upper-bound critical value of 5.176, allowing the null hypothesis of 'no cointegration' to be decisively rejected. Moreover, the corresponding p-values under both the I(0) and I(1) assumptions are 0.000, providing further confirmation of a stable long-run cointegration relationship.

Model Diagnostics and Robustness Checks: To ensure the reliability and stability of the ARDL-ECM model, the underlying assumptions are tested systematically before the regression coefficients are interpreted. The diagnostic and robustness checks examine whether the model exhibits problems of autocorrelation, heteroskedasticity, or non-normality, and whether its results are distorted by 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 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

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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.

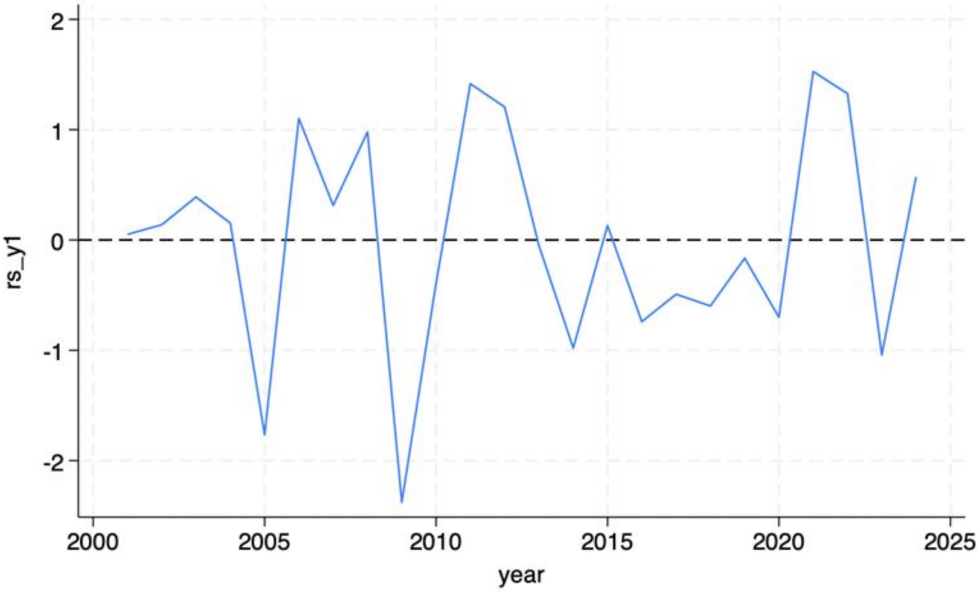

Figure 3: Standardized Residual Time Series (China)

Table 6 shows that the ARDL-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 (2), 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.

Table 6: 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

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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

The diagnostics confirm that the ARDL-ECM model for China is well-specified 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 7: 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)	—
$ln\, ln\, PA_t$	0.488** (0.200)	—
$ln\, ln\, REER_t$	1.628*** (0.345)	—
$ln\, ln\, IUI_t$	0.377* (0.212)	−0.226** (0.088)
$ln\, ln\, SET_t$	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 7 presents the ARDL-ECM estimation results for India, showing both long-run and short-run effects on ICT service exports. From the ECT, we can see the coefficient of ECT(t-1) is -0.366 ($P<0.01$), which shows that when ICT service exports deviate from long-run equilibrium, 36.6% of the disequilibrium is corrected within the first period. It shows that the ICT service export volume of India has a long-run self-correcting ability but is also

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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 ($p < 0.01$), which shows that exchange-rate competitiveness is strongly associated with India's ICT service export volume.

By contrast, the long-run coefficients on digital infrastructure (0.377, $p = 0.093$) and human capital (0.169, $p = 0.708$) are weakly significant and statistically insignificant, respectively. 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, the first-differenced coefficient on digital infrastructure is -0.226 ($p < 0.05$), suggesting that short-run increases in internet penetration are associated with adjustment costs that constrain ICT service exports in the short term.

