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INVESTIGATING EFFECTS OF ICT INFRASTRUCTURE ON ECONOMIC GROWTH: DATA FLOW PERSPECTIVE BASED ON CHINA'S EVIDENCE

Rui LIU[1], Jingfeng YUAN[1]✉, Bing ZHU[2], Lei ZHANG[1], Bingsheng LIU[3]

[1]*Department of Construction and Real Estate, School of Civil Engineering, Southeast University, 211189 Nanjing, China*
[2]*Department of Civil and Environmental Engineering, Technical University of Munich, Munich, Germany*
[3]*School of Economics and Management, Hebei University of Technology, Tianjin, PR China*

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Abstract. This study employs a mediating effect model and the Generalized Method of Moments (GMM) approach to examine the direct effect of ICT on the economy and the mediating role of data flow in the ICT – economic growth nexus. The results indicate that ICT significantly enhances data flow intensity, which in turn promotes economic growth. Moreover, both the direct effect of ICT and the mediating role of data flow are more pronounced in developed regions compared to underdeveloped areas. Further analysis shows that with the implementation of the policy, the mediating effect of data flow shifted from being insignificant (2006–2010) to significant (2011–2019). This study contributes to the understanding of the digital divide, highlighting potential drivers such as disparities in ICT infrastructure and data flow inequality. The government should develop tailored ICT development policies based on the region's economic level to fully harness the benefits of digitalization.

Keywords: ICT infrastructure, economic growth, mediation effect, regional disparity, digital divide.

JEL Classification: O10, O33, R11.

✉Corresponding author. E-mail: ***jingfeng-yuan@seu.edu.cn***

1. Introduction

Infrastructure projects are innovative stimuli that can, directly and indirectly, enhance economic growth (Ruiz & Guevara, 2020). In the digital economy era, Information and Communication Technology (ICT) infrastructure, including communication equipment and application software, is crucial for social-economic growth (Jurado-González & Gómez-Barroso, 2022). It has transformed global work and commuting patterns by the development of diverse information application scenarios (e.g., online education platforms and digital transport) (Myovella et al., 2020). In today's increasingly digital world, data flow refers to the vast and complex sets of raw data resource generated from a wide range of sources (e.g., social media, sensors, transaction logs). Data flow has become a critical asset, with the global volume of data growing by 27% in 2019, encompassing both private and public data streams. Private data often includes sensitive information resources such as customer records, financial data, and proprietary business insights (Custers & Uršič, 2016). Public data refers to information resources that is freely available on websites and can be accessed by anyone, such as government statistics, weather data, traffic information, or open research findings (Janssen et al., 2012).

Data flow, which is continuously generated through the application of ICT in different regions, significantly influences consumption activities, operational mechanisms, social lifestyles, and economic growth when utilized effectively (Bibria & Krogstie, 2017). First, data flow originates from all environments with ICT infrastructure, including files, materials, recordings, pictures, and electronic data. It can be acquired by sensors and tracking devices, recorded by electronic devices, and transmitted over the internet (Besher et al., 2021). In developed countries, data is generally more accessible due to well-established ICT infrastructure. Many of these countries have implemented open data policies, providing public data portals, such as data.gov in the U.S. and data.gov.uk in the U.K., which help provide available large volumes of government datasets. By contrast, in underdeveloped countries, data sharing by governments and corporations is often more restricted due to administrative, political, or security concerns. Subsequently, the sharing and mobility of information can accelerate the cross-regional diffusion of traditional production factors (such as labor and capital) and improve economic efficiency (Kim et al., 2021). The concept of the 'digital economy' further reflects a new stage of economic growth driven by ICT and data resources (Wu & Yu, 2022). As a distinct factor of production, data resources possess unique characteristics, including non-rivalry, low marginal cost, and the potential for increasing returns. For example, multiple entities can utilize the same data without diminishing its inherent value. Data also can be processed, replicated, and shared at minimal cost. Data flow has the potential to reshape traditional economic models by driving innovation and enhancing productivity. Therefore, data flow can be considered an essential channel through which ICT fosters economic growth.

Existing studies have examined the relationships between ICT, data flow, and economic growth from different perspectives. Researchers have linked ICT to economic growth through exogenous theory, which treats technological change as external to the economic model (Solow, 1956; Swan, 1956), and endogenous theory, which views it as generated within the model itself (Lucas, 1988). Meanwhile, studies have found the positive effect of ICT on economic growth, c.f., Jurado-González and Gómez-Barroso (2022), Yeo et al. (2023), Pradhan et al. (2016b), Kumar et al. (2016), and Edquist et al. (2018). In addition, mediation channels between ICT and economic growth have been explored by considering population growth, capital accumulation, technological progress, production efficiency (Kumar et al., 2016), financial development (Pradhan et al., 2016a), and urbanization (Pradhan et al., 2021). As the informatization of cities has elevated the importance of data flow, there is a small and growing body of literature that theoretically analyses its positive contribution to the economy (Cai et al., 2022; Ciampi et al., 2021; Pang et al., 2022).

However, there are some research gaps in this stream of research. First, there is no unified measurement for ICT development level. Second, prior research kept silent on the role of data flow in the digital economy era. Thus far, previous studies have not integrated both ICT and data flow into a theoretical model to demonstrate the driving force behind economic growth. Third, an economic unevenness is likely to exist due to the gap in ICT and data flow intensity across different regions and time periods. Previous studies have attached little importance to the spatiotemporal heterogeneous effects of ICT and data flow on the economy. Using a dummy binary variable to examine the relevant effects of ICT cannot accurately reflect the differences in ICT level between regions and periods.

Over the past decade, China has developed and deployed the world's largest ICT infrastructure, creating a solid foundation for fully harnessing data flows. To address the decentralization of data resources, the government has proposed high-quality data flow supply and application policies (e.g., the strategy of channeling computing resources from east to west). Encouraging cross-regional integration and data flow applications has become an important approach for fostering economic growth and reducing economic disparity between developed and underdeveloped regions in China.

Therefore, this study aims to provide empirical evidence on the mediating effect of data flow in China. More precisely, the following research questions are proposed: (1) How to represent and measure ICT development level? How do ICTs improve economic growth through the direct and mediating effects of data flow? (2) What specific impacts do ICT infrastructures and ICT-related data flow have on economic growth, considering regional and temporal variations? (3) How can policymakers promote the efficient use of ICT infrastructure, maximize the mediating effect of data flow, and narrow the economic gap across China?

As such, the contributions of this study are fourfold: First, our study sheds light on the representation and measurement of ICT development level, establishing a composite index based on mobile cellular, internet usage, and mobile broadband. Second, in addition to technological change, labor and capital inputs, this study offers empirical support for the theoretical derivation perspective that considers data flows as a new production factor within growth theory. Third, the ICT gap describes the disparities or inequalities between regions/socioeconomic levels in access to, use of, or skills related to ICTs, which is called the "digital divide" in prior studies (Adam & Dzang Alhassan, 2021; Cariolle, 2021; Philip et al., 2017). Our study further supplements the traditional understanding of the digital divide. Specifically, the digital divide encompasses disparities in access to and use of digital technologies and data sources across different populations or geographic regions (Bezuidenhout et al., 2017). It includes physical access to devices (e.g., smartphones, computers) and connectivity (e.g., broadband, mobile networks), as well as the skills, literacy, and opportunities required to make effective use of these technologies and the availability, completeness, or representativeness of data flow. Fourth, the findings can help policymakers formulate specific ICT policies by considering the uneven data flow in different regions and periods, thus supporting the digital upgrading of traditional infrastructure and promoting balanced economic growth nationwide.

The remainder of this paper commences with a review of the existing literature to provide a research backdrop and hypothesis. Then, the research method and results are reported. Next, this study discusses the positive effect of data flow, an extended analysis, theoretical implications, policy implications, and robustness analysis. Finally, the findings and future studies are discussed.

2. Literature review and hypotheses development

2.1. Effects of ICT infrastructure on economic growth

The economic multiplier for infrastructure investment is much higher than that for other forms of public spending. Despite the significant growth-promoting effect of infrastructure investment, blind investment in infrastructure should be avoided (Yue et al., 2024). According to Du et al. (2022), the investment should be made in the right kind of infrastructure which can meet the needs of society in different eras. In the past, the way to build up a country's productive potential and raise per capita income was to expand the capacity for producing goods, which required roads, railways, water pipes, schools, and hospitals (F. Zhang et al., 2023). In the digital economy era, ICT infrastructures have become part and parcel of human existence and socio-economic growth (Y. Li et al., 2024). First, constructing supporting facilities such as base stations and data centers generates short-term benefits by stimulating local economic activity (Fernández-Portillo et al., 2020). Second, increasing demand for ICT products and services worldwide has made the ICT sector an essential source of revenue. Third, the investments in ICT can induce complementary innovations, which have a more substantial impact on economic performance than do traditional capital investments. Theoretical analysis also confirms this observation. According to exogenous theory, technological change is not explicitly incorporated into the model, leading to what is termed the "Solow residual" (Kenis & Provan, 2009). Any observed growth beyond what can be attributed to labor and capital inputs is attributed to the Solow residual, reflecting the impact of technological change on growth. By contrast, the endogenous theory incorporates technological change as an endogenous variable of economic growth (Pack, 1994). Nonetheless, both exogenous theory (Solow, 1956; Swan, 1956) and endogenous theory (Lucas, 1988) confirmed that ICT can be considered a factor in improving economic growth, despite the different nature of these theories.

The effect of ICT on economic growth is well documented worldwide, as shown by the recent literature reviews by Y. Li et al. (2024), Yahyaoui (2024), Bakry et al. (2023), Das and Chatterjee (2023), Nair et al. (2020), Myovella et al. (2020), Edquist et al. (2018), Fernández-Portillo et al. (2020), and Haini (2019). For example, Edquist et al. (2018) and Myovella et al. (2020) investigated how broadband diffusion has influenced economic growth. With the improvement of mobile network infrastructure in subsequent years, Haini (2019) and Fernández-Portillo et al. (2020) respectively used variables related to the use of mobile Internet and phones to measure the role of ICT as a source of growth. Besides, a composite index has been used to measure ICT levels in recent years, including telephone landlines, mobile telephones, internet users, internet servers, and fixed broadband (Das & Chatterjee, 2023; Nair et al., 2020).

Despite this body of research, there is an absence of internationally standardized measures for ICT development level. The widespread adoption of mobile networks has transformed telecommunications worldwide and led to a decline in the use of fixed-line phones. Therefore, landline telephones are difficult to accurately measure the ICT development level nowadays. Furthermore, although a few researchers have used a composite index to fully capture the characteristics of ICT infrastructures, the proxy variables for ICT could be further expanded. Specifically, society is currently experiencing an ICT revolution, and one of the major innovations during the last decade is the use of mobile broadband (Edquist et al., 2018). According to GSMA Inteligence (n.d.), mobile broadband connections increased at an annual average growth rate of 113%. Hence, mobile broadband also can be added to the discussion alongside ICT. Based on the above, we propose the following hypothesis:

H1: *ICT infrastructure through the increased use of mobile phones, mobile Internet, and broadband has a significant positive impact on economic growth.*

2.2. The mediating effect of data flow between ICT infrastructure and economic growth

The conception of data flow, digitalization, and information diffusion captures the pathway from raw data movement to organizational transformation and finally to social impact. Data flow refers to the technical movement of raw data within a system or network, describing how data resources are transferred, processed, and utilized by databases, applications, and network components to improve efficiency, access, and decision-making (Silva et al., 2016). Data flow deals with raw, unprocessed, structured information that has yet to be interpreted or analyzed, including numerical, transactional, sensor-based, or other forms of raw input. Digitalization is the process of transforming traditional processes into digital formats using information technologies and data resources to automate and improve business operations (Frank et al., 2019). In contrast, information diffusion is social- and communication-centric, focusing on the spread of processed, meaningful information among individuals, groups, or societies, such as knowledge, insights, or messages, spreads (Kumar & Sinha, 2021). This study focuses on data flow, which is a new factor of production for economic growth.

The emergence of big data is closely linked to advanced ICTs. The capture, sharing, and storage of data flow require a strong ICT infrastructure (e.g., sensors, computing power, and artificial intelligence) (Brandín & Abrishami, 2024; Igwama et al., 2024; Myovella et al., 2020). The developed regions that install various ICT devices are hyper-connected information worlds where people and things leave data footprints. For example, in Milton Keynes (the UK), Eindhoven (the Netherlands), and Singapore, ICTs, such as multi-source and real-time perception facilities, are installed alongside highways and linked to traffic management websites to collect and disseminate data on road conditions (e.g., road traffic records and train schedule records). By contrast, in many underdeveloped countries (e.g., Central African Republic, Malawi¸ and Yemen), due to limited financial support for ICT, less data flow is available for informed policy decisions in the operation and maintenance of various infrastructure (Appiah-Otoo & Song, 2021). For instance, high poverty rates and political instability make the Central African Republic a challenging environment to allocate sufficient funds for ICT development and data application (World Bank, 2022). It is obvious that ICT has the potential to be developed in underdeveloped countries.

Of the two main types of data flow, it is relatively more difficult to obtain private data flow due to corporate and personal privacy and interests, thus public data flows are used in this study. Public data flow encompasses a range of formats and sizes, as well as both processed structured data and raw unstructured data, which are available to anyone on different websites. In the U.S., public data is typically kept and accessed on corporate or government websites, including Data.gov, HealthData.gov, World Bank, U.S. Bureau of Labor Statistics, and Kaggle. For instance, HealthData.gov is a website that catalogs healthcare-specific data sets. Thousands of global development data sets are publicly accessible on the World Bank's website. Kaggle is an online website that aggregates data sets of the tech industry. In China, Data.gov.cn offers datasets on demographics, economics, environment, transportation, and healthcare.

Leveraging data flows on related websites can be used to improve socio-economic efficiency, such as by improving traffic conditions and predicting the duration of construction projects (Eliwa et al., 2024; Kušić et al., 2023). Dui et al. (2024) and Kušić et al. (2023) suggested that real-time data on speed, traffic congestion, directions, and even the locations of speed traps empower users to navigate their routes effectively and make informed decisions when they visit digital websites. As such, data resource is guiding corporations, governments, the media, and non-governmental organizations across regions to invest in data, driving forward socio-economic growth.

The above discussion examines the relationship between ICT and data flow, as well as between data flow and economic growth. Growth theories have recently evolved by expanding traditional factors and redefining the roles of endogenous and exogenous variables. For example, in addition to capital and labor, technological progress has been integrated into growth models (Solow, 1956). Furthermore, the digital economy encompasses a series of economic activities that rely on data resources as a key production factor and ICT as a crucial driving force to enhance and optimize economic structures (Gao et al., 2023). As an emerging economic paradigm shaping the future, the digital economy underscores the interdependent relationship between ICT, data flow, and economic growth.

A small body of literature has tried to theoretically demonstrate the positive effect of data flow on the economy (Cai et al., 2022; Ciampi et al., 2021; Fast et al., 2023; Gao et al., 2023; Veldkamp & Chung, 2024). For instance, Cai et al. (2022) built a general equilibrium framework to show that data flow can promote the productivity. However, previous studies ignored the fact that data flow, a new production factor, originated from ICT application; therefore, a new growth function analysis (including ICT, data flow and economic growth) has not yet been undertaken. Meanwhile, some studies provide empirical evidence that ICT contributes to economic growth through some mediation channels, such as big data analytics, technological diffusion (Q. Li & Wu, 2023), financial development (Wang et al., 2024), and urbanization (D. Li et al., 2023). However, there is still a lack of empirical studies in economics that extend these mediation channels to data flow.

Therefore, this study integrates both ICT and data flow into a growth theory to demonstrate that they are driving forces behind economic growth; meanwhile, data flow is a valid mediation channel between ICT and growth in the digital economy era. We formulate the following hypotheses:

H2: *ICT infrastructure and data flow are positively related.*

H3: *Data flow has a positive mediating effect on the relationship between ICT infrastructure and economic growth.*

Based on the above analysis, this study proposes a conceptual model, as shown in Figure 1.

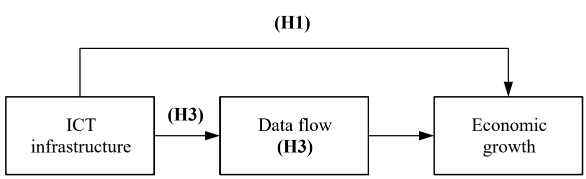

Figure 1. The conceptual model

3. Method and data

3.1. Variables and data

The data in this study are drawn from provincial-level data for China from 2006 to 2019. We selected 2006 as the starting point for the sample because ICT data were incomplete before that year. The latest data for the mediating variable (data flow intensity) was available in 2019. Subsamples of 2006–2010 and 2011–2019 were also used in the analysis. Referring to X. Chen et al. (2019), this study used data from 30 provincial-level regions in China (i.e., all regions excluding Xizang, Hong Kong, Macao, and Taiwan due to missing values for the key variables). Further, subsamples of 19 eastern and central regions (developed regions) and 11 western regions (underdeveloped regions) were used. The data were collected from multiple sources, including the China Statistical Yearbook, Statistical Report on Internet Development in China, China Science and Technology Statistical Yearbook, and China Information Almanac. After combining the datasets from these sources, we constructed a panel dataset for the analysis. Table 1 presents the summary statistics.

Table 1. Summary statistics

Variable type	Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable	*Economy*	420	4.2357	2.6664	0.6103	16.4563
Independent variable	*ICT*	420	1.3303	1.3141	0.1469	10.2467
Mediating variable	*DF*	420	3.3501	6.9250	0.0990	52.2640
Control variables	*RD*	420	1.5669	1.0721	0.2048	6.3015
	EP	420	5.1127	4.6215	0.0880	27.5958
	POP	420	7.9680	1.0305	5.2675	9.3424
	THR	420	4.6388	0.9228	2.9792	8.3688

First, economic growth (*Economy*) was set as the dependent variable. Following Shiha and Dorra (2023) and Myovella et al. (2020), we used the gross domestic product (GDP) per capita of each province to measure *Economy*.