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: To test for a long-run equilibrium relationship between India's ICT service exports and the explanatory variables, this study applies the Bounds Testing approach (Pesaran et al., 2001). 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 8: 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 8, 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.

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Model Diagnostics and Robustness Tests: To ensure the reliability and stability of the ARDL-ECM model, the underlying assumptions are systematically tested prior to interpreting the regression coefficients. The diagnostic and robustness checks assess whether the model encounters issues such as autocorrelation, heteroskedasticity, or non-normality and whether its results are influenced by 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.

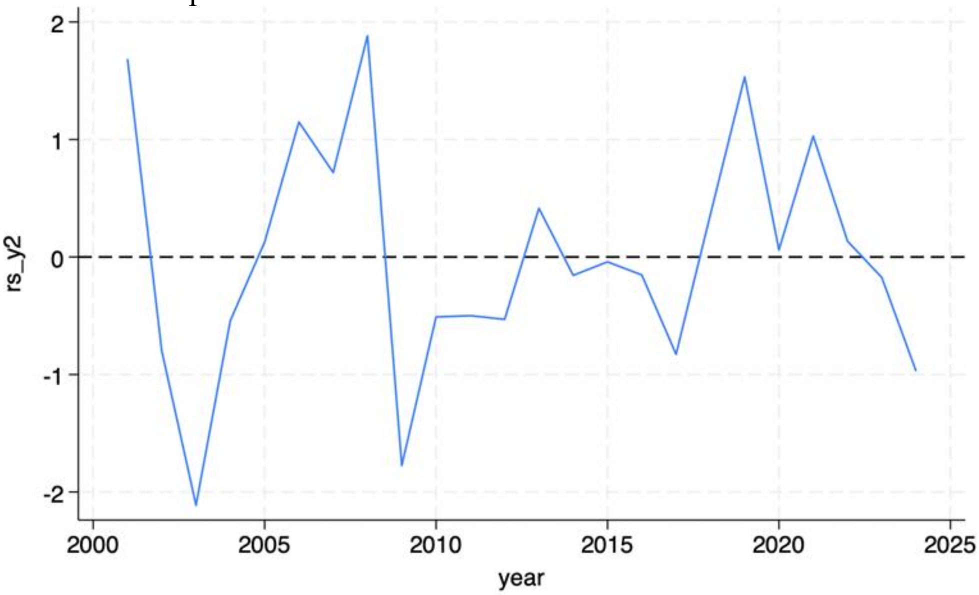

Figure 4: Standardized Residual Time Series (India)

The data from Table 8 reveals that the ARDL-ECM model satisfies standard econometric assumptions, and the result is highly reliable. From the autocorrelation test, the Portmanteau (Q) test yields p-values of 0.591 and 0.685 at lag (1) and lag (2), 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

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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 diagnostics confirm that the ARDL-ECM model for India is well-specified and provides a robust foundation for the empirical results.

Table 9: 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

Building on the empirical analysis presented above, this section synthesises the results across both economies, focusing on long-run equilibrium relationships, short-run adjustments, dynamic characteristics, and cross-country differences in transmission mechanisms.

The empirical results confirm that ICT service exports share a stable long-run cointegrating relationship with innovation capability, digital infrastructure, human capital, and the real exchange rate in both economies. China exhibits a faster speed of adjustment, while India's adjustment is more gradual and its export expansion depends more heavily on innovation capability and exchange-rate competitiveness. The table below shows the details of the comparison of the two countries.

Table 10: 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)

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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 Autocorrelation (Portmanteau / Ljung–Box)	Q (1) p = 0.6396; Q (2) p = 0.2788 (Passed)	Q (1) p = 0.5905; Q (2) p = 0.6846 (Passed)	Residual 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

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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.