Second, a composite index of ICT (*ICT*) was the key explanatory variable. Previous studies commonly used a separate index of mobile phones, mobile internet, and broadband to measure *ICT* variable. Vu (2011) pointed out that mobile phones portray the diffusion of modern telecommunications infrastructure; mobile internet depicts the development of communication technologies; and broadband portrays the penetration of broadband infrastructure. The Principal Component Analysis (PCA) is a statistical technique used to transform a set of correlated variables into a smaller set of uncorrelated variables, known as principal components (Greenacre et al., 2022). To comprehensively reflect the characteristics of ICT, we used PCA to combine the separate indices commonly used by previous studies[1]. This ICT composite index using PCA also eliminates the issue of high correlation between predictors (including,

[1] PCA can transform an underlying set of indicators into a smaller set of linear factors, thereby overcoming the problem of multicollinearity (Pradhan et al., 2019). According to Verspagen (2009), principal components with eigenvalues above one should be used to extract the components.

mobile phones, mobile internet, and fixed broadband) in a regression model. According to Mirshojaeian Hosseini and Kaneko (2011) and Pradhan et al. (2014), this study first normalizes all indicators before performing PCA, so that all indicators in the ICT composite index are on the same scale. In this composite index, data on mobile cellular subscription (per 100 people) was used as the empirical measure for mobile phones; for mobile internet, the data series on "individuals using the internet (per 100 people)" were used; and "broadband subscriptions (per 100 people)" was used to measure fixed broadband. In our analysis, the first principal component had an eigenvalue of 2.82, thus explaining approximately 90% of the variation in these three factors.

Third, we used data flow intensity (*DF*) as the mediating variable. The use of publicly available data (e.g., videos, text, figures, statistical data, and audio files) as a proxy is considered acceptable in the literature (Bezuidenhout et al., 2017). Although data flow is integral to daily lives, measuring intangible data flow and collecting the data over the period from 2006 to 2019 remains challenging. Websites consist of a building program (code) and a database, where various types of information are stored. A common method for sharing and utilizing real-time data is continuous access to different public websites (Bezuidenhout et al., 2017; Mueller & Grindal, 2019). For example, in smart rail infrastructure, operators and passengers can obtain vast amounts of data on trains, passenger flow, and natural disasters via visiting relevant public websites. Public websites facilitate data sharing and dissemination. In 2012, Google processed approximately 2 million search queries per minute, Facebook users shared nearly 700,000 pieces of content, and Twitter users posted around 100,000 tweets per minute (Hilbert, 2015). According to Mueller and Grindal (2019), visiting a website involves requesting data from an information source; hence, a larger number of websites in a province generally reflects higher data flow intensity. Mueller and Grindal (2019) examined the relationship between data flows generated by website requests and the flows of goods and services trade. Similarly, Bezuidenhout et al. (2017) noted that an increasing amount of data is becoming accessible through personal websites. Liu et al. (2025) used websites to measure data flow intensity, exploring its links to digital transportation and sustainable development. According to these studies, we consider the number of websites a valid proxy for data flow and, accordingly, use the number of websites per capita as our measure.

Finally, we considered several control variables. We controlled for traditional production factors, including technology level (*RD*) measured by R&D investment (Hong, 2017), and labor force intensity (*EP*) measured as the ratio of the total employed population to the resident population (Niebel, 2018). Population growth fosters the accumulation of human capital, which in turn drives economic growth (Furuoka, 2018). Additionally, the development of tertiary industries, including the service sector, transportation infrastructure, and educational infrastructure, significantly contributes to economic growth (Myovella et al., 2020). Thus, we also controlled for population size (*POP*), measured by the logarithm of the resident population (Katpatal & Thorat, 2022), and tertiary industry development (*THR*), measured by the ratio of the added value of tertiary industry to the total added value.

3.2. Model specification

(1) The model

The recursive equations were constructed as follows to explore the mediating effect of *DF* on the relationship between *ICT* and *Economy*. We considered an autoregressive dynamic panel model of order one, and the Hansen test was used to demonstrate the validity of the instruments:

$$Economy_{i,t} = \alpha + \beta_1 Economy_{i,\,t-1} + \beta_2 ICT_{i,t} + \beta_3 X_{i,t} + \mu_i + V_t + \varepsilon_{i,t}; \tag{1}$$

$$DF_{i,t} = \delta + \varphi_1 DF_{i,t-1} + \varphi_2 ICT_{i,t} + \varphi_3 X_{i,t} + \kappa_i + \eta_t + \theta_{i,t}; \tag{2}$$

$$Economy'_{i,t} = \tau + \chi_1 Economy'_{i,t-1} + \chi_2 ICT_{i,t} + \chi_3 DF_{i,t} + \chi_4 X_{i,t} + \kappa'_i + \eta'_t + \xi_{i,t}, \tag{3}$$

where $Economy_{i,t}$ is the economic growth level in province i at time t, $ICT_{i,t}$ denotes ICT development level, $X_{i,t}$ represent the control variables, and $DF_{i,t}$ represent data flow intensity (the mediating variable). μ_i, κ_i and κ'_i are province fixed effects; V_t, η_t and η'_t are time fixed effects; and $\varepsilon_{i,t}$, $\theta_{i,t}$ and $\xi_{i,t}$ are the random errors in Eqs. (1)–(3), respectively.

The interpretation of the coefficients involves three steps.

Step (1): To test H1, Eq. (1) is estimated in which parameter β_2 captures the total effect of *ICT* on *Economy*.

Step (2): To test H2, Eq. (2) is used in which the significance of parameter φ_2 captures the impact of *ICT* on *DF*.

Step (3): To test H3, χ_2 captures the impact of *ICT* on *Economy* after including the mediating effect of data flow intensity, while χ_3 reflects the direct effect of *DF* on *Economy*. When φ_2 and χ_3 are significant, $\varphi_2\chi_3$ represents the mediating effect. Notably, the significance of $\varphi_2\chi_3$ should be tested using the Sobel test, in which z should be above 1.64 for the unilateral test (Caron, 2019).

(2) Estimation method

A variety of methods have been adopted to deal with panel data, e.g., Fixed Effect Model (FEM), Random Effect Model (REM), and Generalized Method of Moments (GMM). The estimation of panel data can overcome two problems, namely, omitted-variable bias and potential endogeneity problems (C. J. Lee et al., 2018). FEM can be used to eliminate omitted variable bias caused by the unobserved effects (see μ_i, κ_i, κ'_i and V_t, η_t, η'_t in Eqs. (1)–(3)). Notably, according to existing studies (c.f., Ndoya et al. (2023), Haftu (2019), and Chien et al. (2020)), the impact of ICT on economic growth is likely to unfold over time, and thus a dynamic panel-data model was used in this study. By using FEM in dynamic panel data, the accuracy of parameter estimation should be focused on. Specifically, in Eqs. (4)–(6), the differenced error terms are $\Delta\varepsilon_{i,t}$ (i.e., $\varepsilon_{i,t} - \varepsilon_{i,t-1}$), $\Delta\theta_{i,t}$ (i.e., $\theta_{i,t} - \theta_{i,t-1}$), and $\Delta\xi_{i,t}$ (i.e., $\xi_{i,t} - \xi_{i,t-1}$), which include $\varepsilon_{i,t-1}$, $\theta_{i,t-1}$, and $\xi_{i,t-1}$; thus, they are correlated with $\Delta Economy_{i,t-1}$ (i.e., $Economy_{i,t-1} - Economy_{i,t-2}$), $\Delta DF_{i,t-1}$ (i.e., $DF_{i,t-1} - DF_{i,t-2}$), and $\Delta Economy'_{i,t-1}$ (i.e., $Economy'_{i,t-1} - Economy'_{i,t-2}$), respectively. FEM in first differences produce inconsistent parameter estimates because $E\left(\Delta Economy_{i,t-1}, \Delta\varepsilon_{i,t}\right) \neq 0$, $E\left(\Delta DF_{i,t-1}, \Delta\theta_{i,t}\right) \neq 0$, and $E(\Delta Economy'_{i,t-1}, \Delta\xi_{i,t}) \neq 0$. As such, the FEM estimator is not the fittest model for dynamic panel data.

Moreover, endogeneity means that an explanatory variable in a statistical model is correlated with the error term, which can lead to biased results or inaccurate conclusions. For dynamic panel data, FEM is not suitable for solving endogeneity problems (Ndoya et al., 2023). Although REM can be efficient under strict assumptions (no correlation between unobserved effects and regressors), it does not handle endogeneity or dynamic structures well.

$$\Delta Economy_{i,t} = \beta_1 \Delta Economy_{i,\ t-1} + \beta_2 \Delta ICT_{i,t} + \beta_3 \Delta X_{i,t} + \Delta\varepsilon_{i,t}; \tag{4}$$

$$\Delta DF_{i,t} = \varphi_1 \Delta DF_{i,\ t-1} + \varphi_2 \Delta ICT_{i,t} + \varphi_3 \Delta X_{i,t} + \Delta\theta_{i,t}; \tag{5}$$

$$\Delta Economy'_{i,t} = \chi_1 \Delta Economy'_{i,t-1} + \chi_2 \Delta ICT_{i,t} + \chi_3 \Delta DF_{i,t} + \chi_4 \Delta X_{i,t} + \Delta\xi_{i,t}. \tag{6}$$

GMM estimators can be used as an alternative approach to capture lagged relationships between variables and overcome endogeneity, as GMM replaces the strict OLS assumption with a set of moment conditions. Meanwhile, GMM leverages lagged values of endogenous variables as internal instruments, enabling consistent estimation. The endogeneity of the lagged dependent variable and other explanatory variables are combined by creating a matrix of internal instruments, which can avoid dynamic panel bias. This generalizes Anderson and Hsiao's (1982) instrumental variable estimator that uses $Economy_{i,t-2}$, $DF_{i,t-2}$, and $Economy'_{i,t-2}$ as instruments for $\Delta Economy_{i,t-1}$, $\Delta DF_{i,t-1}$, and $\Delta Economy'_{i,t-1}$, respectively. This is a valid approach because $Economy_{i,t-2}$, $DF_{i,t-2}$, and $Economy'_{i,t-2}$ are related to $\Delta Economy_{i,t-1}$, $\Delta DF_{i,\ t-1}$, and $\Delta Economy'_{i,t-1}$, respectively, but not with $\Delta\varepsilon_{i,t}$, $\Delta\theta_{i,t}$, $\Delta\xi_{i,t}$.

This study applied the GMM approach to estimate Eqs. (1)–(3) for several reasons. First, as there are twice as many individual dimensions as the time dimension, our sample meets the primary requirements for using GMM. Second, endogeneity could arise from measurement errors and omitted variables in this study (e.g., ICT, data flow intensity, and economic growth are known to be associated with measurement errors), and GMM can overcome this issue. Third, GMM shows improved estimation efficiency when heteroscedasticity is present (Tariq et al., 2021). The heteroskedasticity in all the equations was checked by using a modified Wald test. We use GMM because the finite sample properties of this technique are better when instruments are weak. Accordingly, this study uses the two-step system GMM estimator, which is more efficient than the one-step estimator, especially for system GMM (Canarella & Miller, 2018). Meanwhile, the robust standard errors are reported in this study. We also use the Hansen test to verify the exogeneity of the instruments. Specifically, the null hypothesis of the Hansen test is that the instruments are valid (i.e., exogenous). A large p-value (usually more than 0.05) suggests that there is insufficient evidence to reject the exogeneity assumption, and the instruments are more likely to be valid (Greco et al., 2015). Besides, in dynamic panel GMM estimation, the Arellano-Bond AR (1) and AR (2) tests check for serial correlation in the first-differenced residuals (Canarella & Miller, 2018). If significant second-order (or higher-order) autocorrelation arises, it suggests that the instruments may be correlated with the error term, undermining the validity of the GMM framework (Arellano & Bond, 1991). According to Arellano and Bond (1991), the tests should ensure that the first-order sequence AR (1) is correlated and that the second-order sequence AR (2) is irrelevant.

4. Results

4.1. Mediating effect at the national level

Table 2 reports the direct and mediating effects of ICT infrastructure on economic growth at the national level. In Model 1, the p-values of the Hansen test are all above the 0.05 threshold. Meanwhile, the AR (1) test confirms the presence of first-order serial correlation, and the AR (2) test does not reject the null hypothesis of no second-order serial correlation. These results confirm the validity of our GMM specification. The coefficient of *ICT* is significantly positive at the 1% level in Model 1(i), indicating that a 1% increase in ICT infrastructure is related to a 0.6186% increase in GDP per capita. The finding is consistent with Jorgenson et al. (2016), Hasbi (2020), and Fernández-Portillo et al. (2020), who verified the positive impact of ICT on the economy in different countries, including the US, Asia, Sub-Saharan Africa, and OECD countries.

Table 2. Mediating effect of data flow between ICT and economic growth at the national level

Dependent variable / Other variables		Model 1(i)	Model 1(ii)	Model 1(iii)
		Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*
Independent variable	*ICT*	0.6186*** (0.0303)	4.1952*** (0.3165)	0.4582*** (0.0408)
Mediating variable	*DF*	–	–	0.0818*** (0.0092)
Control variables	*RD*	0.7545*** (0.0562)	4.5160*** (0.2192)	0.0643 (0.1032)
	EP	0.2816*** (0.0246)	–1.5970*** (0.1442)	0.3622*** (0.0311)
	POP	0.2809*** (0.0802)	6.2983*** (0.5100)	0.1516 (0.0981)
	THR	1.0573*** (0.0584)	2.9587*** (0.2790)	1.1231*** (0.0710)
Constant		–6.3523*** (0.7104)	–65.0506*** (4.1919)	–5.0191*** (0.8721)
Observations		420	420	420
R-squared		0.7841	0.4480	0.7609
Arellano-Bond test for AR (1)		–1.94*	–2.28**	–2.40**
Arellano-Bond test for AR (2)		1.15	0.73	1.15
Wald test		216.31***	272.68***	249.16***
Hansen test		0.328	0.180	0.327
No. Instruments		44	39	44
Sobel test		7.3869 > 1.64		
95% confidence intervals		[0.2522, 0.4344]		
Mediating effect		0.3433***		

Notes: The parentheses ( ) indicate standard errors. The significance of the mediating effect was determined using the Sobel test. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. Model diagnostic tests for the system GMM are based on a robust estimation method.

In Model 1(ii), *ICT* is significantly positive, confirming that ICT infrastructure can facilitate data flow. Model 1(iii) shows that *ICT* and *DF* are positive and significant at the 5% level. The mediating effect is 0.3433 (4.1952*0.0818), indicating that 0.3433% of the increase in economic growth is mediated by data flow. Finally, the Sobel test confirms the significance of the mediating effect. Hence, H1, H2, and H3 are supported in Model 1.

In Model 1(iii), economic growth has a significant positive relationship with *EP* (labor force intensity) and *THR* (tertiary industry level). Labor force intensity acts as a driver of economic growth, as highlighted by Yi et al. (2019). The continued expansion of tertiary industries persistently introduces new technologies and services, thereby enhancing productivity and efficiency in other sectors (e.g., transportation and healthcare). This aligns with the findings of Yan et al. (2023) and P. Zhang et al. (2022), who argued that the main drivers of China's economic growth have shifted towards upgrading industrial structure and boosting overall productivity.

4.2. Regional variations in the mediating effects

The distribution of data flow in China is uneven, which is likely to contribute to economic disparities between developed and underdeveloped regions. Based on the research data covering the period from 2006 to 2019, we constructed maps to visualize the distribution of China's data flow in 2006, 2011, 2016, and 2019. As shown in Figure 2, in 2006, only Beijing and Shanghai in eastern China exhibited high-intensity data flows. By 2011, the data flow intensity in eastern cities had continued to increase, further exceeding that of western regions. In 2016 and 2019, although some western regions, such as Sichuan and Xinjiang, experienced an increase in data flow intensity, it remained lower than in central and eastern China. Overall, the data flow intensity in the developed regions (central and eastern China) has remained higher than in the underdeveloped regions (western China). To investigate how the mediating effect of data flow varies across regions, this study categorized the samples into two subsamples: the eastern and central regions (developed regions) and the western region (underdeveloped regions).

Table 3 illustrates the mediating effects across different regions, with all regressions therein satisfying the relevant diagnostic tests (including the AR (1), AR (2), and Hansen tests). For central and eastern China, Model 2(i) shows that the total effect of ICT infrastructure on economic growth is positive at the 1% level. This indicates that every 1% increase in ICT raises GDP per capita by approximately 1.8596%. The mediating effect of data flow in Models 2(ii) and (iii) is 0.7145 (8.1561*0.0876) and the Sobel test is significant. These results verify H1, H2, and H3 in Model 2, demonstrating the partial mediating effect of data flow in developed regions. The big data initiatives of certain developed countries have been explored, supporting Hajirahimova's and Aliyeva's (2017) view that the use of large volumes of data can enhance the efficiency of decision-making processes and organizational activities, as long as there is adequate support in terms of financial and foundational infrastructure.

Moreover, Model 3 in Table 3 shows a significant positive relationship between *ICT* and *Economy* in western China (Models 3(i) and 3(iii)), indicating that ICT infrastructure directly fosters economic growth. However, the effect of *DF* on the *Economy* is insignificant in Model 3(iii), indicating that the mediating role of data flow in western China is not significant.