The dominance of digital infrastructure (0.859, $p < 0.01$) and human capital (0.867, $p < 0.01$) as long-run drivers, coupled with the insignificance of resident patent applications, suggests that China's ICT exports are propelled by scale, platform-based service delivery, and labour-force absorptive capacity rather than by patent-intensive technological breakthroughs, consistent with the digital-economics view that platform scale and reductions in search, replication, and tracking costs reshape the channels through which digital services are produced and traded (Goldfarb & Tucker, 2019). India's profile is fundamentally different i.e., long-run growth is driven by innovation capability (0.488, $p < 0.05$) and exchange-rate competitiveness (1.628, $p < 0.01$), reflecting an export trajectory anchored in knowledge intensity and price advantage in global outsourcing markets. The negative short-run coefficient on digital infrastructure (-0.226, $p < 0.05$) further indicates that infrastructure expansion in India entails transitional adjustment costs before its long-run benefits accrue. Taken together, these patterns indicate that innovation contributes to digital trade competitiveness through distinct channels in the two economies, reflecting differences in developmental stage and context and limiting the effectiveness of a uniform policy approach.

Conclusion

This study examines how innovation capability shapes digitally deliverable service exports in China and India over 2000-2024, applying an ARDL-ECM framework that captures both long-run cointegrating relationships and short-run dynamic adjustments. Its principal contribution is a stage-differentiated comparative account of two of the world's largest emerging digital exporters, demonstrating that innovation, digital infrastructure, human capital, and exchange-rate competitiveness operate through structurally different transmission channels in each economy. To our knowledge, this is among the first studies to apply the ARDL-ECM approach to digitally deliverable service exports in a comparative China-India setting using data through 2024.

The empirical findings support three central conclusions. First, although both economies display a stable long-run cointegrating relationship, the speed of adjustment differs sharply, with China correcting roughly 83.9% of any short-run disequilibrium per period (ECT = -0.839, $p < 0.01$) compared with 36.6% for India (ECT = -0.366, $p < 0.01$). Second, China's long-run export performance is driven primarily by digital infrastructure (0.859, $p < 0.01$) and human capital (0.867, $p < 0.01$), with resident patent applications and the real exchange rate showing no significant direct effect. This is

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consistent with an export model anchored in scale and platform-based service delivery rather than patent-intensive innovation. Third, India's trajectory is innovation and price-led: resident patent applications (0.488, $p < 0.05$) and the real effective exchange rate (1.628, $p < 0.01$) emerge as the principal long-run drivers, while digital infrastructure plays a weakly positive long-run role accompanied by transitional short-run adjustment costs (-0.226, $p < 0.05$).

Country-specific policy implications follow directly. For China, sustained gains in digital trade competitiveness will depend less on volume-based patent expansion than on continued investment in digital infrastructure, tertiary education quality, and the digital workforce's absorptive capacity. For India, the centrality of innovation capability and exchange-rate competitiveness suggests that strengthening domestic R&D incentives, intellectual property infrastructure, and macroeconomic stability is likely to deliver the largest export gains, while infrastructure expansion should be sequenced to mitigate the transitional adjustment costs identified in the short-run estimates. More broadly, these findings caution against transferring digital trade strategies wholesale across emerging economies: effective policy design must be calibrated to each country's stage of structural development.

Three limitations should be acknowledged. First, the sample is constrained to $N = 25$ annual observations per country, which restricts the number of regressors and reduces statistical power, despite the suitability of ARDL bound testing for small samples. Second, innovation capability is proxied by resident patent applications, which capture only one dimension of innovation activity and may under-represent the business model and platform innovations central to digital service exports. Third, the analysis abstracts from institutional quality, regulatory environment, and trade policy indicators that may mediate the innovation-trade relationship. Future research employing panel data across a broader set of emerging economies, alternative composite innovation indices, or institutional-quality measures would extend and strengthen these inferences.

Whether innovation builds digital bridges or widens digital divides depends not on innovation alone but on its interaction with the structural, infrastructural, and macroeconomic context in which it is deployed. The contrasting Chinese and Indian experiences show that there is no universal route to leadership in digital trade, only routes that fit the foundations on which they are built.

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