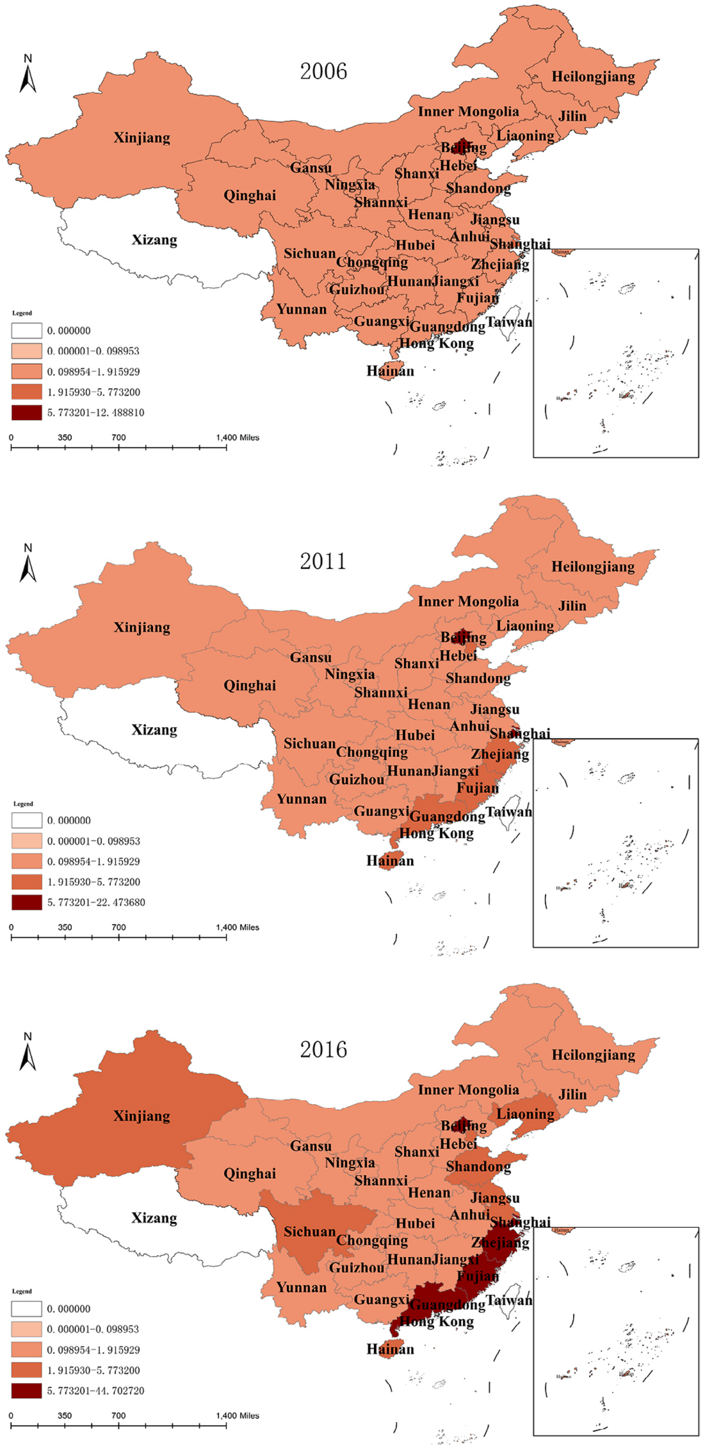

Figure 2. *Continued on next page*

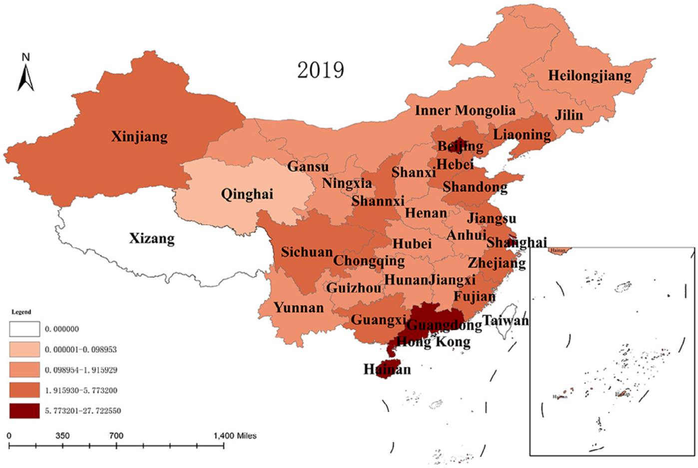

Figure 2. Spatial distribution of China's province-level data flow for the years 2006, 2011, 2016, and 2019, respectively

These findings imply that in economically underdeveloped regions, ICT infrastructure promotes growth primarily through direct effects rather than indirectly via data flow. Two possible explanations may account for this result. First, underdeveloped areas face challenges in achieving the digital transformation of traditional industries. Consequently, relatively few local websites exist to support information sharing within local industries. Second, fewer websites are available in western China, limiting access for developed regions to data resources and computing capabilities in western regions. Small-scale data flow is difficult to empower traditional production factors, such as labor, capital, and technology, and thus there is an insignificant promoting effect on economic growth (Tao et al., 2018).

4.3. Temporal variations in the mediating effects

Various policies and significant events can amplify the mediating effect. The China Smart City report, released in 2009, was followed by several ICT forums in 2010. Notably, the launch of the iPhone 4 in 2010 sparked a global smartphone craze and simultaneously drove the rapid expansion of mobile internet usage in China. These pivotal policies and events around 2010 played a crucial role in the maturation of ICT. Since then, large-scale ICT development has taken place in China, leading to the generation and accumulation of vast amounts of data resources. As such, the application of ICT and data resources can thus be divided into two stages: the initial development stage from 2006 to 2010 and the explosion period from 2011 to 2019. Kurniawati (2020) and Sandoval Hamón et al. (2022) have used data from pre-2010 and post-2010 periods to investigate the relationships between ICT and economic growth in China.

In Table 4, all regressions satisfy the relevant diagnostic tests (AR (1), AR (2), and the Hansen test). Models 4 and 5 indicate that the mediating effect of data flow between 2006 and 2010 is insignificant, but becomes significant thereafter. The results suggest that, after 2010, the rapid development of ICT infrastructure spurred data flow and, in turn, bolstered economic growth. The finding supports Bąk and Borkowski (2015), who argued that policy support and key events are crucial for infrastructure-induced prosperity.

Table 3. Mediating effect of data flow between ICT and economic growth at the regional level

		Central and eastern China			Western China		
Other variables \ Dependent variable		Model 2 (i)	Model 2 (ii)	Model 2 (iii)	Model 3 (i)	Model 3 (ii)	Model 3 (iii)
		Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*	Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*
Independent variable	*ICT*	1.8596*** (0.0976)	8.1561*** (1.0329)	2.3783*** (0.1677)	0.4080*** (0.1316)	0.2451*** (0.0304)	0.3813** (0.1616)
Mediating variable	*DF*	–	–	0.0876*** (0.0163)	–	–	0.0091 (0.3333)
Control variables	*RD*	1.4172*** (0.0918)	4.8561*** (0.5330)	–1.1378*** (0.1159)	1.4012** (0.6717)	0.0782 (0.1877)	2.2811* (1.2836)
	EP	0.2679*** (0.0200)	–2.8236*** (0. 4111)	0.2536*** (0.0310)	0.1370 (0.1722)	0.3386*** (0.0597)	0.4255* (0.2283)
	POP	0.5606*** (0.1153)	12.6640*** (1.7739)	0.2379 (0.1722)	0.1751 (0.3955)	–0.0426*** (0.0858)	–0.6399 (0.5079)
	THR	–0.1528 (0.1140)	3.3678*** (0.8565)	–0.8990*** (0.1289)	1.4502*** (0.4039)	–0.2132** (0.0949)	1.1131*** (0..3537)
Constant		–5.7264*** (1.0271)	–116.1239*** (14.6626)	–0.0087 (1.2119)	–7.1730 (4.4586)	3.7215*** (0.8089)	–1.1626 (3.9915)
Observations		266	266	266	154	154	154
R-squared		0.8121	0.3691	0.8212	0.6256	0.6867	0.6112
Arellano-Bond test for AR (1)		–1.93*	–2.40**	–2.34**	–0.64	–2.18**	–2.25**
Arellano-Bond test for AR (2)		–0.18	0.54	–1.05	1.23	0.54	1.74*
Wald P-value		1479.50***	315.56***	689.38***	111.57***	420.77***	81.09***
Hansen test		0.443	0.186	0.048	0.479	0.671	0.526
No. Instruments		34	28	29	29	30	29
Sobel test		4.4429 > 1.64			0.0273 < 1.64		
95% confidence intervals		[0.3989, 1.0304]			[–0.1579, 0.1624]		
Mediating effect		0.7145***			0.0022		

Notes: The parentheses ( ) indicate standard errors. The significance of the mediating effect was determined using the Sobel test. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. Model diagnostic tests for the system GMM are based on a robust estimation method. Western regions: Inner Mongolia, Guangxi, Sichuan, Chongqing, Yunnan, Xinjiang, Guizhou, Gansu, Qinghai, Ningxia, and Shaanxi. Central and eastern regions: Henan, Hubei, Hunan, Jiangxi, Shanxi, Heilongjiang, Jilin, Anhui, Beijing, Shanghai, Zhejiang, Jiangsu, Tianjin, Guangdong, Fujian, Hebei, Liaoning, Shandong, and Hainan.

Table 4. Temporal variations in the mediating effects of data flow at the national level

		2006–2010			2011–2019		
Other variables \ Dependent variable		Model 4 (i)	Model 4 (ii)	Model 4 (iii)	Model 5 (i)	Model 5 (ii)	Model 5 (iii)
		Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*	Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*
Independent variable	*ICT*	0.5293*** (0.1679)	7.6974*** (2.6943)	0.4257*** (0.1498)	0.4430*** (0.0920)	2.5973*** (0.2150)	0.2816*** (0.0598)
Mediating variable	*DF*	–	–	0.0642 (0.0482)	–	–	0.0722*** (0.0153)
Control variables	*RD*	1.1116*** (0.3264)	6.0678*** (1.7695)	0.4179 (0.3862)	1.1537*** (0.1518)	3.6594*** (0.1915)	0.4245** (0.1640)
	EP	0.5363** (0.2203)	–3.0871* (1.6390)	0.4647*** (0.1530)	0.6080*** (0.1135)	–0.2708*** (0.0478)	0.4356*** (0. 0554)
	POP	–0.2982 (0.4135)	12.3413* (6.4030)	–0.1392 (0.3400)	–0.5858* (0.3550)	1.9841*** (0.4214)	–0.2681 (0.1925)
	THR	.47291 (0.3660)	2.6168 (1.7604)	0.8042*** (0.2789)	0.5123*** (0.1862)	3.2225*** (0.3271)	0.8755*** (0.1222)
Constant		–0.7702 (3.6166)	–111.0871 (53.0394)	–2.1975 (2.6974)	0.9696 (2.9315)	–36.5064*** (4.1109)	–1.0492 (1.6435)
Observations		150	150	150	270	270	270
R-squared		0.7089	0.2326	0.7424	0.6461	0.6977	0.7251
Arellano-Bond test for AR (1)		–2.01**	–2.09**	–2.63***	–1.73*	1.95*	–2.03**
Arellano-Bond test for AR (2)		1.00	1.14	1.05	1.13	0.30	1.23
Wald P-value		179.66***	101.02***	277.11***	102.35***	58.78***	199.88***
Hansen test		0.144	0.309	0.962	0.449	0.135	0.255
No. Instruments		41	28	62	26	33	37
Sobel test		1.21 < 1.64			4.3955 > 1.64		
95% confidence intervals		[–0.3087, 1.2971]			[0.1038, 0.2714]		
Mediating effect		0.4942			0.1875***		

Notes: The parentheses ( ) indicate standard errors. The significance of the mediating effect was determined using the Sobel test. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. Model diagnostic tests for the system GMM are based on a robust estimation method.

5. Discussion

5.1. The role of ICT infrastructure and data flow on economic growth

We find that the total effect of ICT is more prominent in eastern and central China (1.8596***) than in western China (0.4080***). These results prove that in regions with a high ICT level, ICT has a more significant effect on economic growth. Consistent with Philip et al. (2017) and Cariolle (2021), this finding confirms the digital divide in China. Underdeveloped regions (western China) have limited access to digital technologies due to high costs, low market demand, and insufficient supporting facilities, while developed regions (eastern and central China) have greater access to ICT (Samara et al., 2022). This intensifies regional inequality, as ICT can improve citizens' social connections, economic capital, and ability to participate in society. For example, developed regions, which have a concentration of ICT and digital innovation resources, can be more likely to develop smart cities (e.g., intelligent transport infrastructure and smart medical infrastructure), thus leading to economic growth.

In line with Lu et al. (2022), disparities in infrastructure are a major factor behind the wide and persistent imbalance in regional growth. The positive effect of ICT infrastructures on economic growth is similar to that of physical infrastructures, reflecting a Matthew effect (Sun et al., 2021). For instance, in eastern regions with well-developed transportation networks, reduced transport costs and enhanced accessibility for producers, retailers, and customers help improve productivity and efficiency in urban areas. By contrast, remote regions with low transport network density find it difficult to prompt the flow of labor and industry development due to the high transport costs. Consequently, gaps in transportation infrastructure further exacerbate regional disparities in economic growth.

Furthermore, Table 5 confirms the more prominent mediating effect of data flow on economic growth in eastern and central China. Traditional interpretations of the digital divide emphasized emerging ICT disparities as a primary cause, e.g., Jang and Gim (2022), Philip et al. (2017), and Cariolle (2021). Our findings extend this understanding by suggesting that the digital divide is driven not only by ICT gaps but also by data inequality (see Figure 3). As users can access a wide range of data resources via websites, regions with a higher concentration of websites are able to offer more abundant data flows, indicating a stronger promoting effect on local economic efficiency. Given that data flows have the potential to widen regional economic disparities, data inequality represents a new and critical dimension of the digital divide. In developed regions, where ICT infrastructure is more advanced, there are greater opportunities to promote industrial digitalization. Consequently, more industry-specific data can be generated, shared, and diffused through websites, resulting in greater digital dividends. In contrast, underdeveloped regions face considerable barriers in both data access and utilization. This unequal ability to leverage data flows may further exacerbate regional economic imbalances, reinforcing a positive Matthew effect in well-developed areas and a negative one in disadvantaged regions (Philip et al., 2017).

The results from Model 3 indicate that the promotion of the economy in western China is primarily driven by direct effects rather than through the mediating effect of data flow, as also shown by Vu (2011), S. H. Lee et al. (2012), Edquist et al. (2018), Nair et al. (2020), Myovella et al. (2020), Fernández-Portillo et al. (2020), Niebel (2018), Hong (2017), Pradhan et al. (2018), and Haini (2019). As ICT can boost tax revenue and increase profits in the construction industry, building infrastructure such as base stations, communication facilities, and data centers in western China can directly contribute to economic growth. However, it is important to note that this positive effect is marginal. According to Kumari and Singh (2023), the implementation and operation of ICT require significant investment, which can create a substantial financial burden for underdeveloped regions. Investing in ICT without considering regional economic conditions may lead to overcapacity, resource waste, and diminishing returns. Moreover, the insignificant mediating effect of data flow can be attributed to the ineffective diffusion and sharing of data across regions. While some ICT infrastructure has been established in western China (e.g., the supercomputing center in Guizhou), there is a lack of digital platform companies to facilitate data collection, storage, and application.

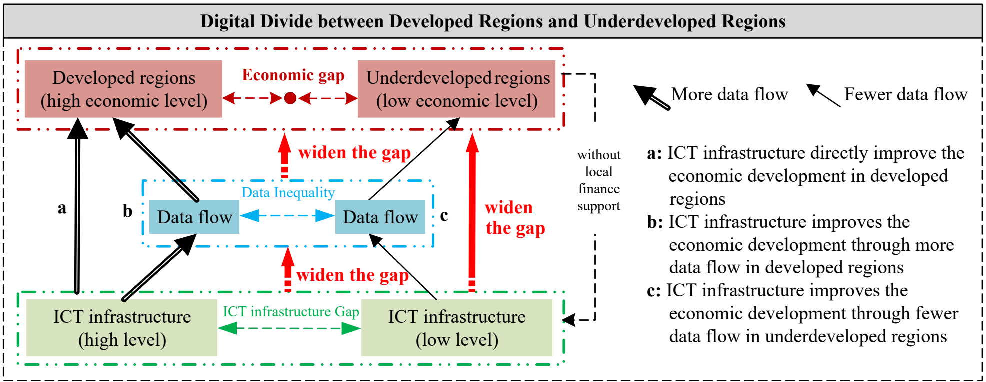

Figure 3. Digital divide between developed and underdeveloped regions

Due to limited energy consumption indicators and high land costs in eastern China, the government has proposed building ICT infrastructure in the western region to store data flow from the east. However, eastern China faces challenges in accessing computing platforms or artificial intelligence centers in the west. As a result, the enabling effect of data flow on traditional production factors remains underutilized (Tao et al., 2018). More digital platforms are needed to allow developed regions to access and effectively use data resources from underdeveloped regions.

Furthermore, the mediating effect of data flow went from insignificant to significant after China's 2010 policies and initiatives, which substantially enhanced ICT infrastructure and data accessibility. This indicates the critical role of policy support and aligns with Reggi and Gil-Garcia (2021), who asserted that national and local ICT policies play critical roles in developing digital skills and infrastructure. The steadily increasing mediating effect from 2006 to 2019 indicates the growing marginal benefits of data-related economic activities. This trend contrasts with traditional production factors (land, capital, and labor) associated with industrial production. According to the information network effect related to data flow, the marginal costs of network construction and data transmission are zero, while the costs of information collection, processing, and production show a significant downward trend (Simoni et al., 2015). Meanwhile, network revenues rise with the expansion of network scale, reinforcing the cumulative advantages of digital infrastructure and data utilization.

5.2. An extended analysis: industrial variations in the mediating effects

ICT infrastructure plays a critical role in driving digital transformation across industries. According to China's National Economic Industry Classification, the economy is divided into three main sectors: the primary sector (e.g., agriculture, forestry), the secondary sector (e.g., industrial production), and the tertiary sector (e.g., transport, logistics, and finance). Following Ding et al. (2020), this study examines both the direct and indirect effects of ICT infrastructure on the primary, secondary (industrial), and selected tertiary sectors. Given the broad scope of the tertiary sector, we focus specifically on transportation and warehousing, as well as the financial sector – two areas of significant economic relevance – to capture sector-specific dynamics and avoid masking heterogeneity across sub-industries (Y. Chen, 2024). To assess economic performance, we use the per capita output values of the primary industry, industrial sector, transportation and warehousing industry, and financial industry. These indicators are derived from data reported in the China Statistical Yearbook.

Models 6(iii) through 9(iii) in Table 5 illustrate the positive direct effects of ICT infrastructure on various specific industries. These results are consistent with previous research (C.-C. Lee et al., 2025; Moldabekova et al., 2021; Oyelami et al., 2022), reinforcing the view that ICT infrastructure significantly contributes to industrial development in the digital era.

Furthermore, as shown in Models 6–9, the mediating effect of data flow is statistically significant in the transportation and warehousing sector as well as in the financial sector, but remains insignificant in the primary and industrial sectors. These findings suggest that data flow functions as a key resource driving digital transformation in certain industries, aligning with insights from Song et al. (2021). Specifically, ICT infrastructure enhances the operational capabilities of road, rail, and logistics systems through advanced data perception, analytics, and predictive modeling across broad spatial and temporal dimensions, thereby significantly improving transportation efficiency. Meanwhile, ICT infrastructure supports the growth of digital finance by increasing the speed, scalability, and accessibility of financial data, enabling innovations such as neobanks, peer-to-peer lending platforms, and real-time payment systems (Ozili, 2018).

In contrast, the absence of a significant mediating effect in the primary and industrial sectors is likely due to their relatively lower levels of digital integration and limited intensity of

Table 5. Mediating effect of data flow between ICT and economic growth at the industry level

		Primary sector			Industrial sector			Transportation and warehousing sector			Financial sector		
Dependent variable / Other variables		Model 6 (i)	Model 6 (ii)	Model 6 (iii)	Model 7 (i)	Model 7 (ii)	Model 7 (iii)	Model 8 (i)	Model 8 (ii)	Model 8 (iii)	Model 9 (i)	Model 9 (ii)	Model 9 (iii)
		Step 1: *Pri_ Economy*	Step 2: *DF*	Step 3: *Pri_ Economy*	Step 2: *DF*	Step 2: *DF*	Step 3: *Trans_ Economy*	Step 1: *Trans_ Economy*	Step 2: *DF*	Step 3: *Trans_ Economy*	Step 1: *Finan_ Economy*	Step 2: *DF*	Step 3: *Finan_ Economy*
Independent variable	*ICT*	0.4521*** (0.0205)	4.1952*** (0.3165)	0.3828*** (0.0210)	0.9773*** (0.0449)	4.1952*** (0.3165)	0.9845*** (0.0431)	1.9763*** (0.0405)	4.1952*** (0.3165)	2.1523*** (0.0450)	2.8294*** (0.0567)	4.1952*** (0.3165)	1.8063*** (0.0850)
Mediating variable	*DF*	–	–	0.0030 (0.0024)	–	–	0.0034 (0.0147)	–	–	0.0807*** (0.0109)	–	–	0.2413*** (0.0224)
Control variables	*Control Variables*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		420	420	420	420	420	420	420	420	420	420	420	420
R-squared		0.7706	0.4480	0.7049	0.6699	0.4480	0.6807	0.8659	0.4480	0.8037	0.7691	0.4480	0.7927
Arellano-Bond test for AR (1)		–1.73*	–2.28**	–2.22**	–1.94*	–2.28**	–1.65*	–1.75*	–2.28**	–1.82*	1.68*	–2.28**	1.72*
Arellano-Bond test for AR (2)		0.92	0.73	0.90	0.24	0.73	0.13	1.54	0.73	1.04	1.07	0.73	0.89
Wald P-value		158.38***	272.68***	135.37***	286.21***	272.68***	275.85***	3824.25***	272.68***	277.11***	109.48***	272.68***	156.09***
Hansen test		0.110	0.180	0.121	0.460	0.180	0.127	0.164	0.180	0.137	0.538	0.18	0.132
No. Instruments		28	39	31	28	39	28	41	39	32	48	39	41
Sobel test		1.2445 < 1.64			0.2428 < 1.64			6.4637 > 1.64			8.3597 > 1.64		
95% confidence intervals		[–0.0073, 0.0328]			[–0.1066, 0.1349]			[0.2362, 0.4411]			[0.8941, 1.3503]		
Mediating effect		0.0126			0.0143			0.3386***			1.0123***		

Notes: The parentheses ( ) indicate standard errors. The significance of the mediating effect was determined using the Sobel test. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. Model diagnostic tests for the system GMM are based on a robust estimation method.

data flows. The large-scale, conventional production processes typical of these sectors often require longer time horizons to realize the benefits of ICT infrastructure. Unlike tertiary industries, where data flows can directly enhance efficiency and inform real-time decision-making, the primary and industrial sectors tend to be less responsive to data-driven transformation, thus limiting the mediating role of data flow in improving economic outcomes.

5.3. Theoretical implications

This study makes important theoretical contributions. First, as the scale of data flow has increased exponentially in recent years, data flow has been considered a new production factor that drives economic growth. This study extends the production factors (labor, capital, technology) to include data flow. Specifically, we empirically demonstrate the positive effect of data flow on growth, complementing that ICT and data flow can be included in economic growth theory in the digital economy era. The finding further provides a new theoretical perspective for understanding the driving force of growth in the digital economy era.

Second, previous studies have emphasized the digital divide in terms of ICT gap, including ICT access, usage, and outcomes (Cariolle, 2021; Philip et al., 2017). In fact, regions with stronger data flows have greater impacts on economic growth, indicating that data flow can widen the economic gap across regions. This study complements the understanding of the digital divide, arguing that, in addition to the ICT gap, data flow inequality should also be considered among the potential causes of the digital divide.

5.4. Policy implications

This research provides practical and insightful implications for policymakers. As previously mentioned, the composite index of ICT levels was used to verify its positive effect on economic growth. Consequently, governments are encouraged to implement effective policies and offer subsidies to enhance ICT infrastructure, particularly in mobile phones, mobile internet, and broadband technologies, to stimulate economic growth. For example, offering matching funds or preferential tax incentives (such as waiving import duties on essential ICT hardware) to private telecom companies could facilitate network expansion (Jurado-González & Gómez-Barroso, 2022). The widespread adoption of ICT would enable businesses to reap greater benefits by improving production efficiency.

Empirical evidence from the models above also underscores the crucial role of data flow in a country's growth. Future policies should focus on deploying data-related ICT infrastructure to maximize the efficient use of data flow (Lythreatis et al., 2022). Specifically, for data with high access frequency and ultra-low latency, relevant ICT infrastructure (e.g., edge computing base stations) should be constructed locally (Caiazza et al., 2022), while off-site infrastructure can be used to store and analyse data with lower access frequency and higher latency. For instance, in autonomous driving scenarios, local base stations can collect and process traffic data in real-time, while financial institutions can use off-site ICT infrastructure to back up customer data. This approach would not only facilitate the efficient storage and analysis of data but also enhance the overall effectiveness of ICT utilization.

Furthermore, the heterogeneous effects of ICT and data flows on economic growth across more developed and less-developed regions have exacerbated the digital divide within China. In response, China has prioritized addressing the regional gaps in digital skills and capital investment (Peng & Dan, 2023). The digital divide, however, remains a global challenge. In contrast to China's approach, the EU's Digital Compass and South Korea's Smart City initiative explicitly focus on narrowing regional gaps in digital infrastructure and technological innovation; and Singapore's Smart Nation strategy focuses more on closing socio-demographic gaps in digital access and capabilities (Sweeney & Winn, 2022; Yang et al., 2021). From the perspective of spatial and governance scale, China's digital-divide agenda is primarily concerned with development imbalances between urban and rural areas; the EU's Digital Compass seeks to ensure coherence across countries (member states); South Korea's smart-city agenda operates mainly at the urban and community scale, developing flagship smart-city exemplars; whereas Singapore's Smart Nation strategy focuses less on spatially defined digital disparities and more on digital gaps between different social groups.

Targeted policies tailored to the specific needs of different regions should be designed to effectively address and alleviate the digital divide in China. Policymakers in developed regions can prioritize enhancing ICT network connectivity and promoting the integration of ICT into diverse industries (e.g., e-commerce and digital transportation) and government sectors (e.g., e-government) to improve operational efficiency (Vu, 2011). Additionally, governments in developed regions are expected to enact effective measures, such as establishing a unified data standard framework, to fully leverage the benefits of data flows. For example, governments can define clear data classification standards and develop comprehensive metadata specifications to enhance data security, interoperability, and credibility, thereby further supporting digital innovation (Vetrò et al., 2016).

In contrast, ICT and data flow have yet to significantly impact economic growth in underdeveloped regions (western China). One possible reason for this limited impact is the high investment costs coupled with constrained local financial resources, highlighting the necessity for targeted policy support. Policymakers in western China should implement inter-provincial and inter-organizational economic strategies to expand ICT facilities, such as leveraging technical and financial resources from private entities and governmental bodies in ICT-developed regions (Liu et al., 2025). Additionally, the governments in western China should promote the provision of remote ICT services from underdeveloped to developed regions, such as cloud computing operations and maintenance, network security monitoring, and data storage, which can help increase the fiscal revenues in underdeveloped regions. Furthermore, there is a need for governments in western China to introduce incentive measures, such as financial support or tax incentives, thereby stimulating data openness and sharing across departments, regions, and industries. By referring to the theory of the digital divide, another critical strategy involves improving digital literacy and education, particularly among the younger generation. Developing a workforce skilled in data analytics will empower western China to better leverage data resources (Hasbi & Dubus, 2020; Vahid Aqili & Isfandyari Moghaddam, 2008). Ultimately, these policies can help bridge the ICT gap, reduce data flow inequalities, and thereby eliminate rural-urban inequalities in economic growth. There is a need for governments in western China to collaborate with digital platform companies to enhance access to information and promote data-sharing initiatives. For instance, Yunmanman is a Chinese digital transportation platform that connects cargo owners with truck drivers via mobile and web apps. This platform can help mitigate digital inequalities by providing more equal opportunities for mobility, especially for residents in underdeveloped areas (Wei et al., 2024). Another example is e-commerce platforms such as Alibaba and JD.com, which play a pivotal role in expanding market access for businesses in western China. These platforms also assist rural entrepreneurs in navigating digital mobility systems and e-commerce tools by providing essential training and technical support. This, in turn, would boost economic opportunities in underserved regions and help bridge the digital divide.

5.5. Robustness analysis

To ensure the consistency of our results, we performed several robustness checks (see Table 6). First, instead of using mobile phones, internet usage, and broadband subscriptions, we used fixed investment in information transmission infrastructure per unit area as the proxy for ICT infrastructure level (see Model 10) (Mano, 2021). We measured this variable as the ratio of fixed investment in information transmission infrastructure to the area of each province. Second, we excluded four municipalities (Beijing, Shanghai, Tianjin, and Chongqing) as their distinct economic structures compared to other regions in China (see Model 11). Third, to account for the influence of external factors on economic outcomes (see Model 12), we included additional control variables: global trade (*GT*), intellectual property regulation (*IPR*), and foreign technology introduction level (*FTI*). Following previous literature e.g., Dollar and Kraay (2004), and Park (2008), we used the logarithm of import and export values, the ratio of patent authorizations to patent applications, and per capita foreign technology acquisition expenditure to represent the *GT*, *IPR*, and *FTI* variables. Finally, referring Jha (2019), and Rezgallah et al. (2019), we collapses the instrument matrix to avoid instrument proliferation. The results from Models 10–13 remain consistent and robust, further validating the impact of ICT infrastructure on economic growth, with data flow intensity mediating this relationship.

6. Conclusions and future research

The significant development of ICT infrastructure over the past decade has contributed to productivity and economic growth. With the rapid increase in data availability globally generated by ICT infrastructure, data flow has become a new production factor with unprecedented efficiency and infinite value. Therefore, examining the mediating effect of data flow on the relationship between ICT infrastructure and economic growth from a spatiotemporal heterogeneity perspective is crucial for optimizing ICT investment and improving the economy.

Addressing the first research question, this study uses PCA to establish a composite index of ICT levels, including mobile cellular, internet usage, and broadband. ICT can directly stimulate economic growth. Meanwhile, data flow, a new production factor, mediates the relationship between ICT and economic growth in the digital economy era. For the second research question, we verify the mediating effect across regions with different economic levels and during different periods. The mediating effect of data flow is more significant in developed regions (central and eastern China) than in underdeveloped regions (western China).

Table 6. Robustness test results

Other variables / Dependent variable		Model 10 (i)	Model 10 (ii)	Model 10 (iii)	Model 11 (i)	Model 11 (ii)	Model 11 (iii)	Model 12 (i)	Model 12 (ii)	Model 12 (iii)	Model 13 (i)	Model 13 (ii)	Model 13 (iii)
		Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*	Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*	Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*	Step 1: *Economy*	Step 2: *DF*	Step 3: *Economy*
Independent variable	*ICT*	1.3353*** (0.2443)	8.0198*** (2.0002)	1.3416*** (0.2360)	1.4419*** (0.0751)	0.5325*** (0.1366)	0.3515*** (0.0193)	0.7264*** (0.0419)	5.6138*** (0.6863)	0.5608*** (0.0455)	0.3547*** (0.1322)	7.1139*** (1.9787)	1.4062*** (0.2176)
Mediating variable	*DF*	–	–	0.0984*** (0.0111)	–	–	0.2811*** (0.0226)	–	–	0.0877*** (0.0110)	–	–	0.1145** (0.0489)
Control variables	*RD*	0.9898*** (0.1071)	11.1129*** (0 9464)	0.2972** (0.1298)	0.5295*** (0.0993)	2.2270*** (0.1655)	1.5445*** (0.0810)	1.5516*** (0.1139)	3.9112*** (0.5976)	0.7461*** (0.1250)	1.306 (1.0350)	8.1097*** (1.6597)	–0.6299 (0.7335)
	EP	0.4777*** (0.0614)	–1.8093*** (0 .2623)	0.4485*** (0.0594)	0.2411*** (0. 0228)	0.4245*** (0.02605)	–0.02826 (0.0212)	0.2915*** (0.0330)	–2.3654*** (0.2611)	0.4105*** (0.0345)	0.0483 (0.0773	–5.7608*** (1.7090)	0.5639*** (0.0786)
	POP	–1.0805*** (0.0865)	2.6270 (1.6647)	–0.8048*** (0.0892)	0.6428*** (0.0860)	–3.4125*** (0.2641)	0.4301*** (0.0473)	0.3138*** (0.0997)	8.2851*** (1.0853)	0.1686* (0.0982)	0.7031*** (0.0878)	19.3416*** (5.8192)	–0.0247 (0.2382)
	THR	0.3407*** (0.1196)	–2.7887* (1.4750)	0.4196*** (0.1158)	0.2388*** (0.0571)	–1.2644*** (0.2276)	1.5523*** (0.0492)	0.6390*** (0.0811)	1.7964*** (0.4424)	0.7858*** (0.0824)	2.4290*** (0.4587)	5.3498*** (0.9130)	0.7279** (0.3211)
	GT	–	–	–	–	–	–	–0.2874*** (0.0501)	1.5672*** (0.6050)	–0.3358*** (0.0517)	–	–	–
	IPR	–	–	–	–	–	–	4.2618*** (1.0788)	37.9495*** (8.9769)	0.1892 (1.0843)	–	–	–
	FTI	–	–	–	–	–	–	–0.038*** (0.010)	0.030 (0.064)	–0.0246** (0.0097)	–	–	–
Constant		6.2046*** (0.8693)	–19.2139 (17.1763)	4.5413*** (0.8605)	–6.2824*** (0.7927)	29.0261*** (2.3134)	–9.3623*** (0. 4788)	–2.75** (1.2313)	–105.6244*** (9.0784)	0.0067 (1.2375)	–15.3986*** (0.8637)	–168.2959*** (45.7692)	–3.095 (2.0912)
Observations		420	420	420	364	364	364	420	420	420	420	420	420
R-squared		0.6888	0.3638	0.7050	0.6020	0.2900	0.7061	0.7443	0.3476	0.7464	0.7222	0.1030	0.5764
Arellano-Bond test for AR (1)		–2.28**	–1.78*	–2.00**	–1.64*	–2.22**	1.69*	–1.68*	–2.56**	–2.32 **	3.14***	–3.15***	–5.78***
Arellano-Bond test for AR (2)		0.93	–0.27	0.86	1.26	–0.16	–1.44	0.59	0.25	0.48	–0.01	1.24	1.55
Wald P-value		83.64***	140.48***	113.47***	232.58***	67.16***	111.57***	1641.85***	805.37***	758.76***	7954.63***	298.05***	4149.89***
Hansen test		0.662	0.454	0.629	0.536	0.238	0.312	0.112	0.129	0.542	0.013	0.597	0.379
No. Instruments		52	21	52	42	29	42	42	30	53	7	9	10
Sobel test		3.6532 > 1.64			3.7198 > 1.64			5.7093 > 1.64			1.9635 > 1.64		
95% confidence intervals		[0.3656, 1.2130]			[0.0708, 0.2285]			[0.3235, 0.6612]			[0.0015, 1.6277]		
Mediating effect		0.7891***			0.1497***			0.4923***			0.8146**		

Notes: The parentheses ( ) indicate standard errors. The significance of the mediating effect was determined using the Sobel test. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. Model diagnostic tests for the system GMM are based on a robust estimation method.

In addition to the ICT gap, this study further argues that a potential cause of the digital divide is data flow inequality. Meanwhile, ICT infrastructure's impact on economic growth and its mediating effect through data flow shifted from being insignificant (2006–2010) to significant (2011–2019) with the introduction of ICT policies. We also identify sector-specific impacts of ICT infrastructure and data flow, demonstrating that ICT notably contributes to industry-specific development. Data flows play a mediating role in specific industries such as transportation and warehousing and finance. As a result, the third research question is addressed as effective and targeted recommendations, such as deploying data-related ICT infrastructure, promoting trading systems for big data resources, developing specific investment policies of ICT infrastructure (e.g., transfer payments), and eliminating ICT-related capability inequalities caused by gender and rural-urban divides. Together, these measures provide guidance for strengthening ICT infrastructure and fostering more balanced economic growth.

Despite its contributions to the literature, future research is needed to address certain limitations. First, this study uses the number of websites per capita as a proxy for data flow, which may not fully capture all relevant dimensions. In addition, the website data primarily cover public websites, excluding non-commercial or inactive sites that are more difficult to access, limiting the diversity of opinions and the generalizability of the results. Future research should employ additional indicators and draw on broader datasets as more comprehensive information becomes available. Moreover, while the control variables selected for this study are reasonably appropriate, future research could consider adopting micro-level frameworks (such as firm-level data on data exchange and utilization) if such data become available, to further reduce the influence of confounding variables. Furthermore, the significant positive effect of ICT on economic growth has been empirically confirmed in the context of China. However, given that ICT policies and socio-economic environments differ across countries, future research could broaden its data collection to improve the generalizability of these findings and account for cross-country variations.

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Dislosure statement

The author declare that they have no competing interests.

Author contributions

Rui Liu: conceptualization, data curation, formal analysis, software, funding acquisition, methodology, writing – original draft. Jingfeng Yuan: conceptualization, data curation, formal analysis, software, supervision, funding acquisition, methodology, writing – review & editing. Bing Zhu: methodology, supervision, writing – review & editing. Lei Zhang: data curation, methodology, formal analysis. Bingsheng Liu: conceptualization, funding acquisition, supervision.

Data availability statement

The data supporting this study's findings are available from the corresponding author upon reasonable request.

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